A quantitative analysis of politically right-leaning residents' attitudes to climate assemblies and climate policy in rural England.

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Abstract

This interdisciplinary thesis considers the views of English rural residents in climate policy-making, incorporating both spatial and ideological dimensions of identity. I ask how the perspectives of rural, politically right-leaning residents could be better incorporated in climate policy-making, and situate the research within ongoing tensions by highlighting the broken social contract whereby rural communities are exploited for climate solutions while neglected in policy support.

After reviewing literature on political identities (populism, nationalism, and conservatism) and their interactions with rural concerns such as landscape, place attachment, and tradition, the thesis addresses three research questions. First, does political identity lead to differential rates of participation in Climate Assemblies and differences in attitudes towards their legitimacy? Second, how can resistance to rural climate policy initiatives be reliably measured? Third, what are the pathways by which political identity, populism, and rural identity shape resistance to rural climate policy in England?

In addressing the first question, I use evidence from multiple Climate Assemblies and an original survey to demonstrate that political identity shapes willingness to participate, as well as views on process design, raising questions about assumed political neutrality in standard recruitment practice.

I then develop a novel, psychometrically validated scale measuring Resistance to Rural Climate Initiatives (RRCI) and apply this in a Path Model to address the remaining research questions. This reveals divergent causal routes to policy resistance across party groups, repositioning Conservatism as a statistical centre-ground driven by protective rurality and national identity, and demonstrating that Reform UK resistance operates through a substantially different and more ideologically oppositional structure.

By combining practitioner insight with robust quantitative methods, this thesis advances understanding of the political, cultural, and spatial barriers to inclusive climate policy-making in rural England.

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Author Declaration

I, the undersigned hereby declare that I am the sole author of this thesis.

To the best of my knowledge this thesis contains no material previously published by any other person except where due acknowledgement has been made.

This thesis contains no material which has been accepted as part of the requirements of any other academic degree or non-degree course, in English or in any other language.

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Rachel T. Coxcoon, November 2025

1 Introduction

1.1 Background

In 2021, I left a senior role in an environmental charity where I had worked for 16 years, to undertake doctoral research, a move that resulted from a gradual accretion of concerns about whether the work I had been doing would have impact where it really mattered.

I had led a team developing local responses to the challenge of climate change across England and, over a decade, I had trained hundreds of community energy activists, local politicians, and planners. Having noted that support for renewable energy often fractured along political lines within local communities, I'll admit that, at least in the early years, this phenomenon elicited no particular intellectual engagement from me: as a senior representative of a left-leaning environmental charity with strongly held collective norms on the importance of global social justice, it was clear to me that 'the conservatives' were just plain wrong. Parochial attachments to unspoiled views, when set against the survival of vulnerable communities on the other side of the world, seemed no more than transparent selfishness hidden behind veils of 'heritage preservation' and 'local character'.

Doubts began to creep in as it became more obvious that resistance to *community-owned* renewable energy (particularly politically segmented opposition) was often markedly lower than for very similar *commercially-led* infrastructure projects. A significant jolt occurred when I had the opportunity interview a prominent anti-wind campaigner. Having failed to prevent construction of commercially owned turbines near his village, he'd channelled unused campaign funds to a similar campaign a few miles away. When that also failed, both communities had helped a third, not even particularly close to them, and then another. Of course he understood that wind turbines work, he told me. Of course he was worried about

climate change. But then he said something that resonated so strongly that I still recall it now: "*I don't know how I got here. I feel like Wat Tyler[1]. I feel like I'm at the head of an angry mob. Nobody listens, they just ride roughshod over us.*" For me, this interview was eye-opening and, along with similar subsequent interviews, moved me from a position of dismissiveness about NIMBYism or selfishness, to questions of agency, ownership, scale, community and perceptions of fairness around who ought to benefit.

This ultimately led me to develop practitioner resources for detailed community-led energy planning, including the Future Energy Landscapes method (Coxcoon, 2016), on the straightforward premise that, if people's primary sphere of moral concern and practical engagement is their immediate locality (maybe only at the scale of a couple of villages), then energy planning should also happen at that scale. Rather than framing renewable energy as a response to a global crisis (which requires people to subordinate local concerns to abstract, distant obligations), I sought to design processes that focused on local benefits, decentralised infrastructure, and transparent local reinvestment of profit.

Working increasingly with rural communities also forced me to confront my own urban privilege, in relation to 'sustainable living'. Having reflexively associated the greenness of rural areas with sustainable lifestyles, I had not fully appreciated the challenges of living a truly sustainable life in such spatially disconnected communities. I had not needed a car in the city; there were buses every few minutes and all necessary amenities within walking distance. But workshops in rural areas revealed a different material reality; limited public transport, greater distances to services, and older and less energy-efficient housing stock, meant unavoidably higher carbon footprints simply as a function of where people lived.

One rural workshop provided another jolt to my urban consciousness when a participant left one breakout group in tears while I worked with another. She never returned, and when I asked the other participants, they said it had been triggered

[1] Wat Tyler was the unofficial leader of the Peasant's Revolt in 1381, one of the most significant popular uprisings in English history.

by the group talking about the need for veganism. She got in contact that evening. A fourth-generation beef farmer, she apologised for her emotional outburst and sudden exit, explaining that, over a few short years, her entire family story seemed to have been recast from 'guardians of the countryside' to 'evil villains', and how hard she was finding it to adjust to what she felt as constant opprobrium.

Over time, I began to conceptualise the contestation of climate policy in rural places as embodying a kind of broken social contract between urban and rural areas, a form of 'rural exploitation', with rural areas seen as zones of opportunity for climate solutions (sites for wind farms, solar arrays, and forestry plantations for carbon sequestration). Industrial-scale environmental interventions are regularly imposed on the countryside, often with profits flowing elsewhere, while the specific environmental challenges facing rural households and communities (transport poverty, housing inefficiency, land price inflation driven by carbon offset schemes competing with local agriculture), receive comparatively little policy attention or funding, and farmers feel increasingly demonised.

However, I found that this conception of rural exploitation in the wider field of climate activism did not always find a willing audience, because it challenged comfortable narratives in which rural resistance to renewable energy could be straightforwardly read as affluent reactionary, conservative obstruction of progress, rather than as a comprehensible response to a pattern of extraction, neglect and cultural dismissiveness. Similarly, straightforwardly embracing a 'conservatively localist' approach to energy projects within some grant-funded projects required contending with funder imperatives emphasising conceptions of abstract rights, and global justice, or the comprehensive inclusion of every conceivable minority group. Organisational culture seemed increasingly to demand that every document must signal adherence to a particular cosmopolitan worldview, regardless of its relevance to the specific context or community.

The final catalyst came through my unexpected entry into local politics. Having moved to a rural area, I stood as a Liberal Democrat in the Cotswold District Council election in 2019, motivated by frustration with poor local planning policy. In a result

surprising enough to make news in Germany, the 'ever-Conservative' Cotswolds flipped to Liberal Democrat control. Having been permitted to insert ambitious environmental commitments into a manifesto nobody really expected we would implement, I became, almost overnight, Cabinet Member for Climate Change and Forward Planning for a local authority covering over 1,000 square kilometres, including most of the Cotswolds Area of Outstanding Natural Beauty, one of the most iconic landscapes in the UK. Returning to my urban charity office in Bristol, filled with like-minded progressives, became increasingly jarring. An urban outsider in the rural area where I now lived and served, I felt increasingly like a rural outsider in the urban professional world I still inhabited. I came to suspect that the things I had taken for self-evident truths were merely the social norms of my particular professional and political milieu. Everything was oriented around globalist frameworks and abstract language about rights and justice.

The sudden proliferation of Citizens' Assemblies on climate change occurred at exactly that time, during the heightened public concern over climate change following publication of the IPPC's 2018 Special Report on limiting future temperature rises to less than 1.5˚C. Such assemblies seemed to be an obvious democratic good: more deliberation means more participation means more policy legitimacy, surely? But among Conservative politicians with whom I regularly interacted or trained, they were viewed with deep suspicion, a procedural sleight of hand designed to smuggle through a radical agenda. What I saw as democratic *enhancement,* they saw as democratic *subversion,* and once again, I began to wonder if these might be just different values, not positions that were inherently right or wrong.

It finally occurred to me that I had never really paused to examine the difference between my normative preferences and what I had assumed were objective truths, or indeed, whether such a distinction was ever even coherent. The body of research presented here largely emerged from that rather unsettling recognition.

1.2 Research Question

Drawing on the narrative laid out above, this thesis aims to centre the views of politically right-leaning individuals in the process of climate policy making. I first posed the following over-arching research question: "***How can climate policy making be made more inclusive of the views and concerns of rural, politically right-leaning communities in England?"***

To answer this question, I examined two aspects of English climate policy-making. Firstly, the climate policy-making process itself, through examining whether the democratic innovation of Citizens' Assemblies on climate change are more or less acceptable to people with different political world views. Secondly, I examine rural publics' attitudes to the specific types of climate policies that will need to be deployed in rural areas, through the development of a new measurement instrument, and advanced causal modelling techniques.

As my Literature Review progressed and designs for the empirical work progressed, more specific research questions emerged that provided more specific, workable frameworks for data collection and analysis:

1. Does political identity lead to differential rates of participation in Climate Assemblies and differences in attitudes towards the legitimacy of these policy-making forums? (See Chapters 4 & 5).
2. How can resistance to rural climate policy initiatives be reliably measured? (See Chapter 6).
3. What are the pathways by which political identity, populism, and rural identity shape resistance to rural climate policy? (See Chapter 7).

1.3 Situating the research questions

1.3.1 Situating the research in the literature

Understanding levels of support for climate policy is an intensely-researched area of scholarship, in particular, the impact of political partisanship on support for climate policy (which is explored further in Section 2.5 of the Literature Review).

Many papers link conservatism, populism, or both together as predictors of reduced climate policy support (see for example, McCright and Dunlap, 2011, 2013; Severson and Coleman, 2015; Singh and Swanson, 2017; Hamilton, 2018; Huber, 2020; Kulin, Johansson Sevä and Dunlap, 2021). However, a significant proportion of the research has a US focus, and other scholars suggest caution in extrapolating US research on conservative attitudes to climate policy outside of the USA itself, due to its uniquely partisan political system (Båtstrand, 2015; Hornsey, Harris and Fielding, 2018; Smith and Mayer, 2019). Additional research from within the UK also points to a the substantial influence of right-wing populism on reduced support for climate policies, and the Conservative-Libertarian tensions that have led to fluctuating support on the centre-right (Carter, 2014; Carter and Clements, 2015; Lockwood, 2018; Carter and Little, 2021; Lockwood and Lockwood, 2022).

A rural-urban gap in support for climate policy has also been noted in research, principally in the US and Scandinavia (for example, Brobakk, 2018; Bonnie, et al, 2020; Mittenzwei et al., 2023), and recently-published UK-specific research demonstrates that urban residents are more supportive of mandatory climate targets and that lower population density predicts lower support for policies that restrict transport choices (Bretter and Schulz, 2023).

Taken as a whole, the existing scholarship suggests both political (left-right) and spatial (rural-urban) dimensions to support for climate policy, but leaves a research gap in relation to the situation in England specifically. In addition, while the body of evidence comparing rural and urban communities is insightful, it leaves open the question of whether it is rurality per se, or political identity, which is the main driver of differential support for climate policy. Only by conducting a 'within-rural' (rather than 'between-urban-and-rural') study can this be explored. In addition, while the provisions of the Climate Change Act operate at a UK-wide level, England's overwhelming dominance in population terms (compared with the other constituent parts of the UK) means that what England wants, England gets (as the lesson of Brexit shows us, on which see Henderson et al., 2017). Understanding English policy preferences, and English national sentiment is therefore fruitful for the UK as a whole.

This research contributes to filling those gaps by focusing on rural English communities, using political alignment as a lens through which to examine support in rural communities for both how climate policy is made, and what it contains.

1.3.2 Situating the research in the UK climate policy context

The UK's Climate Change Act (2008) was the first of its kind. Though closely followed by a similar piece of legislation in France, it represented the first time that a national legislature had self-imposed a target for emissions reductions and enshrined this into national law[2]. It legislated initially for an 80% reduction in the UK's greenhouse gas emissions by 2050, based on a 1990 baseline, and established the Committee on Climate Change (CCC) to act as an independent advisor to government on modelling, carbon budgeting and progress reporting.

The Act survived unscathed from the Labour administration, through the Conservative-Liberal Democrat coalition of 2010-2015, and the subsequent carousel of Conservative Prime Ministers Cameron, May, Johnson, Truss and Sunak under Conservative majority rule from 2015 to 2024. Theresa May's administration, in 2019, strengthened the initial targets from an 80% reduction by 2050 to 'net-zero' by 2050, based largely on the recommendations of the CCC (Committee on Climate Change, 2019), and modelling work by the Intergovernmental Panel on Climate Change (IPCC, 2018). In doing so, the May administration inadvertently pushed the technocratic terminology of 'Net Zero' firmly into the public consciousness, arguably creating fertile ground for later accusations of bureaucratic target-chasing for the then incipient but now fully-fledged new political force of the political right, Reform UK, whose leadership have made no secret of their disdain for the term and its targets (BBC News, 2024; Lepone, 2025; Moore, 2025; Parkin, 2025).

[2] https://www.legislation.gov.uk/ukpga/2008/27/pdfs/ukpga_20080027_en.pdf (Legislation as enacted, 2008), current version available at https://www.legislation.gov.uk/ukpga/2008/27/contents

For the emissions mitigation targets associated with the Climate Change Act to become a reality, wholesale changes will be required across the UK. Energy generation, transmission and distribution will need to transition from centralised power generation (from increasingly imported fossil fuels) to decentralised, locally generated renewable and nuclear power. Heat loads will need to shift from gas to electricity. New transport hierarchies will require sizeable transport modal shifts, minimising the use of internal-combustion engine vehicles, maximising the use of active and public travel, and replacing remaining motorised transport with electric vehicles[3] (Climate Change Committee, 2025b). Food and diets will need to be transformed, with plant-based meals replacing a substantial proportion of those that currently contain meat, and the potential for novel sources of protein to be incorporated. Consumer demand for goods will need to fall, with a focus on re-use and minimising the use of virgin materials in supply chains. The energy efficiency of the UK's building stock, among the worst in Europe (Baker et al., 2022), will have to radically improve, with new building designs increasingly replacing familiar vernacular architecture.

Climate change *mitigation*, through this emissions reduction, is only one side of the story; policy targets also show how the UK will need to *adapt* to the climate changes already locked-in as a result of past emissions, and contribute to ongoing sequestration (carbon capture and storage). Carbon capture forestry, re-wetting of carbon stores such as peatlands and marshlands, and upland tree planting to slow the progress of stormwater runoff through major water catchment areas will increase. (DEFRA, 2023b, 2023a; IUCN UK, 2024 p.21).

At a 'big-picture' level, the CCC have stated that the provisions of the Climate Change Act could be delivered at a cost to the UK of just under 0.2% of GDP per annum to 2050, which modelling suggests would be largely offset by associated savings to the

[3] Notably, the most recent modelling from the CCC all but abandons the idea of modal shift in rural areas, focusing largely on urban areas for public and active travel and modelling the shift in rural areas as almost exclusively based switching to EVs. What could be read as pragmatic 'big lever' policy advice could also be read as dismissiveness of rural communities.

public purse, principally in savings in public health spending (Climate Change Committee, 2025b).

1.3.3 Situating the research in rural areas

The aforementioned 'big picture' ambition will, in reality, need to be delivered through a series of 'little pictures'; a vast assortment of policy imperatives, delivered through a collection of policy directives, regulatory and planning frameworks (responsibility for which sits with multiple government departments), as well as through a complex mix of public and private financial mechanisms.

Crucially, those 'little pictures' are overwhelmingly place-based, and there are intrinsic inequalities related to which areas of the country must host the most significant infrastructural changes, and which areas of the country are likely to receive the bulk of policy attention for household-level support. Rural areas are largely viewed as areas of 'big-lever' opportunity to solve the climate crisis; the wind farms, solar farms, electricity transmission infrastructure, carbon capture forestry plantations, and altered agricultural practices will largely be situated in the countryside.

But the household-level support, which will more likely improve individual household circumstances, is concentrated in urban areas. For a combination of reasons, including of economy of scale (for public and active transport infrastructure), the potential to more easily retrofit vast numbers of architecturally and structurally similar building in urban areas, and larger, better staffed urban authorities that can better access competitive funding, climate policy support that directly improves daily lives for UK citizens has tended to be targeted at cities and towns. (Hearn, 2021; Philips and Dyson, 2023). While at the big picture level, models can be built of wholesale transport modal shift, improved housing, and dietary changes, the policy delivery is often short-term, spatially restricted, and temporally disjointed. In particular, no coherent plan or funding mechanism exists to deliver alternative transport infrastructures in rural areas, and what services did exist have already reduced sharply (Burbidge, 2023; National Audit Office, 2025).

When combined with measurable cultural and political differences between rural and urban populations (Bell, 2010; Claassen, et al, 2024), and the wider importance of rural landscapes to national identities (Darby, 2000; Readman, 2008, 2018), lack of attention to this inequality is likely to exacerbate social differences between rural and urban areas, creating a sense of grievance that is easily manipulated for short-term political gain by those who wish to undermine climate action in general.

1.3.4 Situating the research in English political realities

In England particularly, the focus of this thesis, rural and urban areas display markedly different political character. When I began this research, of the 24 County Councils in England, 21 were Conservative controlled. By contrast, 30 of the 36 Metropolitan boroughs (unitary councils dominated by large urban areas) were Labour controlled, along with most London boroughs. Of the remaining 58 unitary councils (large 'county-sized' councils that combine the responsibilities of county and district) the 26 that were overwhelmingly rural in nature were also Conservative controlled. Of the remainder, the 18 Labour-controlled unitary councils were overwhelmingly urban, and a smattering of Liberal Democrat, one Green control, and a handful of coalition-controlled unitaries made up the difference. The parliamentary picture was similar. Thus, while only 9.7 million of England's 56.6 million residents live in rural areas, their elected representatives (overwhelmingly Conservative) between them had policy control over the statutory bodies controlling around 90% of England's land area.

Fast-forward four years, and the rise of Reform UK has changed the electoral map somewhat. Standing candidates for the first time *en masse* in the 2025 local elections, Reform UK took 677 seats (41% of all those being contested) and control of ten local authorities. [4], (BBC Elections Coverage, 2025; Buchanan, 2025).

[4] Including the largest rural council in England (Kent), along with Derbyshire, County Durham, Lancashire, Lincolnshire, Leicestershire, North Northamptonshire, Nottinghamshire, Staffordshire, Worcestershire and Warwickshire.

This work is situated therefore in both the spatial and political reality of *rural* England as a markedly different place to *urban* England.

1.4 Thesis Structure

The remainder of the thesis is structured as follows:

1.4.1 Chapters

Chapter 2: Literature Review. This chapter synthesises the diverse topical and theoretical perspectives explored while formulating the research question.

Chapter 3: Methodology. This chapter addresses research methodology and researcher positionality, before detailing research methods, data collection and sampling strategies, statistical techniques deployed in each chapter, and analytical decision-making guidelines.

Part 1: Deliberative Mini Publics and Climate Policy Making

The first two results chapters consider whether the recent rise in the use of Deliberative Mini Publics as a method for making climate policy is a politically non-partisan democratic innovation, and address the Research Question 1: "*Does political identity lead to differential rates of participation in Climate Assemblies and differences in attitudes towards the legitimacy of these policy-making forums?*"

Chapter 4: Investigating political bias in the Herefordshire Citizens Climate Assembly *(HCCA).* This introductory chapter explores a specific rural climate assembly, and provides initial evidence that political identity affects both intention to participate, and views on the fairness and legitimacy of a climate assembly. The novel contribution of this chapter is that it provides, for the first time, evidence that political identity may affect volunteering rates for such processes.[5]

[5] Much of the work in this chapter has already been published *(Coxcoon, 2024),* and it *has had* real-world impact. Political identity is now routinely used as a selection criteria for DMPs where it would not previously have been included.

Chapter 5: Investigating attitudes to Climate Assembly recruitment and participation. Building on Chapter 4's findings from a single assembly, this chapter introduces data from Sortition Foundation recruitment processes for three climate assemblies, alongside the results of a purpose-designed large-n survey. It demonstrates that political affiliation affects support for using DMPs for climate policy, drives differential volunteer rates, shapes participation motivations, and influences views on appropriate recruitment criteria.

Part 2: Resistance to Rural Climate Interventions

The final two results chapters explore the root causes of resistance to change in rural areas that will come from climate policies, and how the paths to this resistance differ by political identity.

Chapter 6: Development and Testing of the RRCI scale. This chapter addresses Research Question 2: *"How can resistance to rural climate policy initiatives be reliably measured?"*, and documents the development of an 18-item Resistance to Rural Climate Initiatives (RRCI) scale through piloting, full survey, and Exploratory and Confirmatory Factor Analysis. The scale itself is the novel contribution of this chapter, a reliable and stable measurement tool with a bifactor structure that distinguishes abstract resistance rooted in identity and tradition from concrete resistance to specific interventions like renewable energy and rewilding.

Chapter 7: A Path Model Analysis of resistance to rural climate policy. Using RRCI General Factor scores from rural English residents, this chapter addresses Research Question 3: *"What are the pathways by which political identity, populism, and rural identity shape resistance to rural climate policy?".* The chapter explores relationships between resistance, party alignment, and deeper identity markers (Populism, Rural Identity, National Identity). The novel contribution is the revealing of party-specific pathways to resistance and, exploiting the patterns revealed by Reform UK's emergence, repositioning Conservatism as a statistically centre-ground position with moderate climate policy resistance, largely driven by rural character. The analysis demonstrates substantial populism gaps between Conservatives and

Reform UK, suggesting that undifferentiated 'right-wing-friendly' climate framings will prove insufficient.

Chapter 8: Discussion and Conclusions. This chapter draws on theory provided in the Literature Review to provide an analysis of the deliberative democracy results provided in Chapters 4 and 5, as well as the findings that underpin the scale development in Chapter 6 and the differential political paths to rural climate policy resistance identified in Chapter 7. The chapter aims to explain the phenomena revealed in the results chapters and discusses what this might mean for existing practice in using Deliberative Mini Publics for climate policy in the future. It also provides insight into the implications of the different paths to climate resistance on the political right, considers how populism, nationalism and rurality underpin those differences, and the profound implications this has for framing climate policy in rural areas.

1.4.2 Annexes and Appendices

All appendices are numbered to indicate the specific results chapter they supplement.

Annex A – Methods Tutorial. Chapters 6 and 7 use Factor Analysis and Structural Equation Modelling. This Annex emerged initially as a working document to solidify my own learning this area of work, which was new to me, evolving into a more comprehensive primer. Written largely without mathematical notation, it is included here to provide more detailed background to the analytic choices, which may be of use to readers with similarly non-quantitative backgrounds. As such, it does not represent a formal part of the thesis, hence its 'relegation' to the Annex

2 Literature Review

2.1 Introduction and background

This thesis is highly interdisciplinary, drawing on multiple themes that each have vast bodies of scholarship associated with them, including markers of identity such as nationalism and populism, political-ideological alignment and the moral frames that underpin it; spatial considerations (the rural/urban divide); and policy-making mechanisms (Deliberative Democracy), maintaining a link to the over-arching theme of climate change and the urgent need to drive forward workable climate policy in the UK.

My interest in these somewhat disparate threads emerged during the early part of my studies, and required a choice early on about whether to focus on one aspect or to try to maintain a more interdisciplinary approach. The idea that there might be a complex interplay between these topics convinced me to pursue the latter course. The trade-off here is that a comprehensive account of so many themes could easily have required the word limit for the entire thesis. As such, this Literature Review provides a high-level overview of each area, aiming to tie them together into a coherent whole that sets the scene for the empirical results chapters and conclusions that follow.

The schematic below in Figure 1 is an attempt to provide an overview of the structure of the Literature Review, representing the relationships between various topic areas and the political tension at the heart of climate policy.

The individual pictograms are used throughout the text to help orient the reader. The crude dichotomy of 'left and right' is shown to be underpinned by core values that are either more universalist (left) or parochialist (right) in nature. Because the focus of this thesis is on right-leaning communities, the schematic also illustrates

thematic concerns that affect them more than they do those on the left (national identity and rural issues), which both feed each other, and offer anchors for Populist politicians to attach emotive messaging to. Finally, the schematic draws attention to the use of deliberative democracy methods for climate policy making, which is shown to appeal to left leaning individuals, but also to populists.

The numbered boxes indicate in which section of the literature review this topic is covered.

Where Figure 1, below illustrates how the Literature Review topics relate to one another and to the central tension at the heart of climate policy, Table 1, on the next page, details how the content of each section of the Literature Review links to the research questions and the empirical results chapters that follow.

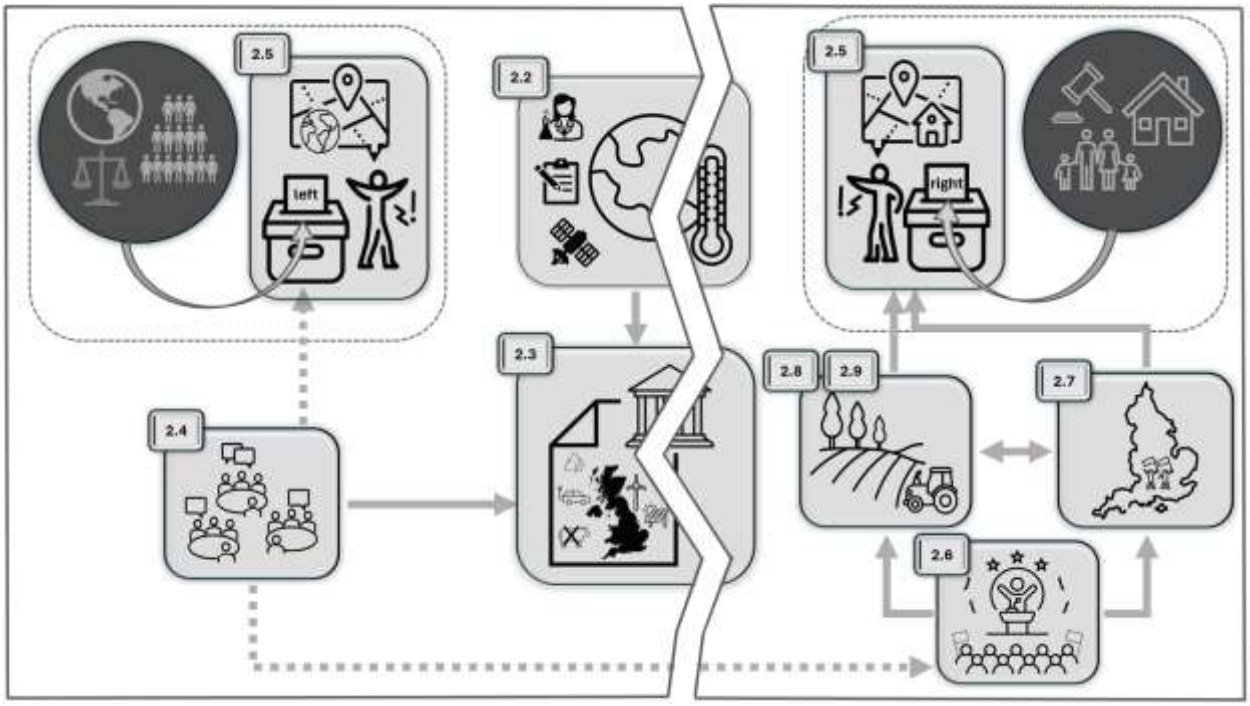


Figure 1: Literature Review topics and central tension

Literature Review theme/section/page	Research Question	Chapter
Climate science evidence base; theories of public understanding of science. (Section 2.2, p. 17-23).	All research questions	All Chapters
Brief history of climate policy development in the UK. (Section 2.3, p. 23-25).	All research questions	All Chapters
Principles of Deliberative Mini Publics (DMPs) as policy-making forums; use of climate DMPs in UK; Conservative and other political theory critiques of DMPs. (Section 2.4, p. 25-32).	**RQ1:** Does political identity lead to differential rates of participation in Climate Assemblies and differences in attitudes towards the legitimacy of these policy-making forums?	Chapter 4 Chapter 5
Left-Right political divide and climate policy; social psychology theories of left-right differences; environmental political theory; history of UK party positions on climate and environmental policy. (Section 2.5, p. 32-44).	All research questions	All Chapters
Defining populism, right-wing populist positions on climate policy; populists as performers of national identity. (Section 2.6, p. 44-49).	**RQ3:** What are the pathways by which political identity, populism, and rural identity shape resistance to rural climate policy?	Chapter 7
Defining nationalism; nation states and climate policy, English nationalism and the limited political representation of English voters. (Section 2.7, p. 49-56).	**RQ2:** How can resistance to rural climate policy initiatives be reliably measured? **RQ3:** What are the pathways by which political identity, populism, and rural identity shape resistance to rural climate policy?	Chapter 7
Landscape; Place attachment theories; landscape change in England; landscape and English national identity. (Section 2.8, p. 56-61).	**RQ2:** How can resistance to rural climate policy initiatives be reliably measured? **RQ3:** What are the pathways by which political identity, populism, and rural identity shape resistance to rural climate policy?	Chapter 6 Chapter 7
Rural disadvantage in England; rural politics; rural climate policy; conceptualising rurality. (Section 2.8, p. 61-68).	**RQ2:** How can resistance to rural climate policy initiatives be reliably measured? **RQ3:** What are the pathways by which political identity, populism, and rural identity shape resistance to rural climate policy?	Chapter 6 Chapter 7

Table 1: Linking the literature review to research questions and chapters

2.2 Climate Science

This thesis does not purport to be a 'climate science' thesis, in that it does not deal with the modelling of climatic change or the geophysical, social or economic impacts of that change. However, a brief introduction to the current state of climate science knowledge is provided here, because it is helpful to frame at the outset what is understood about how the climate has changed and how it is predicted to continue to change, and the complexities that underpin how publics in the UK engage with that information.

2.2.1 The climate science evidence base

The Intergovernmental Panel on Climate Change, established in 1988 by the World Meteorological Association and the UN Environment Programme is largely considered among the most authoritative sources of climate science information in the world (though its work is not without controversy (Asayama *et al*, 2022)). Its role is to assess climate science, impacts, risks, and potential solutions for policymakers, providing evidentiary support for the ongoing international policy negotiations that underpin the UN Framework Convention on Climate Change. The IPCC does not carry out original research; it relies instead on regular, large-scale synthesis of a substantial body of peer reviewed evidence, from which it produces periodic 'Assessment Reports', the most recent of which was AR6 (IPCC, 2021, 2023). In synthesising many hundreds of other studies, the IPCC makes accessible the findings of a vast body of work that is simply too large and too methodologically complex for most members of the public to engage with (and is in any case, largely hidden from the public behind publishing paywalls).

The IPCC 'Summary for Policymakers' report for AR6 provides a broad overview of the current understanding of climate change. Table 2, below, provides an overview of the scale of change, impacts and predictions contained within that, which I have organised by the 'hierarchical' type of each knowledge claim made.

IPCC reports are very carefully "policy-relevant but not policy-prescriptive"; they present scientific information, future projections, and possible options, but have no role in setting policy. It is for individual governments, (semi) compelled by international agreements such as the Paris Agreement, to implement strategies and legislation in line with the evidence presented by the IPCC, and whatever additional evidence is produced through nationally embedded research institutions and practices.

IPCC statement	**Category**
Global surface temperature was 1.09 [0.95 to 1.20]°C higher in 2011–2020 than 1850–1906, with larger increases over land (1.59 [1.34 to 1.83]°C) than over the ocean (0.88 [0.68 to 1.01]°C).	Detection
Historical cumulative net CO_2 emissions from 1850 to 2019 were 2400 ± 240 $GtCO_2$ of which more than half (58%) occurred between 1850 and 1989, and about 42% occurred between 1990 and 2019 (high confidence).	Detection
In 2019, atmospheric CO_2 concentrations (410 parts per million) were higher than at any time in at least 2 million years (high confidence), and concentrations of methane (1866 parts per billion) and nitrous oxide (332 parts per billion) were higher than at any time in at least 800,000 years (very high confidence).	Detection
Human activities, principally through emissions of greenhouse gases, have unequivocally caused global warming, with global surface temperature reaching 1.1°C above 1850-1900 in 2011-2020.	Attribution
The likely range of total human-caused global surface temperature increase from 1850–1900 to 2010–2019 is 0.8°C to 1.3°C, with a best estimate of 1.07°C.	Attribution
Observed increases in well-mixed GHG concentrations since around 1750 are unequivocally caused by GHG emissions from human activities over this period.	Attribution
Human-caused climate change is already affecting many weather and climate extremes in every region across the globe. This has led to widespread adverse	Attribution and Causation

impacts and related losses and damages to nature and people (high confidence).	
It is unequivocal that human influence has warmed the atmosphere, ocean and land. Global mean sea level increased by 0.20 [0.15 to 0.25] m between 1901 and 2018. The average rate of sea level rise was 1.3 [0.6 to 2.1] mm yr-1 between 1901 and 1971, increasing to 1.9 [0.8 to 2.9] mm yr-1 between 1971 and 2006, and further increasing to 3.7 [3.2 to 4.2] mm yr-1 between 2006 and 2018 (high confidence). Human influence was very likely the main driver of these increases since at least 1971.	Attribution
In urban areas, observed climate change has caused adverse impacts on human health, livelihoods and key infrastructure. Hot extremes have intensified in cities. Urban infrastructure, including transportation, water, sanitation and energy systems have been compromised by extreme and slow-onset events, with resulting economic losses, disruptions of services and negative impacts to well-being.	Causation
Continued greenhouse gas emissions will lead to increasing global warming, with the best estimate of reaching 1.5°C in the near term in considered scenarios and modelled pathways. Every increment of global warming will intensify multiple and concurrent hazards (high confidence)	Prediction
Continued global warming is projected to further intensify the global water cycle, including its variability, global monsoon precipitation, and very wet and very dry weather and climate events and seasons (high confidence).	Prediction
With further warming, every region is projected to increasingly experience concurrent and multiple changes in climatic impact-drivers. Compound heatwaves and droughts are projected to become more frequent, including concurrent events across multiple locations (high confidence).	Prediction
Due to relative sea level rise, current 1-in-100 year extreme sea level events are projected to occur at least annually in more than half of all tide gauge locations by 2100 under all considered scenarios (high confidence).	Prediction

Table 2: High level summary of the main findings from IPCC AR6 report

I turn next to how this scientific evidence-base is understood and negotiated by publics, before moving on to consider how it has been incorporated into the current UK policy and legislative context.

2.2.2 Public understanding of science

The term 'climate science' is itself a rather problematic construction, since this umbrella term contains within it a 'hierarchy' of claim types (as indicated in Table 2, above), a sequential acceptance of which is central to widespread public support for climate action. In Table 3, below, I define these claim types and map them onto the climate scepticism taxonomy established by Cocks *et al,* (2025), who identify three forms of scepticism in UK press narratives on climate: Evidence Scepticism (questioning whether climate change is real or human-caused), Process Scepticism (questioning scientific methods) and Response Scepticism (dismissing policies as flawed or inappropriate). Cocks *et al*' reveal how the first two have dramatically reduced since 2013, while incidences of the latter have remained steady, but changed target (e.g. from specific technology resistance to broader critiques of costs of Net Zero overall).

Claim Hierarchy	**Cumulative acceptance process**	**Scepticism Type (Cocks *et al*, 2025)**
Change Detection	In what ways has the climate changed?	Evidence scepticism
Change Attribution	*Assuming* we accept the climate has changed, how did these changes happen?	Evidence scepticism
Impact Causation	*Assuming* we accept that the climate has changed *and* that particular actions caused that change, how do we know that the impacts we are seeing are definitely caused by the changes in climate?	Process scepticism
Impact Prediction	*Assuming* we accept that the climate *has changed*, and that we know *what caused that*, and that we are sure that other	Process scepticism

	impacts *can be associated with that*, how can we be sure what impacts *will occur* in future, and how severe they will be?	
Prescription	Assuming we accept *all* of the above, do we accept the policy prescription of what *ought to be done* now?	Response scepticism

Table 3: Climate science, claim type, and scepticism type

'Climate science' (like many other fields of science) is not, therefore, a monolithic collection of facts that have the same evidentiary salience, or the same emotional valence for everyone, and ample evidence already exists that acceptance of climate science and policy breaks down across ideological lines (Kahan, 2008; Whitmarsh, 2011; Guy *et al.*, 2014).

2.2.2.1 From 'information deficit' to 'civic epistemologies'

Postwar science communication in industrialised nations had long been conceived of in the literature as a 'dyadic' approach, cast as a largely apolitical relationship between scientific institutions (academic and industrial), and the state itself, acting on behalf of citizens. Thus, instances of public rejection of science were, until relatively recently, largely addressed through the 'information deficit model', which assumes that science rejection stems from lack of 'proper understanding' of science, and that this could be addressed through better public education (Jasanoff, 2005; Miller, 2005). While the work of Gillings and Dayrell (2024) and Cocks *et al* (2025) does document a reduction in questioning the basic science of climate change over time, it is clear that as one moves along the claims hierarchy above to the prescriptive stages, there is still substantive policy rejection in the mainstream UK press, from where a reasonable proportion of the population obtain their understanding of climate science (though levels of trust in both newspaper and TV coverage of climate science are mixed). (BEIS, 2019; Gabbatis *et al.*, 2021; Cocks, Painter and Hunt, 2025) .

Understanding why scientific evidence is received differently across society requires examining not just what publics know, but how different societies validate knowledge claims in the first place. It is now more widely accepted that different

cultures have diverse understandings about "*what credible claims should look like and how they ought to be articulated, represented, and defended*" and that science (and any public policy based on it) "*achieves its standing by meeting entrenched cultural expectations about how knowledge should be made authoritative*" (Jasanoff, 2005 p.299). The term given by Jasanoff to these culturally specific, institutionalised ways that particular societies use to test and accept knowledge claims is 'civic epistemologies', and she and others have demonstrated how, at the national level, different countries have discernible, though largely uncodified, cultures of what counts as reliable knowledge for making public decisions.

Jasanoff's highly-cited work on science and democracy in the US and Europe (Jasanoff, 2005) revealed core differences between the US, UK and Germany in the ways in which knowledge claims are produced and evaluated. She categorised US civic epistemology as pluralist (with industry, academia and activist groups all producing knowledge), as well as litigious (often reliant on adversarial, aggressive legal challenges to establish 'truth'), compared with a UK culture that was more communitarian, consultative and negotiated, reliant on trust in long-standing institutions to bring the right people together to discern the facts. Germany, different again, was characterised by expert, committee-based consensus.

Arguably, in the twenty years since Jasanoff's paper, the line between the US and UK civic epistemologies has been blurred by the enormous changes in digital and distributed communication, dominated by US-English content, against which the UK has no linguistic firewall. This is potentially eroding the UK's traditionally more consultative and trust-based approach to establishing authoritative knowledge (Olaniran and Williams, 2020; Seger *et al* 2025). It also is increasingly clear that the differences in support for robust climate policies break down on political lines, and through particular media outlets (Gabbatis *et al.*, 2021), bringing the risk that this erosion of national epistemic culture is concentrated in particular political demographics rather than having diffused throughout the electorate.

2.2.2.2 Politics and cultural values as drivers of climate science acceptance

Wang and Kim (2018) find that political views (which are themselves underpinned by cultural values such as personal freedoms over government regulation, and loyalty to existing hierarchies, systems and authority) will all affect how sceptical people are about climate science. Furthermore, technology optimism is also a fundamental driver of discord over which prescriptive policies people believe will offer the best 'paths out' of the climate crisis (viz. Cocks *et al.*'s 'Response Scepticism'). Those with higher levels of 'techno-optimism' (beliefs that humans are 'outside' nature and that science and technology can be used to solve all problems) are less likely to feel concerned about climate change, even where they fully accept the causes, scale and rapidity of man-made climate change (Dablander *et al.*, 2025).

This sense of humankind as 'outside' of the wider systems of the natural world, and thus able to exert control over it, is a central dividing line in environmental attitudes that has been apparent for decades, and is discussed further in section 2.5.2, below. It has been observed in the many studies that rely on the use of the well-known 'New Ecological Paradigm' scale, the 15 items of which break down roughly into those that take an 'ecologism' view (a relational ontology that views humanity as embedded within nature, rather than separate from it), and those that represent a more Cartesian view that humanity is ultimately able to manipulate and control the natural world for its own ends (Dunlap and Van Liere, 1978; Dunlap *et al.*, 2000; Dunlap, 2008; Valera, 2019).

These fundamental values and beliefs are strong predictors of political alignment, and of support for different types of climate policy, considered in Section 2.5.

2.3 Climate Policy in the UK – a brief overview

The UK's Climate Change Act, introduced by the Labour administration of 2008 with cross-party support, was the first of its kind in the world. It not only committed the UK to a binding carbon emissions reduction target, but also established an independent advisory body (the

Climate Change Committee[6] (CCC)) to provide independent, long-term expertise, propose 5-yearly carbon budgets, and monitor progress against them. The CCC is independent of government, and since its responsibilities, independence, and the requirement for Parliament to consider its advice are all enshrined in the Act itself, it provides long-term policy stability outside of electoral cycles (OECD, 2021b; Climate Change Committee, 2025a). Both the adoption of the Act and the establishment of the CCC are widely considered to have been greatly assisted by a confluence of events at the time: David Cameron's attempts as Leader of the Opposition to 'detoxify' the Conservative brand, a very high-profile campaign by Friends of the Earth (the Big Ask), and the impetus provided by David Milliband's stated ambitions on his appointment as Environment Secretary (Carter and Childs, 2018; Carbon Brief, 2025).

The original carbon reduction target enshrined in the Act required an 80% reduction in greenhouse gas emissions by 2050, against a 1990 baseline. This was later strengthened by Theresa May's administration in 2019, increasing the target to 100% reduction in emissions by 2050, effectively establishing the 'Net Zero' framing that has dominated climate policy discussion since. Controversially, this significant increase in the ambition of the target was achieved through an amendment to the original Act, rather than primary legislation. Only 15 days passed between the laying of the draft and the Order coming into force, and minimal Parliamentary debate time was allocated (Rutter, 2019; Priestly *et al*, 2025), providing ammunition for subsequent critiques of the strengthened target.

That much of that subsequent critique has come from the political right is all the more intriguing because of the vital roles of both David Cameron (Conservative leader in opposition, 2008) and Theresa May (Conservative leader in administration, 2019) in pressuring the Labour administration to adopt the Act in the first place, and rushing through that enhanced target 11 years later. The current leader of the Conservative party (Kemi Badenoch) formally announced the party's rejection of the Net Zero target in March 2025, with the justification that costs to

[6] Originally the 'Committee On Climate Change'.

taxpayers will be unacceptably high, despite CCC figures putting the costs at roughly 0.2% of GDP annually (House of Lords Library, 2025). Some commentators have noted that this significant position-change conveniently aligned the Conservative Party with Reform UK's position just ahead of local elections in May 2025, suggesting an element of political opportunism (Reuters, 2025).

A notable feature of the Climate Change Act is that its provisions are not cascaded down as statutory duties to local authorities, despite some high-profile campaigns demanding this (Hakata *et al*, 2024). This, along with the fast-track approach taken by Theresa May to strengthening the Act in 2019, has led to concerns that there is a 'governance gap' between Parliament and citizens on how exactly the provisions of the Act should be achieved.

2.4 The growth of Deliberative Democracy in UK climate policy-making

Partly as a result of the lack of statutory targets at the local delivery level, Climate Assemblies (a form of 'Deliberative Mini Public' or DMP) have seen an explosion in popularity in the last decade. Their increased popularity is also down to the impetus provided by the public response to the IPCC's Special Report of 2018 on the possibility of limiting global heating to not more than 1.5^{0}C above the pre-industrial average (IPCC, 2018). The report triggered high-profile public demonstrations and the establishment of the protest group Extinction Rebellion, which in turn galvanised action at the local authority level, resulting in over 300 local authorities declaring a Climate Emergency over the next 3 years, many of whom also commissioned some form of climate-focused DMP (Bryant and Stone, 2020; Local Government Association, 2021; Lewis *et al.*, 2023).

The UK has been a leading nation in this respect. While the 'POLITICIZE' dataset, compiled by Paulis *et al.*, (2021) detailed over 100 deliberative processes commissioned by national and regional governments across Europe between 2000 and 2020, the KNOCA database tracked 49 DMPs on climate-related topics in the UK alone between 2019 and 2023 (KNOCA, 2023).

DMPs are only one among several practical approaches to delivering the ideals of 'Deliberative Democracy' in practice, though arguably the most well-known. Deliberative democracy is "*a diverse set of ideas within political theory and practice that focuses on the conditions under which citizens' preferences are formed, and collective judgments made. Simply put, deliberative democracy places reasoned discussion at the heart of democracy*" (Willis *et al*, 2022 p.3). In doing so, it challenges 'thin' notions of democratic engagement, limited to periodic voting, which assume that citizens are either too disinterested or ignorant to discuss policy options in depth. Instead, it assumes that people can come together to deliberate respectfully, resulting in decisions for the common good.

Willis et al (2022) illustrate the tension between those who believe that "*democracy is fundamentally incapable of an adequate response to climate, and the answer must lie in some form of eco-authoritarianism, or at the very least a greater role for experts in steering climate governance*", and contrast these opinions with the alternative view that only massively increased democratic involvement of citizens in climate policy-making will lead to policy outcomes that are both socially acceptable and commensurate with the scale of the challenge. This latter view is what underpins the 'Deliberative Wave' described above (Boswell et al., 2023).

2.4.1 The principles of Deliberative Mini Publics as public policy-making forums

DMPs are defined by Curato and Farrell (2021, p.3) as '*carefully designed forums where a representative subset of the wider population come together to engage in open, inclusive, informed and consequential discussions on one or more issues*'. Various processes are considered to be forms of DMPs (an excellent summary of which is provided by Escobar and Elstub, 2017), ranging from Citizen's Juries with as few as twelve participants, to Planning Cells and Deliberative Polls with as many as five hundred. Curato and Farrell draw attention to four core features that make up their definition. DMPs are 'carefully designed'; requiring thoughtful selection of topics, adequate timing, appropriate choice of speakers and venues, and meaningful facilitation of discussion. DMPs are 'representative of the wider population',

ensuring that a wide range of opinion and ability is present in the process and reflecting those who will be impacted by their recommendations. DMPs are characterised by 'open, inclusive and informed discussion', giving them their truly deliberative character, and setting them apart from other forms of participatory governance that focus more on public interrogation of decision-makers. Finally, DMPs are 'consequential'; participants give up a great deal of time to take part, and commissioning bodies therefore commit to acting in some way on their recommendations.

A central justification for the use of DMPs is the claim that they are representative of the wider public and thus "*the results should represent what informed public opinion would look like, were citizens to organize, become informed, and deliberate*" (Urbinati and Warren, 2008), making them powerful mechanisms for policy-makers to understand the preferences of 'the people'. It follows that, for the outcomes to be perceived as legitimate, accurate representation by the minipublic of the macropublic is vital, else the whole endeavour loses legitimacy (Escobar and Elstub, 2017, Gül, 2019, Curato and Farrell, 2021).

To ensure this descriptive representation, participants in a DMP are selected through a process called 'sortition', which first invites thousands of residents in a given jurisdiction to participate, and then deploys a range of 'fair algorithms' to select from the pool of respondents, in order to return a 'descriptively representative' minipublic (Flanigan *et al.*, 2021). Standard socio-democratic markers such as age, sex, income bracket, educational background etc. are commonly used, often with sampling weightings to ensure inclusion of especially marginalised or very small groups (Gül, 2019, Flanigan *et al.*, 2021). Political alignment has not traditionally been used as a sortition variable.

In practice, DMPs are generally appended to extant decision-making structures, as a mechanism for informing and advising politicians. Avoiding any attempt at a detailed exegesis of the literature on the arguments for or against the idea that DMPs should have binding power to make policy, I merely start and end at the position outlined by Goodin and Dryzek (2006), that for most deliberative processes, the

sovereignty of existing liberal democratic structures remain: a DMP generally informs policy making, but does not compel it.

2.4.2 Use of DMPs for climate policy-making in the UK

Shepherd (2024) provides an overview of the aggregated outputs of 32 UK climate assemblies, revealing that almost 90% made a recommendation for more public communications and engagement on climate,[7] with the next most popular concerns relating to improving public transport, new build standards and housing retrofit support. However, the vast majority of UK DMPs to date were set up to answer a very broad question about 'tackling climate change' or 'decarbonising the country/particular region/particular local authority area', and it is debatable how much their recommendations have truly embedded themselves in climate governance and policy-making, principally due to the broad-brush nature of many recommendations. Ainscough and Willis (2024) have therefore recommended that the next step for climate DMPs is a more precise focus on discrete policy challenges. They demonstrate (through a case study DMP specifically looking at home-owner retrofit which fed straight into the CCC's work on the 7th Carbon Budget) how DMPs can more concretely influence the work of existing policy-making institutions.

2.4.3 Public support for DMPs for climate policy making

There is relatively little evidence on the influence of political party affiliation as a potential predictor of differential support for Deliberate Mini Publics, particularly for the UK-specific context. Evidence from similar countries (e.g. the Netherlands) suggests patterns that may be relevant, with a study by Caluwaerts *et al.*, (2020) demonstrating that "socialist, ecologist and populist parties" in the Netherlands are more supportive of direct and participatory democracy arrangements. Other studies suggest that citizens with more populist attitudes are more likely to support related direct-democracy approaches, such as referenda, regardless of their party

[7] A particularly fascinating finding given the known limitations of the 'information deficit' model, as discussed in Section 2.2.2, suggesting that members of the public are equally as susceptible to this misconception as policy-makers and public-facing scientists have historically been.

preference or trust in government (Jacobs *et al* 2018; Zaslove *et al*, 2021). This supports the contention of Mammone, (2009) that "*The final 'populist' aim is the construction of a new type of democracy: a democracy close to people's needs and desires, and one which allows the direct participation of citizens in political life, especially through the use of referenda and plebiscites*."

In contrast, though, Dijk et al (2023) find that citizens with highly polarised views are *less* likely to feel that DMPs are legitimate.

2.4.4 Conservative theory as a potential challenge to deliberative democracy

Radical innovations that bypass traditional processes, are generally anathema to a conservative worldview, which values the preservation of established systems; eschews utopian ideals in favour of pragmatic solutions; and assumes that radical change is dangerous to social order. (Burke, 1790; Oakeshott, 1962; Hamilton, 2025). It follows that conservative thinkers might view democratic innovations that seek to deliver radical change as suspect. In the absence of substantial empirical literature demonstrating that Conservative voters are less likely to support DMPs, I consider why this might be a likely outcome.

A key element of Conservative thought, which is still a mainstay of its democratic vision, is the conception that 'the people' are largely fallible and cannot be relied upon to deliberate rationally, and that they need to be politically represented by a select and necessarily 'elite' group (selected for some virtue or through election). This can be seen in the work of more recent Conservative philosophers such as Michael Oakeshott, but also earlier writers in the canon of Conservative thought (Burke), all the way back to Aristotle. Though Aristotle could not be claimed as a Conservative in the modern use of the word, he is often claimed as such by Conservative thinkers since, in the Aristotelian view, a robust political system requires the 'rule of the best' (*aristokratia*) (Miller, 2022).

Perhaps the most famous proponent of this concept of representative democracy is the 'father of conservatism', Edmund Burke who, in his 'Speech to the Electors of Bristol' of 1774 stated that "*your representative owes you, not his industry only, but*

his judgment; and he betrays, instead of serving you, if he sacrifices it to your opinion." (Conniff, 1977). From this Burkean position comes the concept that there must be some intellectual filter between the expression of the popular will, and the decisions made by representatives, which should promote the common good overall. In doing so, it is the prerogative of the representative to choose not to directly implement 'popular passions' (Bourke, 2015). Furthermore, Burke extends the Aristotelian idea of *rule* by the best to his view that these representatives are better elected not by the entire population, but by a restricted suffrage of only the most able (Conniff, 1977).

This view continues through the works of Oakeshott, whom Khan (2012) describes as conceiving of politics as a 'gentlemanly affair', describing Oakeshott as contemptuous of the role of ordinary people in representative democracy. Indeed, Khan represents Oakeshott as taking *authority* as the central concept in political theory. In so far as Oakeshott supports deliberation, Khan notes that "*we might describe [Oakeshott's] as a theory of deliberative* ***aristocracy*** *that undervalues the significance of widespread participation*" (my emphasis). In this he is the descendant of Burke, whose belief in the deliberation of the *representatives,* not the people themselves, was the core of good government.

Skorupski (2015) in his 'Conservative Critique of Liberalism', characterises the 'rational Conservative' who, while agreeing with the dialogical impulses of Liberal philosophy (that discursive reasoning allows us to arrive at truth), challenges the notion that all have this capacity equally. Skorupski's Rational Conservative believes that, either through innate inability or the limitations of their situation, not all voices are as capable as others, and that exercise of free thought "*must be mediated by tradition and authority*". Deliberative processes that follow a liberal impulse of equality are, in the Conservative mind, over-optimistic about the competence of all individuals to deliberate, and dangerously unconnected to tradition.

This view of open deliberative democracy as unrealistic also finds voice in the work of Livingston (2012), who argues that deliberative theorists place too heavy a reliance on intellectualism, assuming the possibility of detached debate between

citizens without any intervening bodily or 'visceral' reactions on the content of their discussions, when in reality, communication and deliberation are about much more than dry exchanges of fact and opinion. Livingston's critique of the liberal conception of deliberation is that it believes that feelings themselves can be subject to rational deliberation.

There is little direct *empirical* evidence for Conservative resistance to DMPs, though recent evidence to support the philosophical notion comes from a study by Rojon and Pilet (2021), who identify 'Sceptical Deliberative Democrats', people who do not support the concept of DMPs (because they do not trust the abilities of ordinary people), but *would* take part themselves, (because they see themselves as competent to participate in such a process). The study does not examine voting habits but notes that this group is characterised by higher levels of education and political confidence, portraying them as "elitists with an "entrustment" conception of politics" (comfortably situated people who largely trust their elected representatives), which fits to a large degree with the Conservative viewpoint expounded above. Furthermore, Kersting (2021), in a survey of 1,800 local government councillors in Germany, shows a clear difference between support for Citizens Assemblies, with 56% of Green councillors supporting their use, but only 29% of Conservative councillors. It is reasonable to connect this lower level of support with belief in the primacy of representative, rather than direct forms of democracy.

2.4.5 Political theory critiques of Deliberative Democracy

Despite the very rapid growth in the use of DMPs in climate policy making in the UK, this approach is not without its critics, some of whom argue that, rather than enhancing democracy, the culture of DMPs assume either that the political identities of the participants are irrelevant, or that they can be essentially suppressed by the process. Mouffe (1999) contends that this removes the opportunity for the meaningful political contestation that is the true heart of democracy from the process. Nadia Urbinati goes further, and is particularly critical of DMPs, believing them to be fundamentally *anti-political*, effectively requiring elimination of parties,

ideological groupings, and collective identities, creating what she calls a "*dystopia of a party-less democracy*" (Lafont and Urbinati, 2023).

Cristina Lafont, among others, raises more procedural concerns, that the technocratically-managed processes create opportunities for normative capture by particular world views, in agenda setting and facilitation. Lafont also identifies a paradoxical 'populist-technocratic hybrid' in the theory underpinning DMPs, particularly the common framing that valorises the idea that 'ordinary people' can make better decisions than 'corrupt (political) elites'. This populist tendency is oddly juxtaposed with the technocratic elements that hand significant power to the expert-designers who control what gets deliberated, how processes are designed, and who presents evidence (Lafont & Urbinati, 2023), a concern somewhat borne out by the finding that most DMPs have been commissioned by left and centre-left leaning parties, with design features specific to that normative world view (Ramis-Moyano et al., 2025).

This potential for political identity to be excised from policy-making in DMPs is crucial, because political identity is known to be a robust predictor of attitudes and beliefs about climate change, from scepticism of the causes, through doubt about attribution of impacts, to cynicism about the proposed policies to address it, all of which are stronger on the political right. The next section briefly synthesises the literature on this divide.

2.5 The political divide, and climate policy

2.5.1 Social psychology theories of the 'left-right divide'

A range of competing social psychology theories exist that claim to provide explanatory frameworks for the differences between 'left-leaning' and 'right-leaning' individuals. This area of research is somewhat contentious, partly because much of the research uses the hyper-partisan US political dichotomy that crudely divides people into 'Liberals' and 'Conservatives'. These terms, and the policies supported by the associated parties, do not have consistent definitions across countries (Batstrand, 2015).

Notwithstanding the critique that this literature is US-centric, the competing theories in broad circulation include:

- System Justification Theory (SJT) (Jost and Banaji, 1994; Jost, 1995; Jost, Banaji and Nosek, 2004; Jost and van der Toorn, 2012) which theorises that people are motivated to justify and bolster the status quo in both unconscious and conscious ways;
- Social Dominance Orientation (SDO) (Pratto *et al.*, 1994), a measure of an individual's preference for inequality among social groups;
- Right-Wing Authoritarianism (RWA) (Adorno, 1950; Altemeyer, 1981, 1996), a scale that combines "*political conservatism, authoritarian submission, authoritarian aggression, and conventionalism as key predictors of prejudice, racism, and right-wing extremism*" (APA, 2018);
- Cognitive Style/Motivated Social Cognition (Kruglanski and Webster, 1996; Jost *et al.*, 2003; Berggren *et al.*, 2019), a broad set of concepts related to an individual's desire for structure rather than ambiguity, which have also been linked to authoritarianism;
- Moral Foundations Theory (Graham *et al.*, 2013; Haidt, 2013), which proposes that a set of innate psychological systems at the core of ethical decision-making, which different people weight more or less equally, and which can be used to predict political leanings and other cultural and social attitudes.

SJT and Motivated Social Cognition have faced substantive critique for their strongly normative framings. Since SJT is openly based on Marxist concepts including "false consciousness" and "objective interests" to make value-laden judgments about what beliefs serve or harm disadvantaged groups, it has been critiqued as purpose-designed to pathologise conservative viewpoints (Dohmen, 2024). In a similar vein, RWA, despite still being widely used, must also be situated in its historical context. Emerging shortly after WWII as a way of understanding the pathological behaviours that underpinned German social behaviours under the Nazis, it has faced substantive critiques for failing to analyse or provide a 'sister framework' that would explore similar authoritarian behaviours on the political left (particularly

since much of the work was done during both Stalin's reign in Russia and the Cultural Revolution in China), leading to more recent attempts to produce left-wing variants of this theory (de Regt *et al,* 2011; Costello *et al.*, 2022; Nilsson, 2024).

Against this backdrop, Moral Foundations Theory (MFT), first proposed in 2004 by Jonathan Haidt and colleagues, provides what seems to be the least normatively biased framework for understanding the social psychological differences that underpin individual adherence to particular ideological frameworks. The theory initially proposed five core 'Moral Foundations' (Care/Harm, Fairness/Cheating, Loyalty/Betrayal, Authority/Subversion, Purity/Degradation), and found, through repeated, large scale empirical work, that 'Liberals' (US terminology) rely primarily on the first two for their moral judgements, while 'Conservatives' (US terminology) try to satisfy all of them when making judgements. While Liberty/Oppression was tentatively added as a sixth foundation around 2012, subsequent cross-cultural work has led to a different refinement of the framework, discussed further below. The Care and Fairness dyads are often referred to as 'individualising' foundations, whereas the Loyalty, Authority, and Purity foundations are known as 'binding' (Atari *et al.*, 2023).

In this respect, the individualising foundations speak more strongly to the values espoused by the 'patron saint' of Liberalism, John Stuart Mill, whose works imagine society as a collection of individuals working to a social contract for mutual benefit, anchored on basic and equal rights for all individuals. This automatically leans towards the Care and Fairness foundations. By contrast, the 'binding' foundations better reflect the philosophy of Emile Durkheim. Though it would be incorrect to label Durkheim a Conservative, his views on the importance of social structures, inherited traditions and religious (or at least ritualistic) locally-specific social practices are crucial to the types of social solidarity favoured by conservatives, and these undoubtedly lean towards the foundations of Loyalty, Authority, and Purity (Haidt, 2013 p191-192), explaining why conservatives are less likely to support policies that will lead to radical changes in the social or economic order.

This theoretical understanding from MFT is further supported by empirical work on 'moral circles' by Waytz *et al*, (2019), which demonstrates that tendencies for 'universalist' or 'parochialist' world views reflect core psychological differences "*such that liberals express compassion toward less structured and more encompassing entities (i.e., universalism), whereas conservatives express compassion toward more well-defined and less encompassing entities (i.e., parochialism)*". Notably, the study provides evidence of these tendencies even in *entirely* non-political contexts using abstract imagery, suggesting that these psychological differences for close order or loose structure exist independently of partisan cues, strengthening the case that MFT describes genuine psychological variation rather than learned political positions.

MFT is not immune to criticism. Critics argue that the framework inappropriately legitimises distasteful views (such as Conservative rejection of LGBTQ lifestyles under the 'Purity' moral foundation), and that it does not challenge the ways in which support for 'traditional values' can serve to maintain hierarchy and exploitation (Kugler *et al*, 2014; Strupp-Levitsky *et al.*, 2020). Counter-critiques are that the tool exists to explain and reveal, not to judge, and argue that such moral criticism is itself normatively framed.

Other criticisms relate to the underlying data on which MFT was originally based, which (although from very large samples) was drawn from largely WEIRD [8] (predominantly US) citizens. A recent major review (Atari *et al.*, 2023) drew on a new sample of over 8,700 respondents from 19 countries, rewriting survey items with professional translation to remove cultural bias, and even measuring the WEIRD-ness of participants to calibrate responses. As a result, a new MFT structure is proposed. Broadly-based on the previous structure, it now contains six Foundations (Care, *Equality, Proportionality*, Loyalty, Authority and Purity).

[8] Western Educated Industrialized Rich Democratic, from the work of (Henrich *et al*, 2010), who make the claim that "*members of WEIRD societies, including young children, are among the least representative populations one could find for generalising about humans*."

The replacement of the single 'Fairness' foundation with the two new foundations of 'Equality' and 'Proportionality' through robust, large scale quantitative work is of great relevance to the research in this thesis (and indeed a great deal of other social research). Atari *et al.* (2023) demonstrate that these two concepts, while both related to fairness and often conflated in speech, are empirically distinguishable from one another, showing opposite relationships with political ideology. The Equality Foundation correlates negatively with conservatism, while Proportionality correlates positively.

This provides strong evidence to diagnose one source of tension at the heart of the climate 'culture war', where particular actors on the political left (development NGOs, activist groups etc.) broadly support policies that call for reparations from historically high-emitting countries, along with large transfers of funding to less wealthy nations to support the transition to net zero, an equalising approach that expiates for past sins. On the other hand, those on the political right are more likely to argue that it is not 'fair' to expect the UK to lead the way when its own emissions are now around 1% of the global total while other nations such as the USA and China have a vastly greater impact, pointing as well to the cost of living crisis as a reason why it is unfair to ask UK households to invest in household level energy efficiency and renewables that they cannot afford.

Taken together, this background goes some way towards explaining the undercurrent of climate 'culture war' in the UK, suggesting that divergent moral frames lead different groups to communicate the problem and its solutions in ways that are fundamentally incomprehensible to the 'other side'. This is likely as true of political parties and their activists and campaigners, as it is of voters, bringing us to the topic of how political parties have accommodated environmental concerns (or not) since the mid-1900s, and more specifically, how the UK's political parties have treated climate policy over recent decades.

2.5.2 Environmental politics – from green edges to the red and blue mainstream

The Green political movement emerged as a response to increasingly obvious environmental crises (pollution, overpopulation, resource depletion), heightened public awareness of which is often credited to the 1962 publication of Rachel Carson's book 'Silent Spring'. Less well known is that the early development of the Green movement was also a response to fears about authoritarian, survivalist responses to those very problems, which could themselves threaten democracy and human wellbeing. By the 1970s, green politics and emerging green parties had largely coalesced around four pillars: ecological responsibility, social justice, grassroots democracy, and non-violence, though *humanity's* own wellbeing still sat at the heart (Wong, 2016).

The idea that the world needed something even more radical then began to emerge, as an increasing number of environmental political theorists challenged the notion that 'environmental democracy' (through which the existing regulatory structures and institutions of liberal democracy are used to control the environmental side-effects of industrial growth) would ever lead to meaningful reductions in environmental damage (Meadowcroft, 2007). Others identified a 'straightjacket' of Liberal democratic principles (such as rights and autonomy), arguing that these human-centred rights principles could not easily expand beyond humans to other species, or to elements of the biosphere, limiting ways in which environmental damage could be contained (Eckersley, 2020). The resultant 'Ecological Democracy' movement, which drew heavily on the theoretical work of philosopher Arne Naess, incorporated all four pillars of earlier fringe Green Politics, advocating for "*a radical break with the neoliberal state and transformation toward decentralised, organic and grassroots democratic practices that embody ecological values and give greater weight to non-humans and future generations*" (Schlosberg et al., 2019, p.1). This initiated a move towards Naess's conception of 'Deep Ecology', arguing for a fundamental shift in how humans view their relationship with nature, emphasising biocentric equality (the idea that all organisms and entities in the ecosphere have equal right to live and flourish). This again has political ideology implications; while

the close links between Christianity and Conservatism that strongly characterise US politics are much weaker in UK political culture, the generalised Judeo-Christian perception that nature is created for human use does pervade Conservative world views in general (Dunlap and McCright, 2010).

Also of note is that Ecological Democracy's focus on social justice and grassroots democracy makes it a good fit, normatively, with theories of Deliberative Democracy covered earlier, which prioritise inclusion and equality and promote the idea that good-quality public deliberation uses reason rather than intuition, lending legitimacy to subsequent policy decisions (Estlund, 2007 pp.106-107; Mercier and Landemore, 2012). As we saw in Section 2.4.4, above, this is not necessarily such a comfortable fit with Conservatism.

2.5.3 UK political parties' relationship to environment and climate policy

There is a considerable body of empirical evidence suggesting that right-of-centre voters are less likely than those on the left to believe that climate change is a significant problem (McCright and Dunlap, 2011, 2013); or support climate change policy (Severson and Coleman, 2015); and more likely to reject authoritative scientific sources on climate change (Singh and Swanson, 2017). While there is a US-bias to this body of knowledge, with Tea Party Republicans in particular holding strongly partisan views that reject the foundations of climate science (Hamilton, 2018). Furthermore, Schrøder (2023) also finds that Norwegian citizens with strongly 'pro-economic' world views (valuing economic growth over environmental protection) are more likely to distrust climate scientists than other natural scientists. This is also found (although to a lesser extent than the Tea Party extremes) in other European countries, with anti-climate-action narratives finding additional outlets in right-wing nationalist and populist discourses (Hornsey, et al, 2018; Huber, 2020; Kulin et al, 2021).

It is also important to note that outright scepticism about climate change is not the core issue for Conservatives in the UK; indeed, surveys consistently show high levels of concern about climate change among Conservative voters in the UK, with 66% stating they were either 'very concerned; or 'fairly concerned' about climate change

in a recent survey (IPSOS, 2023). Stanley *et al* (2023) neatly synthesise the wide range of research that points to Conservative resistance to climate policies that require structural or behavioural change. They describe a 'threat imbalance' held by Conservatives, which results in accepting that climate change is a problem, but downplaying the need for radical policy change "*because they fear that action to address the problem will threaten the economy or social order*". In essence, they conclude that many Conservatives fear the cure more than the disease. As we shall shortly see, this has its roots in Conservative thinking about the unforeseen impacts of radical change.

2.5.3.1 Labour's path to environmental enlightenment

Arguably, though, environmental stewardship sits comfortably within Conservative philosophy, while Labour's path to becoming a champion of climate action has been a comparatively tortuous affair. Labour (and the Trade Unions that provided its supporter base) initially viewed environmentalism as middle-class protectionism, incompatible with socialism's focus on economic growth and class struggle (Maccaferri, 2022). Maccaferri also points to the pivotal effect of Joe Weston's 1986 book 'Red and Green' (Weston, 1986), coupled with a more cynical reason for action: recovering voter support lost to the Conservatives as a result of Margaret Thatcher's successes in using environmental rhetoric in her speeches.

Though the Trades Union Congress (TUC) supported environmental initiatives from the 1970s onward, this was inconsistent and it was not until the early 2000s that the Unions' adoption of the 'just transition' framing allowed them to fully resolve the environment-versus-jobs dilemma (Farnhill, 2011). By reframing environmental protection as inherently progressive and directly linked to social justice, Labour's journey to being a pro-climate party overcame the tendency for the party to view this agenda with suspicion.

2.5.3.2 Conservative environmental theory

By contrast, Conservative principles of environmental stewardship are 'baked-in'. They come from the foundational idea that society is a contract between the living,

the dead, and those who are yet to be born. Thus, in relation to traditions, built heritage, landscapes, and the natural environment more generally, it is a strong *social* contract which underpins environmental conservation/preservation actions, and is resolutely local and bounded in practice. (Oakeshott, 1962; Scruton, 2012, 2017). This sets it apart from any 'deep green' motivations that imbue the natural world with rights of its own, which tend to animate environmental protection activity from the 'green party' end of the spectrum, and also from the more abstract notions of *global* social justice that are borderless and disconnected from localities that came to characterise Labour's thinking on environmental issues as a result of the Red-Green shift described above.

For Conservatives, "*The goal is to pass on to future generations, and meanwhile to maintain and enhance, the order of which we are the temporary trustees"* (Scruton, 2012, p.10), and this itself is strongly rooted in the idea (variously expressed by writers such as Milan Kundera and G.K. Chesterton) that nations, and their traditions, are what give individuals a sense of immortality, from whence, their purpose.[9] The animating ideal of Conservatism is thus to pass on the natural and built environment in at least as good a state as it is found. Since another foundational principle of Conservatism is that change, when it is deemed necessary, ought to be based specifically on "*redress of some specific disequilibrium*" (rather than driven by theoretically driven visons of improvement), as well as allowing time to "*address consequences and make appropriate adjustments*" (Oakeshott, 1962), it follows that Conservatives *will* accept environmental change so long as there are strong evidentiary reasons for it, and where ongoing place-based reflection and adjustment is built-in.

In his 2012 book "How to think seriously about the planet", Scruton also emphasises the Conservative ideal that environmental action must be local, must meet local needs, and can only be properly motivated by a concept he coins as '*oikophilia*', or love of home. This runs counter to left-leaning narratives which (although they may

[9] This idea will be returned to in Section 2.7.2 below, on the impact of nationalism and nationalistic sentiments on climate policy

have a focus on community-based action) tend to be rooted in the contention that only global, transnational actions can solve the climate crisis. The Scrutonesque 'small-c' Conservative vision of locally driven, traditionally-informed environmental action has attracted robust critique for being wholly inadequate as a mechanism to tackle a global scale crisis, and for privileging traditional land-management structures. However, the Moral Foundations Theory and Moral Circles of care research detailed in Section 2.5.1, above, suggest that these beliefs are relatively hard-wired.

Arguably then, while a truly Conservative 'Englishness' rejects radical change, it can still accommodate even substantial change where that is rooted in its ideological foundations, especially where that change can be seen to be part of positive stewardship with intergenerational responsibilities (in both directions) at its heart.

2.5.3.3 Reform UK – environmental policies as threats

By contrast, Reform UK is a new force in UK politics, and limited large-scale research has been done to date on the views of its voters beyond a raft of polls indicating voting intentions in general. Very recent emerging evidence from Deo (2025) provides strong evidence that the party's voter base hold between them an unwieldy and contradictory collection of views on priorities for government, lacking a coherent ideology. Many of its voters are principally animated by the simple idea that the mainstream parties have manifestly failed them on a range of issues, from workers' rights and household economic burdens, to river pollution and a degraded public realm, to foundational concerns about pressure on public services and cultural cohesion perceived to be a direct result of excessive levels of immigration.

The evidence presented by Deo indicates that, rather than offering a coherent ideology, Reform UK has built a voter base from a smorgasbord of sometimes conflicting issues, united largely by the conviction that only an intervention from 'outside the system' can deliver the re-set to their fortunes that they need.

Thus, unlike Conservatism, Reform UK (as a populist party) does not present a coherent philosophical theory of change, which has implications for how its

supporters engage with climate policy in general, and the specific potential for rural and landscape change that will result from it. The Reform UK version of Englishness is one of 'identity as adversity', besieged on all sides. In relation to climate change, this siege mentality framing encourages supporters not to engage with the more abstract, globalised threat of climate change itself, but instead encourages them to focus their attention on the primary proximate threat (the policies designed to address it), which it positions as proposals that will create short-term hardships and change valued places. This siege mentality is deepened further by the understanding that the 'elites' proposing the policies are, most likely, hostile to one's values and dismissive of one's concerns.

However, despite the apparent gulf between Conservative philosophy and the (somewhat hazy and internally contradictory) environmental policies of Reform UK, one thing does unite them, and that is a clear focus on national sovereignty over policy. This creates an enormous tension because, as we will return to in Section 2.7, below, climate change is not regarded as a problem that can be solved at the national level.

2.5.4 UK political party positions on climate policy

Despite the now widely accepted narrative that opposing climate action is simply the natural position of political right, evidence shows that environmental action long sat uncomfortably with *both* major UK political parties' economic traditions. Regarding the 'small-c' Scrutonesque notions of environmental stewardship outlined above, the Conservative Party has always struggled to reconcile this end of the party with the more libertarian wing's resistance to restrictions on business. Labour, on the other hand, traditionally resisted any action that would affect major employment sectors such as mining and industry, branding proposals for environmentally-friendly industrial restrictions as 'middle class ladder-pulling' (Carter, 2006; Maccaferri, 2022).

Mainstream parties in the UK capitalised on the growing, but still background, level of concern about the environment from the 1990s onwards. While the Liberal Democrats firmly seized the agenda during this time, Labour and the Conservatives

more tentatively accommodated just enough green policies to neutralise any significant voter loss to either the Liberal Democrats or Greens (Carter, 2006).

By the early 2000s, public concern about climate change moved from the background to the foreground, and the unique confluence of events outlined at the start of Section 2.3, above, led to the brief period of furious agreement between parties that culminated in the 2008 Climate Change Act, while the Conservative party was still in opposition. However, it was not long before Conservative backbench pressure triggered a retreat. The latent ideological position that low taxes, business freedoms and protecting household budgets in the short term should always be prioritised re-emerged rapidly following the global financial crash, and combined with the different pressures of being in administration rather than opposition, manifested in David Cameron's reported exhortation to officials to "*get rid of all the green crap*" (Carter and Clements, 2015).

Since then, the UK, like other Anglophone countries, has seen polarisation levels on climate change closer to the US than continental Europe (Carter, 2013), explained to some degree by shared media environments and the majoritarian political systems that allow for 'all or nothing' control of portfolios (Lockwood and Lockwood, 2022). However, more recently, the issue has become more polarised still due to the realisation on the radical right that climate policy is a uniquely useful wedge issue: while the majority of the voting public believes that climate change is real and 'something must be done', the concern that this 'something' will cost money has been ever-present in voters' minds. (Friends of the Earth, 2025; Smith, 2025).

In the UK, this has allowed the newly emergent Reform UK party to attract voters from both Labour and the Conservatives (as well as large numbers of the sort of 'politically homeless' voters who trusted neither of them). They have achieved this in part by casting climate action as an expense that a hard-pressed country can ill-afford (using costs to business to resonate with the right, and impositions on hard-working people to appeal to left-wing interests). Overall, though, they have successfully attracted more voters from the Conservative party, where underlying scepticism about the cost of climate policies was already higher, due to fundamental

Conservative beliefs about the importance of free markets and economic liberties (Dickson and Hobolt, 2025).

Furthermore, as Stanley *et al*, (2025) demonstrate, Reform UK's ability to weaponise climate policy also has its roots in the inability of successive UK governments to marry the policy ambitions of the Climate Change Act with state financial investment on the scale seen elsewhere. The authors show that the political economy of the UK, long based on London-centric financial markets, has produced path-dependent constraints on state fiscal capacity, unsuited to massive, state-led investment in rapid infrastructure change. Thus, the Net Zero transition in the UK is almost entirely driven by private investment through complex subsidy instruments. This satisfies neither the localist, distributist urges of small-c Conservatives, nor the statist tendencies of those with more socialist tendencies, creating an open goal for Reform UK to campaign on the idea that the transition has no democratic legitimacy, delivering unwelcome change without concomitant growth in jobs and skills for 'ordinary people', while profits flow to private (often foreign) investors.

The rise of Reform UK is unprecedented in UK electoral history; never before has a party with such overtly populist overtones been so close to power. In the next section therefore, we review Populism and its relationship to climate policy.

2.6 Right-Wing Populism and its links to climate policy resistance

2.6.1 Defining Populism

Populism as a concept has long proven difficult to define, with different scholars describing it variously as an ideology that specifically sets the pure people against the corrupt elites (Mudde, 2004), as a political style of performative communication by charismatic leaders (Moffitt, 2016; Weyland, 2017), as well as ranging from narrow definitions of specific populisms, such as "*a rural movement seeking to realise traditional values in a changing society*" (Canovan, 1981) to the widest

definition of all, which defines Populism as constitutive of all politics, through the perpetual making and re-making of 'us' and 'them' (Laclau, 2005). Other theorists consider Populisms as 'thin' ideologies, acting essentially as "*embellishments of, and sustainers of, the features of their host ideologies"*, suggesting that Populisms are plural, and we should view them as merely facets of 'thicker' ideologies, such as Conservatism, Liberalism or Socialism, thereby explaining why we see both left and right wing variants (Freeden, 1998).

In the context of Reform UK, and particularly the role of its leader, Nigel Farage, the definition of populism largely as a performative political strategy seems to hold the most explanatory value, aligning with the work of both Moffitt and also of Weyland. Though not entirely in agreement with one another, their broad focus is on Populism as a political strategy based on performance, increasingly facilitated by the surround-sound media environment (Moffitt, 2016), highly reliant on the personal charisma of individual leaders, but unpredictable both in opposition and in government due to lack of a tightly defined ideology (Weyland, 2017). In other words, populism is something that politicians *do* to secure support, but is not necessarily something that voters *are*, beyond reflecting their immediate desires for simple solutions to their pressing problems.

The ability of charismatic populists to secure what Weyland, (2017 p.50) describes as the "*direct, unmediated, uninstitutionalised support of large numbers of followers*" depends on what Laclau (2005) calls 'chains of equivalence': the aggregation of a set of individual grievances into a seemingly lucid call for 'common sense.' While these underlying grievances are not always unreasonable, nor are they always coherent; Populists' strength lies in their ability to respond to a wide range of circumstances but to centre peoples sense of injustice (Malkopoulou and Moffitt, 2023). Their weakness lies in their "*striking unpredictability, shiftiness, and disorganisation in the exercise of government power or policy making*" (Weyland, 2017 p.60) which is often a direct legacy of collecting together unconnected, and often opposing, sets of complaints on which to campaign. Indeed, recently published research from the campaign group Hope not Hate, which surveyed 11,000 people who say they would vote Reform UK if there were an election tomorrow, finds exactly this: Reform's

current supporter base can be broadly split into five main groups, several of which have entirely opposing priorities, with (for example) equal proportions supporting increased workers' rights and increased minimum wages as those who feel workers' rights and minimum wage requirements should be cut, as well as a significant proportion (30%) who are activated by concern that the current government *does not do enough* on environmental issues such as water pollution (Deo, 2025). This empirical evidence of the Reform UK leadership's populist ability to unite contradictory grievances under charismatic leadership supports the performative-strategic understanding outlined above.

2.6.2 Right-wing Populist parties and climate policy

Lockwood (2018) provides a major theoretical contribution to understanding the specific linkages between right-wing populist (RWP) parties and hostility to climate policy. Though written before Reform UK's establishment, Lockwood's conceptual framework for understanding RWP approaches to climate policy in the UK context (particularly regarding UKIP, which could be considered Reform UK's direct ancestor) offers insights potentially applicable to Reform UK. Lockwood disputes the adequacy of structuralist explanations, which theorise that RWP parties primarily tap into the emotions of 'economically left behind' communities. Instead, he proposes that a stronger driver is ideology, with resistance to climate policy combining nationalist sentiment with anti-elite resistance, particularly focusing on the threats posed to 'ordinary people' by climate scientists and environmentalists representing 'corrupting' special interests aligned with supranational institutions like the UN (the links between populism and *nationalism* in relation to climate policy are explored further in Section 2.7, below). Lockwood also proposes that the interlocking complexity of climate policy is fundamentally unsuited to the simplistic 'direct to the people' messaging favoured by populists.

In a large-scale empirical follow-up, Lockwood and Lockwood (2022) examined right-wing populist opposition to climate policies across EU and anglophone countries (US, UK, Australia), finding that the RWP parties in anglophone countries tend to be more aggressively anti-climate policy than in EU states. However, they

demonstrate this is a function of majoritarian electoral systems rather than national culture; Proportional Representation systems in EU states create a moderating effect, partly because RWP parties wield power through coalitions where they preferentially control portfolios like immigration rather than environment, whereas populists in majoritarian systems control all portfolios when gaining power. The authors note this also means RWP influence in majoritarian systems can be more episodic.[10] Lockwood and Lockwood also find measurable differences between opposition to 'climate policy' more generally (international agreement-based frameworks) and renewable energy policy specifically, documenting RWP parties that maintain climate denial positions while simultaneously supporting domestic renewable energy industries where this can be framed as a national economic good, particularly in countries not rich in fossil fuels.

2.6.3 Populist performance of national identity

Section 2.7, below, considers nationalism and its relation to climate policy in more detail but the overlaps between nationalism and (particularly, but not exclusively, right-wing) populism are considered briefly here before turning to nationalism more directly. This link is made here not least because we turn later to perceptions of rural landscapes and communities as fixed representations of national character, which may provide some explanatory power for understanding rural climate policy resistance. In essence, a funnel exists from protective nationalisms down to protective ruralisms, and both are activated through the 'performance' of rural identities via Populist actors.

Using data from 2007 to 2012, Batel and Devine-Wright (2018) explored whether the rising populist right and Brexit narratives had a measurable impact on UK residents' identities at different scales (local, national, European) and, consequently, how this affected their beliefs about energy infrastructures and the acceptability of EU energy policies. They found a shift in identities over that period (to 'more British

[10] While the authors do not directly state this, it seems reasonable to assume that this is in part due to the failure of populist rhetoric in opposition to deliver solutions when in administration, leading to loss of voter trust.

than European', and away from 'equally British and European'), which correlated with decreased support for UK energy policy to be influenced by EU regulation. They theorised that not only does increased visibility of populist rhetoric foster support for more closed and competitive energy policies, but also a more nativist form of concern about renewables, writing of "*a rise in right-wing populist nationalist political discourses that have put side by side the need to defend Britain and the unique British countryside from migrants and wind farms alike*" (Batel and Devine-Wright, 2018 p.43).

This aligns with wider research that demonstrates how populist politicians 'perform' rurality and farming identities as markers of national identities to be protected. Lambrechts and Cleen (2025) analyse how the Flemish populist radical right party Vlaams Belang (VB) integrates farmers into its discourse through both nationalism and populism. The nationalist dimension positions 'the rural as the nation'; rural landscapes represent authentic Flemish identity and tradition, with family farming particularly romanticised. The populist dimension casts the rural as a politically neglected and economically disadvantaged entity, subject to imposition of unreasonable demands from disconnected urban elites. (We return to this in Section 2.9.1, below, on rural climate policy in the UK, considering the evidence of whether these rural vs urban grievances may be at least in part justified.)

Brooks (2020) also demonstrates how right-wing populists appropriate rural landscapes and 'perform' farming lifestyles as symbols of authentic national identity. Brooks theorises that Labour's dominance from the late 1990s demolished the myth of rural areas as apolitical, harmonious spaces, particularly because of the divisive impact of the ban on fox-hunting, ultimately allowing UKIP to fill the space vacated by the modernising Conservative party under David Cameron, and positioning themselves as defenders of 'rural authenticity', against impositions including wind farms. Brooks is at pains to point out that although rural areas voted for Brexit, *farmers* specifically (according to National Farmers Union surveys) voted 52% Remain, suggesting again that the Leave campaign successfully instrumentalised rural economies, and thus the nation, as under threat from the EU

in the minds of the wider populace, even as the central actors in rural economies themselves (farmers) were not so stridently opposed.

There is evidence that the UK farming community is aware of their co-option in this respect. Speaking at a major farming rally against proposed farm taxes in late 2024, one of the organisers stated that "*We have invited representatives of all political parties to speak and we don't want our event used for political point-scoring. We want it focused on the farmers and the troubles we are facing at the moment*." It is notable that 'representatives of all political parties' specifically did *not* include an invitation to Nigel Farage of Reform UK on this occasion, with organisers making it clear that they did not feel he would genuinely speak *for* them, but rather *about* them, to gain support elsewhere (Quinn and Horton, 2024).

Nationalist sentiment is essentially the primary focal point of much Right-Wing Populist discourse, and symbolic use of particular groups (such as farmers), and places (such as the countryside) as representitatve of, or even constitutive of, the nation is explored in the following two sections on nationalism and landscape.

2.7 Nationalism and climate policy

A central tension for climate policy making is that the global nature of the problem requires collective action and co-operation between states. This makes it an easy target for any political actor whose priorities lie around sovereign control of policy.

Where allied to a right-wing ideology, nationalist overtones can and do create tendencies of 'resource nationalism' and resistance to remote bureaucracies imposing rules that the nation does not self-generate.

Studies of nationalism also provide examples of left-wing nationalist approaches to climate and environment policy (described by Conversi and Friis Hau (2021) as

'Green Nationalisms')[11], which build on very similar 'connections with the land' and 'folk histories' as are used in right-wing resource nationalisms. However, where both are usually characterised by territorial appeals to protect or conserve the physical environments or landscapes, 'resource nationalism' also aligns itself with continued support for extractive industries (e.g. pride in coal, associated with 'strongman leaders' such as Modi, Trump and Bolsonaro). This is borne out in the UK context by groups such as the Net Zero Scrutiny Group and Net Zero Watch, whose strong focus on increasing North Sea Oil extraction is their central message (despite evidence that the limited resource remaining cannot meet the UK's needs in the coming decades (Sheppard, 2025)).

2.7.1 Nationalism – the world's most successful ideology?

'Nationalism', for many people, is a word loaded with fear and loathing, so imbued with ideas of extremism, irrationality, emotion and downright unpleasant exclusionism that it has become almost taboo in polite political circles. But, as Michael Billing lays out in his highly cited book, 'Banal Nationalism' (1995), there is a strong tendency for writers on nationalism to diagnose it in others whilst failing to spot it in themselves.

The defined nation-state, with hard boundaries, official languages, and state monopoly of the means to both attack and respond to external military aggression is a relatively recent phenomenon, really emerging in Europe from the late 1600s. Notably, the word 'international' was only coined in 1789 as a way to specifically discuss how legal matters should be discussed *between* nations (Suganami, 1978).

A brief reflection tells us that nationalism is not always pathological. It can also be seen as a basic ideology that represents "*habits of behaviour and belief which combine to make any social world appear, to those who inhabit it, as the natural*

[11] Note that Conversi & Friis Hau caution that Green Nationalism seems to manifest only in 'minority nations' (such as Scotland, Catalonia etc), that are engaged in an ongoing struggle for independence from a supra-state (the UK, or Spain). Previous examples of Green Nationalism linked to independence movements in ex-USSR states such as Latvia have quickly fizzled out on independence.

world" (Billig, 1995, p.37). The central thesis of 'Banal Nationalism' is that, rather than being an extreme position, nationalism is never far below the surface. It is daily flagged by the state, in political speeches, by media outlets, in sporting endeavours and in ordinary conversations, and it is in the smallest words that the 'unwaved flags' of our national identity are constantly found. 'The people' means 'us'. And 'us' means 'people who are living in this place', not those from 'somewhere else'. Hence, we find that small words such as 'us', 'ours', and 'here' are loaded with a huge number of nationalist assumptions.

It follows, then, that rather than being solely a manifestation of extremist ethno-centric emotion restricted to isolated groups of fanatics, nationalism is in fact "*the most successful political ideology in human history*" (Birch, 1989). There is nowhere on earth that is not covered by a nation-state and a flag, or caught up in an ongoing struggle over the issue of where one nation-state ends and another begins. Furthermore, as Billig points out, even extreme movements for liberation from oppressive states serve to strengthen the underlying ideology that nation-states *are* the natural order; they may be involved in a struggle to break away from a nation state, but this is unlikely to be for any other cause than to establish an independent nation state of their own (or join another existing one).

2.7.2 Nationalism, nation-states, and climate policy

While some academic writers propose climate change responses based on a pluralist or borderless new world order of equality, dignity and solidarity (Wainwright and Mann, 2018, p.178) and other writers put forward visions of human societies ordered along bioregional lines that respect natural systems and potentially straddle territorial boundaries (Bajpai *et al*, 2022; Dann, 2022; Hubbard, 2024), these are not proposals that seem imminently likely to replace the nation-states system. Realist counter-arguments would contend that, however odious one finds the concept of nation states, it represents the only meaningful, if imperfect, mechanism for tackling the climate crisis, at least in the short term where precipitous emissions reductions have to be achieved very soon.

Lieven (2020) takes this position to actively critique the tendency of many climate-change activists to attempt to create a borderless new world order at the same time as tackling the urgent need for massive emissions reductions: "*Concentrating on global agreements and institutions is not wrong in itself, but it tends to downplay three crucial facts: that whatever international agreements are reached will need to be implemented by states; that states will need to be strong enough to implement them; and that democratic and authoritarian states alike will need to motivate their populations to make the sacrifices required*". Other commentators argue that the climate crisis is being used by some on the left as a vehicle to deliver a wider ideological project, which Bröning, (2025) refers to as the political left's '*everything struggle'*, doomed to fail, since attempting to roll every conceivable social and economic issue into the climate crisis is a recipe for political paralysis.

Given the pressing nature of the emergency, Lieven argues that we do not have time to remake the global political order, and thus that the nation-state and existing structures will have to play a leading role in the solution. He concludes that "*the choice then is between stupid, short-sighted versions of nationalism and intelligent, far-sighted ones*." He calls for new forms of 'eco-nationalism' that draw on past nationalist and patriotic struggle-narratives (such as World Wars) as a way of convincing current generations that they must make sacrifices for future ones, quoting Milan Kundera's rationale that '*A man knows that he is mortal, but he takes it for granted that his nation possesses a kind of eternal life'*. As part of this, Lieven believes that state military apparatus must be much more honest with publics about the increasing security threat that climate change (and the associated predicted conflict and mass movement of people) presents. Evidence supporting this contention can be found in the MOD's Global Strategic Trends Assessment (MOD, 2024), which considers the myriad ways in which climate change presents to the UK's security.

Matejova (2021) partially critiques Lieven's work, arguing that the roadmap for cultivating eco-nationalism is not provided, and that this requires substantial and targeted nationalistic communications that must be "*politically centrist to serve as a*

unifying force, free from the condescending preachiness of the ideological left and the stubborn defensiveness of the ideological right" (Matejova, 2021, p.3). Both Lieven and Matejova's arguments would thus require the development of a powerful civic nationalism that could displace the visceral, emotionally manipulative, and often extreme rhetoric that nationalist-populists normally peddle in. From the point of view of England itself (rather than the UK as a whole), this would not need to be invented from scratch, but rescuing it from decades-long decay would be no small task.

2.7.3 Nationalism and democratic representation in England

The focus of this thesis is on rural areas in England, and here another layer of complexity arises, in determining what, exactly, England is, and how the *English* (as opposed to the *British*) flex their democratic muscle.

According to (Birch, 1989, p. 77), the UK is "*a somewhat untidy state, neither federal nor completely unitary, that has no formal constitution and can only be understood in historical terms.*" Within that complex structure sits England, long the dominant force in terms of economic, population and cultural influence, but increasingly left-behind, democratically.

Aughey (2007, p.39) explores how England's political history had long been characterised since the Victorian era by *civic*, not *ethnic* nationalism, describing England as "*a nation subservient to civic institutions*", with core values of justice and fairness, combined with a make-do and muddle-through tendency in relation to policy-making and governance that eschews serious intellectual effort (unlike, for example, the deeply theorised notions of liberty that underpinned the French and American revolutions). In this regard, the culture of civic nationalism called for by Lieven and Matejova is potentially lurking there, waiting to be re-activated in the cause of eco-nationalism, though moribund through several decades of under-use.

The Scottish writer Tom Nairn, in his seminal work on English nationalism (The Break-Up of Britain, 1977), argued that England has a fundamental inability to

imagine a positive national identity stemming from the lack of genuine revolution, due to its aforementioned tradition of 'anti-intellectual muddling through'. Though this critique of the English as 'reluctant revolutionaries' should be read through Nairn's position as a strongly left-leaning academic, it is telling that the specific streak of English anti-intellectualism he notes is echoed by writers on both sides of the political fence. Nairn was convinced that new and specifically *English* forms of democratic representation must be developed, a view echoed 30 years later by Irish academic Arthur Aughey. He argues that, as devolution powers were granted to Scotland and Wales, the English needed, but were not granted, equivalent democratic expression. Aughey also concurs that England lost its civic nationalism story in the 1990s, replaced by a 'critical legend' requiring English expiation for past arrogance, while Black notes how Scotland extracted itself from UK history's negative aspects, leaving England to carry the blame for colonial misdeeds. As Scotland moved away politically and Wales gained its assembly, the question of how and when the English would have a meaningful democratic outlet became more pressing, and has arguably contributed to specifically English vulnerabilities to national-populist messaging.

As an example, since the Brexit referendum, much analysis has focused on English nationalism's role in the outcome. Henderson et al. (2017) showed that Brexit was 'Made in England', because, with 84% of the UK population, the outcome inevitably hung on what the English wanted. Henderson et al. show that 73% of those who felt "English rather than British" voted to leave. Rather than a coherent vision of an England outside of the EU, this *could* just as easily be understood as an attempt to use what seemed a one-time offer for genuine democratic engagement, because the English have surprisingly poor democratic representation compared with the devolved nations.

2.7.3.1 Where is England's democratic heart?

Some have called for an English Parliament, but the mechanics of this are unlikely to work. The Scottish Parliament represents 5.5 million and the Welsh Assembly

(Sennedd) 3 million, while an English Parliament would represent 56 million, raising seismic questions about what role Westminster's existing Parliament would play in such an arrangement.

The next obvious unit is devolution to the English regions, but the Blair/Brown North-East Assembly referendum of 2004 was roundly rejected. Colls (2000) predicted as much, symptomatic of the fact that regionalism, as conceived from the centre in the early 2000's, was merely a technocratic scheme. This kind of devolution was designed to deliver Westminster's agenda, and failed to transfer sufficient power to balance national power. Arguably, this process has been revived through the Conservative government's (2010-2021) approach to 'Devolution Deals', but the combined large urban areas, predicated on elected Mayors as figureheads, have been criticised as cynical exercises, merely creating 'lieutenants' forced to implement central government policy in return for additional power, in a move that Palese (2022) calls 'delegation' not devolution.

The Devolution Deals are also described by Palese as fundamentally undemocratic, hammered out behind closed doors, creating a labyrinthine mishmash of different scales with different powers. They also create profound urban/rural inequalities: while 41% of the population lives within Mayoral Combined Authorities, they cover only 14% of England's land area. Remaining rural areas now face unitarisation under the current Labour government, which will make most authority areas around five times larger, but it is not clear that this will deliver any levelling of the funding playing field between rural and urban areas, nor increase democratic accountability. Richards and Smith (2016) argue that meaningful devolution remains structurally impossible in the UK, since all devolved powers depend upon the executive; Westminster's primacy is baked-in, and Parliament can still pass bills affecting devolved nations without their consent, and the powers offered to regions and unitaries are already less than those available to the Devolved administrations.

The English are also under-represented at local government level. Palese reveals that the average English councillor represents 3,300 people, compared with 600 in

Italy and 130 in France. Unlike the Welsh and Scottish, the English have no opportunity to vote using proportional representation at local authority level. This First Past The Post reliance means many English councils have 'undeserved supermajorities' where a single party holds 75% or more seats on less than 50% of the vote—found in 40% of English councils in 2016 (Palese, 2022).

This exploration of (lack of) English democratic representation within the wider topic of (English) nationalism is a crucial link to climate policy because (as has already been seen) a calling card of populist politicians is to frame climate policy as a supranational imposition on a sovereign state. Galent (2022) shows how a lack of recognition of the English electorate, deprived of a sense of representation, actively led to a search for political solutions outside the established parties, facilitating the rise of populist parties such as UKIP, and subsequently, the Brexit Party and Reform UK. Thus, Populists may both respond to genuine democratic grievances, but also feed back to those same resentfully disenfranchised voters other topics (such as climate policy) for them to feel resentful about.

2.8 Landscape, Place Attachment and English National Identity

As discussed in Section 2.6.3, above, rural places and landscapes are regularly called into service by Populists to stand as physical, metaphorical, and cultural representations of 'the nation'. A sense of national and local identity, and particularly the sense that landscape is central to maintaining it, is also a strong feature of Conservatism, as illustrated in Section 2.5.3.2, above, through the writings of Scruton and Oakeshott. In this section, I consider how landscape specifically, rather than rural places and communities in general, provide a site of contention for the changes that will come as a result of climate policies.

Ample evidence exists to show that individuals can simultaneously be concerned about a global environmental issue like climate change, while holding strong attachments to their hyper-local environment. Complex interactions between

environmental attitudes, and attitudes to 'place' more widely, mean that knowing whether an individual cares about 'the environment' is not enough, particularly where energy infrastructure is proposed. "*What is seen by outsiders as a NIMBY (not-in-my-backyard) reaction is seen by residents as place protective action*" (Brown *et al*, 2011). Over time, simplistic attempts to explain resistance, for example to renewable energy infrastructure, as merely a function of proximity (with those closest assumed to be most resistant), have given way to a more nuanced understanding that recognises the importance of symbolic, affective and socially constructed aspects of energy development, including the ways in which a project comes about, who controls the decision-making process, and ownership structures (Devine-Wright, 2005).

2.8.1 Place attachment

Further influential work by Devine-Wright (2009) built on the already established idea of 'place attachment', by situating it specifically in the UK energy policy context, demonstrating that resistance to energy infrastructure in rural places is not inherently "anti-environment", but often arises when people perceive a threat to places to which they are emotionally attached.

Devine-Wright's place attachment work in turn built on pre-existing, multi-dimensional understandings of people's relationships to place, including Jorgensen and Stedman's 2001 'Sense of Place' (SOP) attitude scale. Their empirical study developed a bifactor model which measures a Generalised Sense of Place construct with three underlying, but distinct facets that had previously only been postulated theoretically:

Place Identity: Initially defined by Harold Proshansky, 'place identity' can be described as the way in which individuals incorporate their relationships with physical places into their larger concept of self (Peng et al., 2020). The concept arose out of concern that psychology had hitherto focused strongly on development of self-identity as a function of personal and social interactions, ignoring the role of physical places in identity formation (Proshansky et al., 1983).

Place Attachment: "*Place attachments are the positive bonds people form with places, arising from affective, behavioural, and cognitive ties*" (Brown et al., 2011, p.1). The strength of an individual's place attachment has been shown (through the work of researchers such as Brown and Perkins (1992); Hidalgo and Hernández (2001); and Manzo (2003, 2005)) to be a function of the longevity of residence in a particular place, the social connections that an individual engages in, and the valued physical attributes of the place. All of these, when combined, greatly increase the likelihood of an individual engaging in 'place protective' behaviours (Manzo and Perkins, 2006; Devine-Wright, 2009).

Place Dependence: This, less abstract, concept defines how well a place serves instrumental values or goal achievement. It is also a more relative measure. Unlike Place Attachment, which is a measure of positive feeling, an individual's perception of how well a place serves their needs can also be negative, if they feel an alternative location would improve their ability to achieve outcomes of value to them (Jorgensen and Stedman, 2001). Where an individual's place dependence is positive (for example, where a place currently helps them achieve a positive outcome), threats to that positive personal outcome will manifest as resistance to changes to the place.

The US social geographer Yi-Fu Tuan was one of the earliest writers to explore the differences between 'spaces' and 'places', and the meanings that people attach to places. From modest-sized homes to expansive landscapes, it is places (rather than spaces) that are treasured for their familiarity and the shared cultural practices we fill them with. "*Space is abstract. It lacks content; it is broad, open, and empty, inviting the imagination to fill it with substance and illusion; it is possibility and beckoning future. Place, by contrast, is the past and the present, stability and achievement*" (Tuan, 1975 p.164-165).

The concept of 'place' intersects with but is distinct from the concept of 'landscape'. When considering changes to rural places, discussion of landscape inevitably arises. Landscapes are simultaneously intrinsically physical but resolutely social, incorporating aesthetic, environmental, historic and cultural aspects. WTJ Mitchell,

in his introduction to the 1994 pivotal collection of essays 'Landscape and Power' (which largely reshaped approaches to landscape studies), suggested that 'landscape' should be used as a verb rather than a noun, with landscapes understood "*not as an object to be seen or a text to be read, but as a process by which social and subjective identities are formed*".

Place attachment in relation to landscapes is inherently emotional and, as described by Riley (1992, p.13), is "*an affective relationship that goes beyond cognition, preference, or judgement,*" a relationship that he is at pains to point out is not restricted to 'special landscapes', but those landscapes that are experienced as a routine part of everyday life.

2.8.2 Landscape change in England

The UK has a highly managed rural environment. Just over 70% of UK land area is agricultural, and 72% of that is grazed land (DEFRA, 2023c). Rather than wilderness, much of Britain's open land is made up of "*very tightly grazed, species-poor swards*", the result of centuries of sheep grazing that prevent natural woodland regeneration (Rewilding Britain, 2024, p24). Within the UK, the landscapes of the *English* countryside represent an extreme example of Setten *et al.*'s processual understanding. England's rural landscapes are somewhat distinct from their Welsh, Scottish and Northern Irish counterparts, valued not for their wildness, or naturalness, but because they are perceived as a sort of stabilised outcome of centuries of socio-technical practices, as per Mitchell's proposition; 'landscape-as-a-verb'. The rapid and radical landscape changes that will occur in England as a result of climate policy are therefore inherently and deeply political, interrupting existing socio-cultural and techno-economic practices.

Of course, a period of rapid and radical change to English landscapes has already occurred (just) within living memory, as post-war politics prioritised security of food production and the modernisation of transport and energy infrastructure. But this period of change happened against a highly specific backdrop that was suited to gaining public support and had crucially nationalistic/national security overtones. By the 1930s, as little as 30% of Britain's food supply was home-grown, and the risks

posed to food import security by an increasingly bellicose Germany led to unprecedented levels of state intervention and support for the agricultural sector, which continued for several decades after 1945 (Short, 2014). Alongside this, post-war rebuilding of a shattered nation with the express purpose of modernising for the national good meant a rapid expansion of energy, water and transport infrastructure. While this transformed rural areas on a scale not seen since the industrial revolution, it was accompanied by narratives of national need and a paternalistic approach to landscape architecture that aimed to embed these infrastructural changes as the "*iconic undertakings of the period*", with the Central Electricity Generating Board in particular required to deliver public amenity, and positioned as "*the modern patron of landscaping art"* (Csepely-Knorr et al, 2020).

2.8.3 Landscape and English national identity

Present proposals for landscape change driven by the climate imperative have not convincingly been situated within the same national-need framework. Setten et al.'s embodied, relational understanding of landscape extends far beyond those who directly work the land or regularly walk through it. Through Billig's 1995 concept of 'banal nationalism' (the daily, unremarked practices through which national identity is reproduced), landscapes become repositories of collective national identity, even for rural residents who do not actively participate in the embodied practices of agriculture or rural leisure pursuits. Indeed, even many urban residents who rarely visit rural places have a conception of the 'rolling green hills,' 'patchwork fields,' or 'rugged moorlands' of England as not just physical spaces, but as part of what Benedict Anderson (1996, 1983) called the 'imagined community' of the nation.

Readman (2018), in his book 'Landscape and the shaping of English Identity', suggests that landscape upheavals (such as the industrial revolution) trigger strong campaigns for preservation of landscapes, since landscapes themselves are a means of maintaining a sense of the continuity of national life at a time of change. This focus on the national is the crucial distinction. Aughey (2007), discussing the work of Richer, et al. 1997, p84 and Smith 1996, p160, posits (in a similar vein to the

Lieven/Kundera quote above, in Section 2.7.2) that this is because "*the nation is a route to immortality in a secular world*". It follows that, for the many people who (consciously or unconsciously) associate landscape with the immortal life of the nation, despoliation will trigger concern that is not just personal, but patriotic in nature. Whether people's beliefs about landscape and how it comes to be are themselves a form of myth-making is irrelevant; it matters only that their beliefs about landscape are congruent with their own personal understanding of their national story (Readman, 2008).

2.9 Rural England, rural disadvantage, and rural climate burdens

Despite the links between rural landscapes, farming communities and national identities touched on above, there is significant risk in assuming that rural communities in England will necessarily see the sense in acting in 'the national interest' with regard to climate change. Rural sociologists have been writing for some decades about the tendency for rural areas to be 'exploited by capital', largely for the benefit of agri-corporations, urban tourists and second-home owners (Mormont, 1983; Marsden, 1984; Woods, 2011), while at the same time, evidence suggests that the social contract that should ensure a decent standard of living for rural communities has not been upheld (Stone and Padley, 2025).

2.9.1 Rural disadvantage in England

Rural communities are places where average earnings are low and access to services is extremely restricted for many, and where the Minimum Income Standard (the measure of whether a household earns enough for an acceptable standard of living) needs to be about 10-20% higher than in urban areas to reach the same standard of living (Hirsch et al, 2010; Stone and Padley, 2025). More people in rural areas are in employment than in urban areas, but average wages are lower, and rural areas are disproportionately reliant on the (more expensive) private rented sector (Rural Services Network, 2025a).

Rural community cohesion is also fraying at the edges, as increasingly unaffordable housing and lack of good jobs, public transport links and digital connectivity leads to a net outflow of younger people from many rural areas (CPRE, 2021).

In this context, it is important that the rural/urban divide is better understood for climate policy making, as rural areas are often presented by policymakers as places of *opportunity* for solving the problem (especially through the generation of renewable energy infrastructure and nuclear power, but also through carbon sequestration and altered agricultural and land management practices). However, despite these assumptions about rural areas as hosts for climate *solutions,* limited policy attention or funding is committed to solving the rural-specific *problems* that drive high per-household carbon emissions in the countryside. In particular, rural areas have larger, older housing stock, more of which is solid-walled, single-glazed and off the gas network than in urban areas – around 20% of rural homes fall into the least efficient F and G rated categories (compared with 2.4% in urban areas), and only 40% are on the gas network (compared with 91% in urban areas). Taken together, energy costs in rural homes are considerably higher (Energy Saving Trust, 2019). Rural areas lack public transport and have limited active travel infrastructure (cycling on narrow, unlit lanes is often dangerous), but average distance to basic services is much higher than in urban areas; as a result urban households' average weekly travel costs are only 66% that of rural households (Rural Services Network, 2022).

2.9.2 Climate policy in rural areas

Despite these challenges, much of the government policy support for low-carbon living in the past 15 years has been targeted at urban areas. Funding for street-by-street household retrofit is easier to distribute in urban local authorities (where the economies of scale in retrofitting vast numbers of very similar terraced and semi-detached homes are greater). Similarly, investments in active and public travel have resulted in a considerable number of high-profile urban bus and cycling schemes, but limited support in rural areas. For example, a report on the Conservative administration's flagship Bus Service Improvement Programme grant revealed that

the 37 largest rural authorities (representing almost half of England's population) submitted Bus Service Improvement Plan (BSIP) bids which collectively totalled £3.6bn, of which only 10% was awarded. Urban areas, by comparison, received 67% of the total funding, despite having seen less steep drops in passenger numbers (Burbidge, 2023).

Climate policies that rely on exploiting rural areas to serve national needs, while at the same time greatly under-funding programmes for transformative change and the opportunity to reap the benefits from a low-carbon transition, are likely to face resistance. The rapid growth of the wind industry under a strongly supportive Labour administration from 1997-2010 provides a cautionary tale, ending as it did in a major 'place protective' backlash (Devine-Wright, 2009), and an effective policy moratorium on further onshore wind development between 2015 and 2024 (GOV.UK, 2024).

Much earlier examples can be found of resistance to 'national interest' reforestation schemes such as those in Sutherland in the 1980s, with tensions still running high today where smallholder interests run up against corporate forestry acquisitions (Mackie, 2014), and negative impacts on land values and land availability result from the growth of the carbon capture forestry industry (McMorran *et al.*, 2022). Many rural residents and associated campaign groups will resist industrial scale climate solutions in the rural environment, even if it is clear these will help tackle the climate crisis, if they cannot see a balance between local impact and benefit (Cox, 2017 Ch.8; CPRE, 2025).

Howarth and Parsons (2021) discuss a range of countryside-based solutions to the nation's wider environmental problems, such as 'ecosystem and biodiversity services'. They also provide evidence that the countryside could produce as much as 45% of the UK's energy demand through renewables. Set against the fact that only 17% of the population actually lives in rural areas (DEFRA, 2017), this can only mean a major exporting of that energy production to urban areas. Howarth & Parsons' suggestion is that demonstrating the "*value of these services is a powerful way to communicate the importance of conservation and effective land use*

management", but surely, this rather misses the point: that 'demonstration of the value' is to the nation *as a whole*, and is ultimately a transfer of value from rural to urban areas. A free-market, neoliberal framing of the countryside as a place that is merely 'providing services' that can have a monetary value applied is likely to trigger the undercurrent of resentment that rural communities often feel; (Munday *et al*, 2011; Perry, 2024) that they are being exploited for the benefit of the urban masses, without any keeping of the other side of that social contract that should then provide them with the basic services they need to maintain vibrant small-scale economies, educate their children reasonably nearby, keep their homes warm and be able to travel around without being entirely dependent on the private car. Evidence shows that rural services are already in serious decline (for example 35% of rural hospitals have closed in the last 15 years, and bus services are at historic lows) (Burbidge, 2023; Rural Services Network, 2025b). That this decline is occurring while demand to locate climate policy solutions in rural areas grows, makes the disparity all the more stark.

2.9.3 From 'rural politics' to the 'politics of the rural'

UK rural politics was, for centuries, largely defined by relatively few farmers and landowners making policy decisions that directly related to farming and land management. Any issue that was not directly linked to agriculture tended to be excluded from meaningful discussion in rural policy spheres (Woods, 2006). Historically then, rural communities were under-served in terms of public service provision, and left considerably less developed than their urban counterparts, except where the provision of infrastructure (such as mains electricity or communications) provided for increased economic productive extraction from the countryside, or (briefly) where it aligned with the postwar social-democratic consensus on universal access to public services. Only during a relatively short period from post WWI to the 1960s were rural areas actively 'modernised' by the state, usually working in cahoots with a small agrarian elite which sought to secure commodity subsidies and production support mechanisms that would create a particular 'sector specific welfare state' for the agricultural industry (through state and then EU subsidy), coupled with a brief flowering of social democratic principles

that drove campaign of universal public provision of services such as education and healthcare after WWII (Woods, 2006).

By the 1970s the situation began to change as the ingrained poverty of some rural areas seemed resistant to the cure offered by agricultural subsidy, and four other phenomena came into play. Firstly, the pre-eminent role of agriculture within the wider UK economy fell dramatically and, within the specific rural economy, agriculture was increasingly challenged by other forms of economic activity such as property trading and tourism. Secondly, increased concern about intensive farming practices from wider urban communities created challenges to the agrarian elites' approach to countryside management; thirdly, the increase in out-migration from towns and cities by wealthy, (often older) people in search of 'the good life'; and, finally, the huge challenge presented to state-subsidised agriculture by the neo-liberal turn in global economics. All this combined led to what Mormont (1987) described as a transformation of 'rural politics' into 'the politics of the rural'. In essence, where 'rural politics' was previously narrowly formulated through the lens of agri-industry, it now centres on debates about the very nature of what rurality means, and the blurring of lines between people who are 'spatially rural only' as opposed to those who are more embedded in rural places and economies. These tensions result in challenges to development, and an increase in 'place protective' behaviours (Devine-Wright, 2009).

2.9.4 Conceptualising rurality

Given that the terms 'rural' and 'urban' are ubiquitous in social and spatial planning, Cloke (2006) describes rural places as conceptually shifty, 'other-than-urban' spaces that can be conceived (at one end of the scale) as functional places defined by sparse settlement patterns and an economy dominated by land-based industry, through to entirely cultural constructions whose definition lies only in the shared practices and cultural meanings attributed to the places.

Cloke also highlights how recent decades have seen a significant influx of urban populations into rural locations. While attracted to rural locations because of the perceived advantages of rural lifestyles, these urban migrants bring with them key

attributes of urban living and levels of expectation which often serve to transform the very communities they had been attracted to. Cloke describes the result as a "post-rurality", in which newly arrived consumers of the rural know that their version of rurality represents an inauthentic pastiche, but this itself has meaning to them.

Despite multiple studies into the 'incomer effect', whereby these new arrivals are hypothesised to have higher levels of resistance to rural change than long term residents, evidence in support of this is mixed.[12] Ulrich-Schad and Qin (2018) provide a literature review of the multiple international studies on this hypothesis, as well as conducting large-scale survey research of their own (in New Hampshire), which again finds mixed results, principally because 'rural' has so many meanings (lending credence to Cloke's discussion of the difficulty of conceptualising 'rural'), and because newcomers themselves are not a monolithic block.

According to Woods (2006), despite these multiple conceptions of rural, there remains a significant thread of 'stability' to conventional discourses of the rural community. "*This includes not only temporal stability – the sense of unchanging values and practices connecting back to a purer, simpler age – but also geographical stability. Rural identity is defined by a rootedness to place, by a belonging to land and locality, and by an understanding of spatial boundaries and an appreciation of and respect for property*." Crucially, these definitions are adopted by incomers too, who come in search of that rural idyll.

This view is also reflected in the qualitative work of Phillips and Dickie (2015) in their study of narratives of transition and stasis in four English rural communities. They identified 'narratives of stasis', by which they mean "*the stories that people tell themselves to excuse their inaction on climate change*" that centred on this idea of the rural as being unchanged and unchangeable, "*a status they could not conceive of altering in the future, even in the face of challenges such as climate change and peak oil*", coupled with a general desire to maintain what they have in terms of way of life;

[12] This is sometimes referred to as the 'gangplank hypothesis', as in, 'pulling up the gangplank' to prevent other new arrivals or landscape changes.

essentially, a sense that they have emotionally and financially invested in their current way of life and would rather not change it, despite mounting evidence that change is coming. With reference to the barriers to rural decarbonisation noted in 2.9.1 and 2.9.2, above, Philips and Dickie find that even where rural dwellers interviewed did accept that change was needed, they struggled to see how they could do this, for example that they are entirely car-dependent due to the lack of any meaningful alternatives, and don't see that changing.

In a similar vein, Kari Norgaard (2011) identifies a tendency of rural residents to absolve themselves of blame for environmental damage, in what she calls 'tools of innocence', by linking their rural lives and activities in the natural world around them (such as hiking and walking the hills) with an innate self-belief that they are therefore intrinsically more environmentally friendly than their urban counterparts "*despite their rising materialism, petroleum development and wealth*" (Pg 149). As a result, expecting rural communities to host solutions to a problem that they conceptualise as being of urban communities' making is problematic.

2.9.5 Rural 'anti-state' sentiment

Ashwood (2018) talks of the tendency for rural areas to tend towards 'stateless' attitudes (the idea that agrarian communities basically don't need state authority, and also tending towards a belief that they do not even need cities). This means that rural thinking can lean towards a small-scale 'anarchist-collectivist culture', whereby rural communities feel they can get along just fine without the state and urban areas (which is increasingly possible as the rise of internet shopping has made it possible to avoid going to 'the big town' to buy clothes, furniture etc. that would previously have meant rural dwellers felt a stronger tie to their nearest urban centre). The flipside of this is that, if rural communities feel they don't need towns, they can also conclude that their only role in the fight against climate change is to provide for their own needs locally, which would lead to them resisting any energy generation or carbon capture infrastructure that is 'oversized' for their local footprint.

Less benign than this 'stateless' position is what Ashwood calls an 'anti-state' position, "*the defensive version of the stateless position, which is held by those who have been wronged by the state, through, for example, natural resource extraction or industrial agricultural production.*" Under this conception, rural actors feel that the state (e.g. through weak planning laws or support for corporate practices such as sewage overflows into rivers) has overtly allowed their environment to be degraded. Trust in the state is low in such areas, and there is thus an uphill struggle for policymakers to convince residents that additional 'environmentally friendly' changes such as solar farms really will make a positive change to the environment, creating easy opportunities for populists to inflame latent anti-state tensions.

2.10 Situating the research in current political events

It is a measure of the seismic change that has occurred in UK politics that in October 2021 (when I began this PhD), Reform UK did not register above the low single digits in opinion polls, while the Conservatives commanded around 40% of the vote (Opinium, 2021; YouGov, 2021). By mid-2024, a General Election had swept the Conservative Party from office, with voters inflicting on them their biggest single loss of seats since 1906 (down from 365 to 121 seats). The Labour Party had secured an outright majority with 411 seats in total. But the UK's first-past-the-post system obscured where much of the real vote shift occurred; the real driver of the result was the Conservative party haemorrhaging support to Reform UK, who came second in almost 100 seats. Thus, far from being a right-to-left swing, the real story was a shift from right to further right (McDonnell, 2024). At the time of writing (autumn 2025) multiple polls suggest that, were a General Election to be held tomorrow, Reform UK would secure the largest vote share of all parties (Difford, 2025), and their strong showing in the local elections of May 2025 (where they took control of 10 local authorities) corroborates this prediction.

It is fortunate for the research presented here that much of the data collection began just at the point when it made sense to offer 'Reform UK' as an option when asking for participants' political alignment. Segmenting the views of voters on the political right has provided valuable additional insight into how the views of supporters of

this new party of the right may align with, or differ from, the views of Conservatives, both about how climate policy is made, and what it prescribes.

2.11 Connecting the literature to the research questions

The Literature Review has been purposely wide-ranging, reflecting the broad and interdisciplinary nature of the research questions this thesis addresses:

1. Does political identity lead to differential rates of participation in Climate Assemblies and differences in attitudes towards the legitimacy of these policy-making forums?
2. How can resistance to rural climate policy initiatives be reliably measured?
3. What are the pathways by which political identity, populism, and rural identity shape resistance to rural climate policy in England?

Taken together, these three research questions represent the operationalisation of the overarching aim of this thesis: to understand how climate policy making can be made more inclusive of the views and concerns of rural, politically right-leaning communities in England.

Table 1, at the start of this Chapter, provides a guide to the connections between the Literature Review sections and the research questions, and is a companion to Figure 1, also at the start of this chapter, which illustrates how the Literature Review topics fit together and connect via the central tension of the left-right political divide in climate policy making.

As Table 1 shows, some elements of the Literature Review form a backdrop to all three of the research questions. Sections 2.2 and 2.3 introduce the climate science evidence base and the UK's current statutory obligations on climate change. It is these policy requirements that dictate the rural land use and energy infrastructure changes that motivated the scale development work that responds to RQ2 (Chapter 6), and provide the context for both that resistance and the causal paths to it that are measured in response to RQ3 (Chapter 7), as well as providing the impetus for the democratic innovations that are now being regularly used as a mechanism for

securing better public engagement in climate policy making (RQ1, Chapters 4 and 5).

The literature on Deliberative Mini Publics and their use in climate policy making (Section 2.4), combined with the literature on the left-right political divide and its relationship to climate policy (Section 2.5), provides the theoretical foundation for RQ1. Section 2.4 provides evidence that while DMPs have grown rapidly as a tool for climate governance, some of their underlying assumptions around representativeness have been insufficiently interrogated with respect to political identity. Section 2.5 establishes that political identity is among the strongest predictors of attitudes to climate science and associated policy. In combination, these sections of the Literature Review provide the context for the empirical work in Chapters 4 and 5.

Returning to the work in Chapters 6 and 7, the theoretical frameworks for understanding landscape attachment (Section 2.8) and the sociology of rural communities and their relationship to the state (Section 2.9) together informed the conceptual structure of a novel measurement scale that is the heart of Chapter 6, and which distinguishes between abstract identity-rooted resistance and concrete resistance to specific interventions. The literature on nationalism (Section 2.7) also informed the inclusion of scale items relating to the potential relationship between English rural landscapes and the way in which some individuals conceive of their national identity. RQ2 (how resistance to rural climate policy initiatives can be reliably measured) thus emerges directly from this cluster of literatures.

Finally, the Path Model analysis in Chapter 7, which examines the causal pathways through which political identity, populism, nationalism and rural identity shape resistance to rural climate policy, draws on the broadest range of the literature reviewed here. The political divide (Section 2.5), populism (Section 2.6), nationalism (Section 2.7), landscape and place attachment (Section 2.8), and rural disadvantage and rural cultures (Section 2.9) all contribute theoretical constructs that appear as variables in the final model. The literature reviewed in these sections both contextualises the path model and provides the theoretical backdrop for the

hypothesised causal structure that is tested in Chapter 7, in response to RQ3: what are the pathways by which political identity, populism, and rural identity shape resistance to rural climate policy?

3 Methodology

Chapter 1 gave a brief overview of the background to and structure of the thesis, and Chapter 2 broadly described the theoretical context in which the study is situated. This chapter explains the research philosophy of this work, describes the methods used in each of the research chapters, and lays out the process of collecting the data used for analysis.

3.1 On methods and researcher positionality

3.1.1 Choice of methods and Researcher positionality

The work in this thesis uses quantitative methods. This has been a complete departure for me, having never before engaged with any of these techniques, and the progression in analytical complexity of the four research chapters directly reflects my own journey getting to grips with the understanding and application of increasingly complex methods.

However, my choice to focus primarily on quantitative techniques was not wholly driven by a personal interest in expanding my own research skills and abilities. It was partly a choice made in the hope that it would provide some sort of 'epistemic legitimacy' for the research outputs in the eyes of the political group that is the subject of the study. I worked on the principle that research based on quantitative methods, with 'scientifically familiar' methods of analysis, emphasising large samples and statistical rigour, and minimising interpretative uncertainty, will be more trusted by a conservative/right-wing audience. It was therefore a pragmatic choice, intended to maximise research impact, because climate change is a highly contested policy topic, and I believe the methods matter not only because of what they might reveal, but also because of whose attention they can command.

This is not to say that I believe my own political alignment is irrelevant to how I have conducted this work; all research reflects the standpoint of the researcher. However, I have attempted to develop a disinterested understanding of what is important to other people within their own frameworks, treating these frameworks as coherent systems of belief worthy of study on their own terms. This became increasingly important to me as I progressed through my early literature review, on encountering published work on right-of-centre political views where methodological choices appeared to me to presuppose certain conclusions, raising questions in my mind about whether the research was designed to understand or simply to pathologise this worldview, and subsequently discovering that this is by no means a new phenomenon (Jost *et al.*, 2003; Haidt, 2013; Krueger, 2013).

3.1.2 Research Philosophy

If there is a research philosophy that underpins this thesis, it is methodological pragmatism, but I did not embark on the project with a strongly philosophically-informed position. Rather, I would say that the entire research endeavour emerged from practical concerns about climate policy implementation and legitimacy. Only on reflection did I come to realise that the assumptions underpinning my approach align with *methodological pragmatism* (the view that research methods should be chosen based on their fitness for answering the question at hand, rather than allegiance to any particular epistemological tradition (Creswell, 2007)). Despite the fact that methodological pragmatism is most often associated with Mixed Methods Research (MMR), there is no reason to believe that pragmatism as a paradigm requires MMR as an approach to research (Morgan, 2014). I focused first on quantitative methods because they offered the most effective means of identifying patterns across a large, politically diverse sample, while maintaining the kind of methodological rigour that would have maximum credibility with the part of the political spectrum I am most keen to engage with.

However, as Morgan also describes, *methodological* pragmatism has to some large degree become unmoored from the *philosophical* Pragmatism that underpins it. I have aimed to keep this connection clearer later in this thesis, in the discussion of

my results (Chapter 8, Section 8.9), since philosophical Pragmatism offers a particularly useful lens for understanding political resistance to climate science, because it recognises that people evaluate claims not only by asking 'is this factually accurate?' but also 'what future would accepting this truth claim commit me to?'. This is an idea developed more by both Morgan (2014) and Gillespie et al. (2024), who emphasise the temporality inherent in knowledge: the way people assess knowledge claims in terms of their potential consequences rather than merely their empirical content in the moment. A Pragmatist interpretation focuses not so much on rejection of empirical evidence itself, so much as rejecting what accepting that evidence would require, which is so crucial when different groups of people have different wishes for how the world should be.

I take this approach because, as someone who still works in the 'real world', training politicians from all political parties, I am increasingly concerned about the social legitimacy of academic research, particularly along partisan lines. While some of the more lurid headlines of catastrophic declining public trust in scientific expertise are overblown, evidence does show a notable decline in trust in academic output in recent years, which is more pronounced along partisan divides (Lupia *et al.*, 2024; Milkoreit and Smith, 2024; Cologna *et al.*, 2025). Because of the risks inherent in increasingly politically polarised trust in science, I believe social science research is most valuable when it maintains a distinction between *normative motivation* and *activist methodology*. I do not argue that researchers should be indifferent to human welfare; indeed, this research is motivated by concerns about the harms that unchecked climate change will bring. Rather, I align with the view that once a research question is formulated, scholarly inquiry requires genuine openness about what the evidence reveals about human difference, and that academic credentials should not be deployed to advance predetermined political conclusions (Büntgen, 2024).

3.2 Research methods

3.2.1 Software

Survey management was carried out in Qualtrics, and downloaded for data cleaning in Microsoft Excel (version 2511). Cleaned and sorted data was imported into Jamovi (Version 2.6.44) for all subsequent analysis.

3.2.2 Data sources and analysis methods by results chapter

Table 4, below, summarises the data sources and analysis methods used in each of the results chapters. More detail and justification for the methods used is provided within the specific research chapters' method sections. **Figure 2**, in Section 3.2.4.1, shows how the same survey underpinned data collection for 3 of the 4 results chapters (Chapters 5, 6 and 7). Full Survey questions can be found in Appendices 3.1 and 4.2.

Results chapter	Data sources	Research Question	Analysis Methods
Chapter 4: Investigating political bias in the Herefordshire Citizens Climate Assembly	Primary Data: Survey 1. Distributed to HCCA participants (26 responses from total possible population of 40). (see Appendix 4.2 for full questions). Secondary Data: None	**RQ1:** Does political identity lead to differential rates of participation in Climate Assemblies and differences in attitudes towards the legitimacy of these policy-making forums?	**Part 1:** Probability testing using the hypergeometric distribution to ascertain whether Conservatives were under-represented in the process. **Part 2:** Non-parametric tests of difference (Mann-Whitney) to explore left leaning and right leaning participant views on the fairness and legitimacy of the process.
Chapter 5: Investigating attitudes to Climate Assembly recruitment and participation	Primary Data: Survey 2. distributed in rural areas. (See Appendix 3.1 for full question list). Secondary Data: Recruitment data for three Climate citizens assembly processes from Sortition Foundation	**RQ1:** Does political identity lead to differential rates of participation in Climate Assemblies and differences in attitudes towards the legitimacy of these policy-making forums?	**Part 1 - Sortition Foundation data:** Descriptive analysis of recruitment data from three Climate Citizens Assembly processes. **Part 2 - Survey data:** One-way ANOVA (Welch's F to accommodate unequal variances) to compare general support for Climate DMPs across party affiliation groups, followed by Tukey post-hoc pairwise comparisons with Cohen's d and Probability of Superiority effect sizes. **(n=714)** Contingency table analysis with Chi-square test and Cramer's V to examine the association between party affiliation and intention/motivation to participate in Climate DMPs. **(n=710)** Non-parametric Friedman Repeated Measures ANOVA to analyse ranked preference data on participant selection characteristics. **(n=668)**, followed by: • Durbin-Conover pairwise comparisons to identify specific differences in ranking criteria • Kruskal-Wallis ANOVAs to identify party affiliation differences in rankings

			• Dwass-Steel-Critchlow-Fligner (DSCF) pairwise comparison method with corrections for multiple tests Chi-square tests to analyse patterns of missing data (Missing Not At Random analysis).
Chapter 6: Development and Testing of the RRCI scale	Primary Data: Survey 2. Distributed in rural areas. (See Appendix 3.1 for full question list). Secondary Data: None	**RQ2**: How can resistance to rural climate policy initiatives be reliably measured?	**Part 1 - Pilot Survey Phase (n=95, 35 items):** Item development for new scale Descriptive statistics and correlation analysis to assess item characteristics. Reliability analysis using Cronbach's alpha and McDonald's omega. Qualitative review of participant feedback to refine item wording, followed by item rationalisation based on correlations and reliability metrics to reduce scale from 35 to 24 items for use in main survey. **Part 2 - Main Survey results, sample division (n=723, 24 items):** Random split-sample allocation for separate EFA (n=345) and CFA (n=378) analyses. MANOVA with Bonferroni correction to verify equivalence of split-sample groups across all items. **Part 3 - Exploratory Factor Analysis (EFA) on split-sample 1 (n=345):** Descriptive statistics including skewness, kurtosis, and item discrimination. Reliability analysis (Cronbach's alpha and McDonald's omega) with reverse-scoring of opposite-valence items and iterative item removal. Bartlett's Test of Sphericity and Kaiser-Meyer-Olkin (KMO) measure to assess suitability for factor analysis. EFA using Maximum Likelihood estimation with Parallel Analysis to determine number of factors (6 iterative rounds):

			• Round 1: Unrotated solution • Round 2: Oblique rotation • Rounds 3-6: Sequential item removal based on cross-loadings and factor loadings <0.4 Ex-post sample size adequacy check (Mundfrom et al., 2005 approach) after factor structure emerged. Final 18-item, 3-factor solution explaining 56.3% of variance. **Part 4 - Confirmatory Factor Analysis (CFA) on split-sample 2 (n=378):** Reliability analysis (Cronbach's alpha and McDonald's omega). DWLS (Diagonally Weighted Least Squares) estimation with robust mean and variance adjustments (WLSMV) to accommodate ordinal data. Iterative model testing (10 rounds) with multiple fit indices (Chi-square test, χ^2/df ratio, CFI, TLI, SRMR, RMSEA, AIC, BIC): • Rounds 1-3: Testing single-factor, uncorrelated 3-factor, and correlated 3-factor models • Rounds 4-6: Refinement based on Modification Indices, adding item covariances • Rounds 7-10: Testing Bifactor Model structure with General Factor and three Specific Factors, sequential removal of non-significant factor covariances **Part 5 - Bifactor Model Assessment:** Calculation of bifactor-specific indices (ECV, PUC, IECV, OmegaH, H coefficient, Factor Determinacy, ARPB) using Dueber's Bifactor Calculator to assess: • Scale unidimensionality • Appropriateness of using General Factor scores • Scale reliability and construct validity • Factor score stability for use in subsequent research

Chapter 7: A Path Model Analysis of resistance to rural climate policy	Primary Data: Survey 2. Distributed in rural areas (See Appendix 3.1 for full question list). Secondary Data: None	RQ3: What are the pathways by which political identity, populism, and rural identity shape resistance to rural climate policy?	**Part 1: Preliminary Regression Analyses (to inform Path Model specification): (n=707)** Hierarchical Linear Regression (in blocks) to test predictors of Left-Right political position and Resistance to Rural Climate Initiatives, examining unique contributions of variables once effects of others are controlled for. Multinomial Logistic Regression with party alignment as outcome, testing rural identity, English nationalism, populism, and left-right position as predictors. **Part 2: Path Model Analysis (Structural Equation Modelling) (n=707):** Path Model specification using effect-coded categorical variables (rather than dummy coding) to represent party alignment as a mediating "prism" through which identity variables influence outcomes. Maximum Likelihood estimation with robust Satorra-Bentler corrections to account for departures from multivariate normality. Bootstrapping (1000 samples) using percentile bootstrapping method to estimate sampling distributions and minimise Type I error. Mediation analysis to decompose total effects into direct and indirect (mediated) effects, testing whether core identity variables (rurality, nationalism, populism) are transmitted via political alignment to impact attitudes to rural climate policy. Model fit assessment using multiple indices (Chi-square test, CFI, TLI, RMSEA, SRMR, AIC, BIC) with df>10 threshold for reliability, and iterative model re-specification to achieve acceptable fit.

Table 4: Summary of research methods by results chapter

3.2.3 Survey design and distribution – Chapter 4

HCCA participants were sent a survey approximately one year after they took part in the Herefordshire Citizens Climate Assembly. The full HCCA survey questions are provided in Appendix 4.1. The HCCA survey blocks included:

- Demographic questions:
  - Age
  - Sex
  - Ethnicity
- Political identity, including:
  - Populism battery from the British Election Study
  - Left-right scale
- Political Party Alignment[13]
- Battery of items from British Election Study measuring 'Active Open-Mindedness'
- 15-item 'New Ecological Paradigm' battery (Dunlap *et al.*, 2000), measuring broad environmental attitude
- Item on belief in Climate Science
- Three batteries on views on participation in the HCCA, largely adapted from OECD guidance on evaluating deliberative processes (OECD, 2021a), including:
  - Motivation
  - Inclusion
  - Legitimacy
- New battery on ideal scope of future, similar assemblies

The survey was circulated by email, with a follow-up email and a final reminder text, which resulted in 26 responses from 39 participants.

[13] Note Reform UK was not offered as a choice due to very low salience popular political discourse at the time the survey was developed.

3.2.4 Survey design – Chapters 5, 6 and 7

I combined data collection for the work in Chapters 5, 6 and 7 into a large single survey, consisting of 56 questions in multiple blocks. While recognising the inherent risks associated with long surveys (chief among which is survey fatigue), this approach was the only way to overcome the time and budgetary constraints inherent in the PhD, while still offering a way to collect enough data to consider all the issues I wanted to study. To overcome survey fatigue risks, I incentivised the survey through the offer of a £250 prize draw. I also paid close attention to question ordering, to minimise respondent priming and bias (DeVellis, 2017).

3.2.4.1 Survey blocks

After 'Block 0' questions (three basic items collecting demographic data, age, ethnicity and sex), the survey was organised into six thematic blocks as shown in Figure 2 below. These blocks were presented to participants in the order shown, though the presentation of the data in the results chapters does not follow this sequence.

The responses to the block of questions on Deliberative Mini Publics (Block 6), although coming at the end of the survey, provide the data for the analysis detailed in Chapter 5 of the thesis. In that chapter, I examine how Political Identity (Block 3) shapes attitudes toward using Deliberative Mini Publics for climate policy-making.

The 'Resistance to Rural Climate Initiatives' items (RRCI, Block 5) initially comprised 35 items in a pilot survey. Following analysis of the pilot results (n=95), this was refined to 24 items for the main survey. Chapter 6 uses the responses to the items in Block 5 of the survey, and documents the scale development process from the pilot, through exploratory confirmatory factor analysis, establishing an 18-item scale and its validity and reliability.

Chapter 7 then uses the factor scores from those 18 items of the RRCI scale, alongside the responses to the items on Rural Identity (Block 1), National Identity (Block 2), Political Identity (Block 3), and Climate Science Beliefs (Block 4), to

develop and test a path model examining how these different dimensions of identity contribute to resistance to rural climate policies.

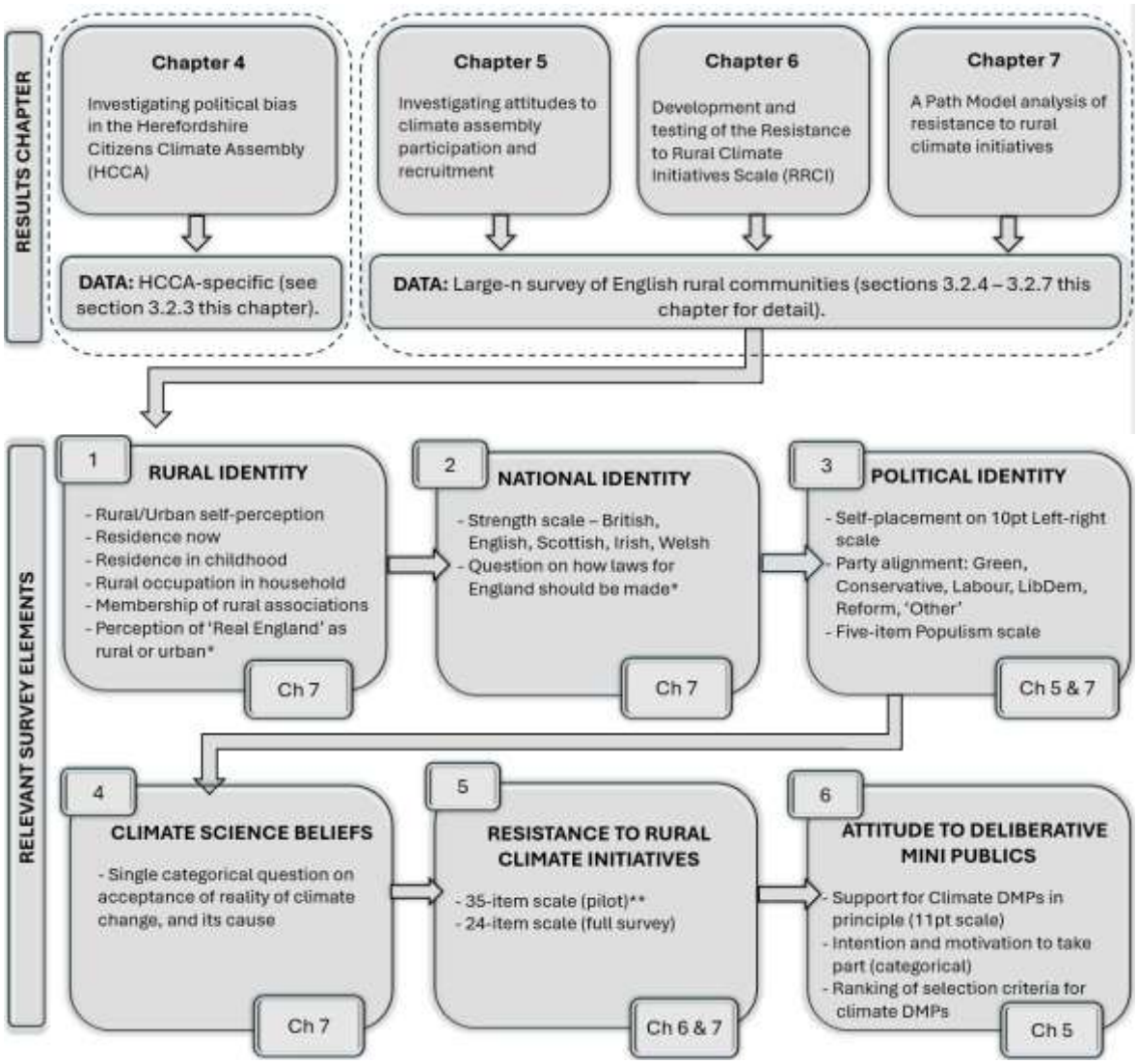


Figure 2: Survey question blocks in order of presentation to respondents, indicating which survey items are used in analysis for which chapter of the thesis. (* item was dropped after pilot due to clear issues with respondent interpretation; ** scale reduced from 35 to 24 items after pilot).

Full item wording, and information on type of variable (ordinal, categorical, Likert etc), with scoring are given in Appendix 3.1.

3.2.5 Survey distribution – chapters 5, 6 and 7

3.2.5.1 Leaflet distribution

Since the aim of the thesis was to capture responses from rural communities, I chose to promote the survey largely via leaflet deliveries, to minimise the amount of online sharing that would occur, where urban respondents would be more likely to see it.

Approximately 22,000 A5 printed leaflets (Figure 3) were hand delivered (largely via paid delivery services) to randomly selected English rural postcode areas from autumn 2023 to early 2024.

Figure 3: Survey promotion leaflet, front and back design

3.2.5.2 Online promotion

Towards the end of the leaflet delivery period, to boost survey responses, I also emailed the survey to around 150 parish councils, and handful of whom put links to the survey on their websites or in newsletters. I also promoted the survey online via Facebook, and Instagram paid advertising for a few weeks, limiting the reach of the adverts to small geographic areas that covered only rural postcodes, and selecting areas of the country where I had not been able to arrange leaflet deliveries. The survey was also promoted on a handful of rural 'Nextdoor' social media networks.

3.2.6 Survey responses – chapters 5, 6 and 7

3.2.6.1 Geographic spread of responses

In total, 856 'survey initiations' occurred, with 723 substantively complete surveys used for the analysis (see section 3.2.7.1 on data cleaning).

Survey responses were received in the end from a good spread of English rural postcode areas, as indicated in the map in Map in Figure 4, below. The vast majority of respondents were rural dwellers, although 59 respondents lived in urban areas, although of those, 16 had had a rural childhood, and a further 8 had rural jobs.

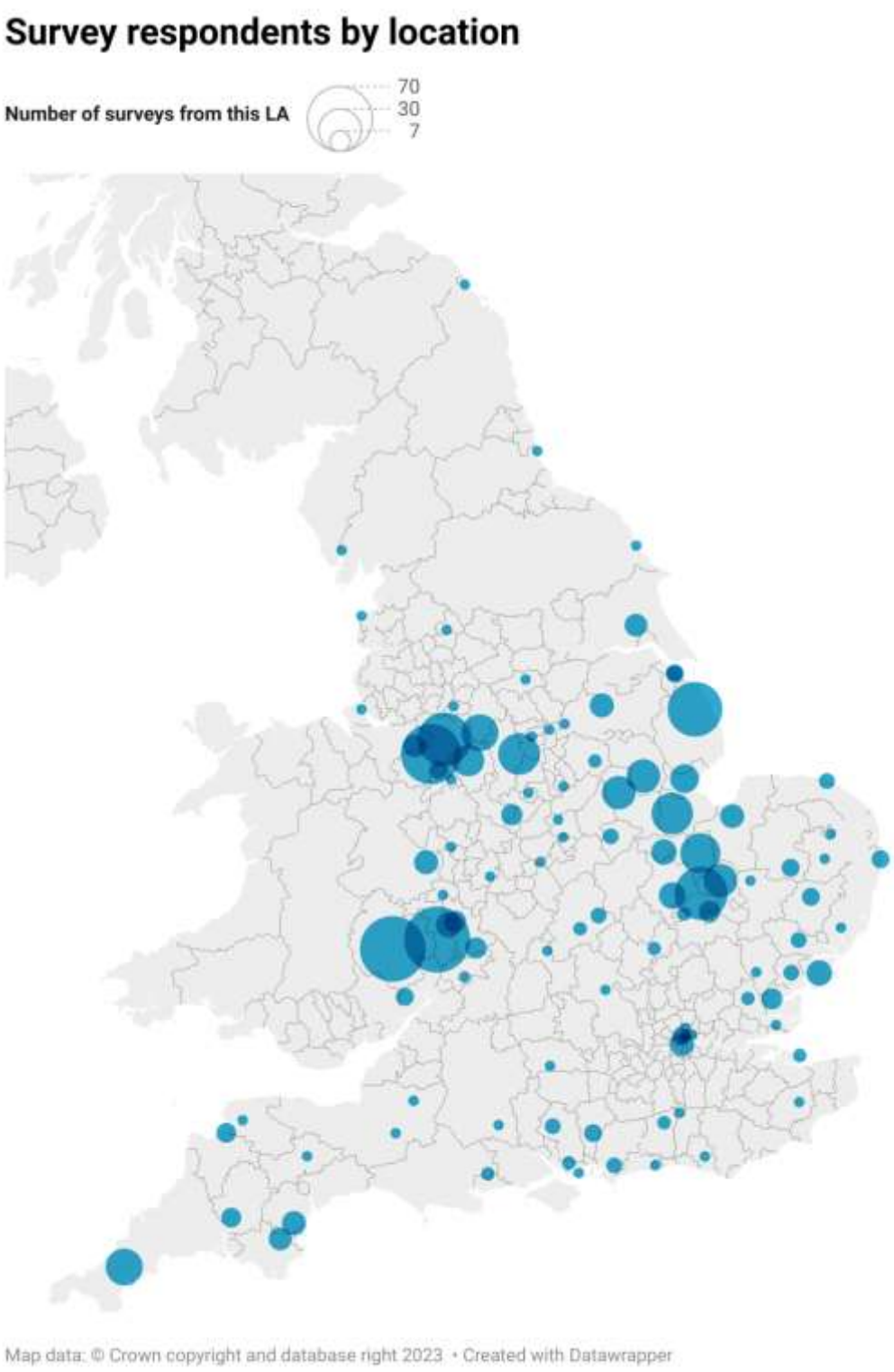


Figure 4: Map of survey respondent locations

(data used for analysis in Chapters 5, 6 and 7)

3.2.6.2 Survey respondents by demographic characteristics

Criteria	Response
Age	• 15-25: 15 (2.1%) • 26-35: 25 (3.5%) • 36-45: 53 (7.3%) • 46-55: 107 (14.8%) • 56-65: 204 (28.2%) • 66-75: 212 (29.3%) • 76-85: 74 (10.2%) • 86-95: 1 (0.1%) • Prefer not to say: 32 (4.4%) Mean Age: 60.7 yrs Median Age: 63 yrs
Ethnicity	• White: 699 (96.8%) • Black/African/Caribbean: 0 (0%) • Asian: 4 (0.6%) • Mixed (two or more ethnic groups): 4 (0.6%) • Other (Arab or any other): 2 (0.3%) • Prefer not to say: 13 (1.8%)
Sex	• Male: 383 (52.97%) • Female 333 (46.06%) • Prefer not to say: 7 (0.97%)
Political Party alignment	• Conservative: 156 (21.6%) • Green: 133 (18.4%) • Labour: 109 (15.1%) • Liberal Democrat: 95 (13.1%) • Reform UK: 119 (16.5%) • Other: 111 (15.4%)* *The political group 'other' includes some people who did indicate another party, including 15 UKIP and 3 BNP. Other comments indicated floating voters that move between parties regularly, or apolitical positions.

Table 5: Survey respondents by demographic characteristics

The sample is skewed older than recent government statistics on age in rural areas would suggest, with a mean age of 60.7 years compared with 45.6 years for all rural areas. However, the same report notes that the more rural the area, the higher the average age, and that over 26% of rural residents are aged over 65, so the older skew is not entirely unexpected, given the very sparsely populated nature of some delivery areas. In terms of ethnicity, the sample is closely representative of rural England as a whole, which is 96% white, compared with 84% white in urban England in general, and 54% white in London (Defra, 2025, reporting figures from 2022).

3.2.7 Sample Size Considerations

Although the number of surveys completed seems low compared to the promotional effort, the response rate is not especially low given that the survey was long, and in the context of general leaflet campaigns, for which average response rates are around 4%. (Direct Marketing Association, 2022).

Importantly, the number of completed surveys satisfied the sample size requirements of the various different analytical approaches used in this thesis. For Chapter 5's ANOVA and contingency table analyses, the final sample of 723 completed surveys provided more than adequate power. For the more complex factor analytical work in Chapter 6, specific sample size considerations relating to item-to-case ratios and factor stability are addressed in detail within that chapter, including post-hoc adequacy checks using the empirical guidelines of Mundfrom et al. (2005). For the structural equation modelling in Chapter 7, adequate sample size and sufficient variability across key variables was the critical target; the resulting sample of n=707 for the final path model provides 11.6 cases per free parameter (61 parameters total), meeting recommended guidelines for structural equation modelling of 10–20 cases per parameter (Kline, 2015), thus providing adequate statistical power for the analysis.

3.2.7.1 Data cleaning and quality

Of the 856 survey initiations, 133 were removed before analysis. Qualtrics respondent engagement flags were used to identify a handful of cases of straight-lining (identical responses across multiple items), which were removed via listwise deletion as indicative of minimal engagement. The vast majority of the 133 cases removed were those that provided minimal substantive data (respondents who completed only the initial demographic items, or dropped out straight after the initial participant consent page). The dataset retained for analysis therefore comprised 723 respondents.

Where missing data occurred within the 723 cases, this principally affected the end of the survey where the question topic changed to the subject of Deliberative Mini Publics (dropouts are clustered in Block 6). However, the pattern of missingness is 'Missing Not at Random', the implications of which are discussed in Chapter 5 as part of the analysis there. No outliers requiring removal were identified.

Item reverse-coding procedures, where applicable, are documented in Chapter 6.

3.2.8 A note on theoretical versus statistical inference from the data

As far as possible within the practical, financial and time constraints of the project, I aimed to ensure a broad spread of responses from across rural England. However, while the sampling strategy goes well beyond convenience sampling (deploying random postcode selection, hand-delivery of leaflets and additional hybrid online recruitment to fill geographical gaps), it does not constitute true probability sampling.

Longstanding debates about the appropriateness of drawing statistical inferences at the population level from non-probability sampling abound, an accessible summary of which is found in Hirschauer *et al.*, (2021). The authors contend that it is inappropriate to make probabilistic claims about population parameters from samples such as mine, and I do not attempt to do so in this thesis.

However, turning to the distinction between *statistical* and *theoretical* inference, (neatly summarised in the work of Highhouse and Gillespie, 2009), I feel that for much social research, it is the latter that is of more importance, and for the research chapters presented here, I adopt a theoretical inference approach only – inference, where drawn, is from a 'this sample behaves like' standpoint, rather than a 'this sample looks like' standpoint. As such, while the research reveals where it may be plausible that similar people, similarly stratified, would 'behave similarly', I make no attempt at probabilistic claims about the exact prevalence of attitudes in rural English populations.

This has different implications for the three research chapters that rely on the main survey for their underlying data, because the methods used are epistemologically distinct:

- Chapter 5 examines whether political party alignment affects willingness and motivation to participate in Climate Assemblies. The results support a theoretical inference that variables measuring political alignment and intentions around climate assembly participation are related *in my sample*. Since the sample is large, drawn from a large geographic area (rather than clustered), politically heterogeneous, and containing a mix of ages, I can at least contend that the relationships observed are unlikely to be artefacts of a demographically constrained group. I further contend from the literature that they are likely to represent theoretically generalisable patterns that could plausibly extend to other rural English communities. But, respecting the position summarised in (Hirschauer *et al.*, 2021), I make no claims of the results representing a true population parameter for rural England.
- Chapter 6, development of the Resistance to Rural Climate Initiatives scale (RRCI) is epistemologically distinct, in that it uses survey data to reveal an underlying construct via Factor Analysis. Here the data reveals the latent structure of the construct itself, rather than describing characteristics of the population from which the sample was drawn, and therefore statistical inferences about the population parameters are not relevant. Although I have used a robust approach including splitting the sample for EFA and CFA,

and demonstrating the unidimensionality and validity of the scale, I make no absolute claim that the scale structure would hold across all contexts and populations, and best practice in scale deployment would always call for further, context specific, Confirmatory Factor Analysis should another researcher wish to use the scale.

- Chapter 7 is the most epistemologically complex of these three research chapters because, using a Path Model, it does make causal claims from a non-probability sample. However, following the approach of Pearl, (2009); Bollen and Pearl, (2013); and Curran and Bauer, (2023), the Path Model presented should be interpreted only as a causal hypothesis that was tested for consistency with the observed data, causal assumptions which *"remain only one study away from rejection*" and which will become more plausible only when they have "*survived a variety of tests in different samples and under different circumstances*" (Bollen and Pearl, 2013 p.321).

3.3 Ethics Approval

This research received ethics approval from Lancaster University's Faculty of Science and Technology Research Ethics Committee (Reference: FST-2022-3299-RECR-1, approved 20/12/2022).

All participants provided informed consent before participating in the surveys. The consent process clearly explained the research purpose, data usage, participants' right to withdraw, and data protection measures.

Data were collected and stored in compliance with GDPR and the UK Data Protection Act 2018 and in line with Lancaster University's information security protocols.

4 Deliberative Mini Publics: investigating political bias in the Herefordshire Citizens Climate Assembly

4.1 Introduction and background

This chapter investigates whether political identity affects both the propensity to volunteer for Climate Assemblies, and participants' beliefs about how such assemblies should be framed and conducted. It uses exploratory methods to examine a single case-study, the Herefordshire Citizens Climate Assembly (HCCA), which was held in January 2022.

The chapter responds to Research Question 1: *Does political identity lead to differential rates of participation in climate assemblies and differences in attitudes to the legitimacy of these forums for policy-making?*

As detailed in Section 2.4 of the Literature Review, the use of Climate Assemblies (a form of Deliberative Mini Public) for policy-making has risen sharply since 2018 in the UK and Europe (Bryant and Stone, 2020; Paulis *et al.*, 2021; Willis *et al*, 2022; Boswell *et al*, 2023; KNOCA). There have been various stimuli for the growth in this form of policy-making, particularly at local government level in the UK. Their use increased significantly after the publication of the IPCC's Special Report assessing whether it was technically and politically feasible to limit global temperature rises to not more than 1.5^{0}C above the pre-industrial average (IPCC, 2018). This report gave new impetus to the need for more comprehensive climate policy, and particularly at the local level, provided useful evidence to concerned local

councillors, local government officials, and (even more so) to concerned citizens who felt that the urgency suggested by the IPCC report was not reflected in their local areas' policy frameworks (Lewis *et al.*, 2023).

At the time of the HCCA (January 2022), although the 'Deliberative Wave' of Climate Assemblies in the UK and Europe was well underway[14], the focus on recruitment for descriptively representative groups of people to participate did not, as a rule, include political identity as a selection variable. Selection had tended to be done on 'standard' demographic markers such as age, sex and ethnicity, combined with a handful of other measures to ensure a mix of participant backgrounds, for example housing tenure, income bracket, education level, and spatial measures such as region or rural/urban classifications. In addition, for Climate Assemblies in particular, a selection variable on level of support for Net Zero policies or belief in man-made climate change was often used as an additional variable (Sortition Foundation, 2023, pers. comm.).

4.1.1 Study motivation

The work in this chapter was motivated by the hypothesis that political identity is arguably more likely to drive differences in opinion on social and economic policy issues than these other commonly used socio-demographic selection variables, particularly for issues with a moral framework and those requiring citizens to weigh perceived trade-offs between economic growth and environmental protection.

I initially focused on Conservative Party supporters in this chapter because, as the dominant right-of-centre party in Herefordshire at the time of the study (2022), the Conservatives represented the primary political opposition to ambitious climate policy in UK discourse. While the right-wing UK Independence Party (UKIP) had previously attracted significant support in the county (see Appendix 4.1), by 2022 UKIP had largely collapsed as an electoral force nationally and locally (Nevett, Joshua, 2023), and it's successor, Reform UK, had not yet emerged.

[14] The HCCA was the twenty-fifth of thirty Climate Assemblies that were run in the UK between 2019 and 2023, documented in Shepherd (2024).

Research suggests that 'conservatives' have different views to people with more left-leaning political identities, with the latter showing more support for regulating industry and ensuring 'ecological economics'[15] approaches that focus on equitable distribution of resources (Neumayer, 2004; Nisbet *et al*, 2015; Schrøder, 2023). However, the beliefs associated with the term 'conservative' can have different meanings in different cultural contexts (Batstrand, 2015), and much of the research has a US-focus (McCright and Dunlap, 2011, 2013; Severson and Coleman, 2015; Kulin *et al*, 2021), where the term is regularly conflated with 'right-wing' in general. Notwithstanding this US-bias, 'conservatism' seemed at the time to be a solid proxy for right-leaning political identity in Herefordshire[16].

As detailed in Section 2.4.4 of the Literature Review, conservative worldviews also tend toward support for representative forms of democracy rather than participatory or direct democracy (Mohrenberg *et al*, 2019) which may affect their propensity to engage with deliberative processes that operate outside traditional representative structures.

The perception that 'ecological economics' viewpoints will be prioritised within Climate Assemblies, along with the mechanism itself being perceived by some as 'bypassing' established representative democracy could have significant implications for the outcomes of climate assemblies. Political identity may affect rates of volunteering for DMPs, potentially skewing the pool from which final participants are selected. Additionally, right-leaning participants might approach the process with scepticism about its legitimacy if they perceive it as inherently framed to favour left-leaning policy preferences. Both phenomena could result in a

[15] Ecological Economics is defined by Neumayer, (2004) as embracing "*sustainability, efficient resourceallocation and equitable distribution and is sceptical towards the ability of unregulated markets to achieve these objectives*"

[16] The UK political landscape has seen a remarkable transformation since this research was conducted, with the recent emergence of Reform UK as a significant right-wing party. In the 2024 General Election, vote-splitting between Reform UK and the Conservatives, and limited campaigning by other left-leaning parties, resulted in an unexpected Green Party victory in the North Herefordshire seat. However, at the time of the HCCA (2022) and this research (2022-2023), the Conservative Party remained the dominant vehicle for right-of-centre political expression in the county, and the fact that the combined vote of Reform UK and the Conservatives for this seat at the 2024 election still comfortably outstripped the Green Party vote suggests that the right-leaning character of the county's electorate persists.

mini-public that is speciously descriptively representative: matching basic socio-demographic markers but tilted towards a particular worldview that could greatly affect policy propositions, undermining assumptions that DMP results can be extrapolated to the macro public.

4.2 Case study context

Herefordshire is a sparsely populated English county, covering 840 square miles, with a population of around 188,000. Approximately 95% of Herefordshire's land area is classified as rural (Herefordshire Council, 2023). The electoral history of the county at the time of the research indicated that it was politically Conservative, making it an appropriate place to investigate Conservatives' views on DMPs. The county contains two Parliamentary Constituencies: North Herefordshire and Hereford & Herefordshire South (Ordnance Survey Election Maps, 2023), Figure 5 below.

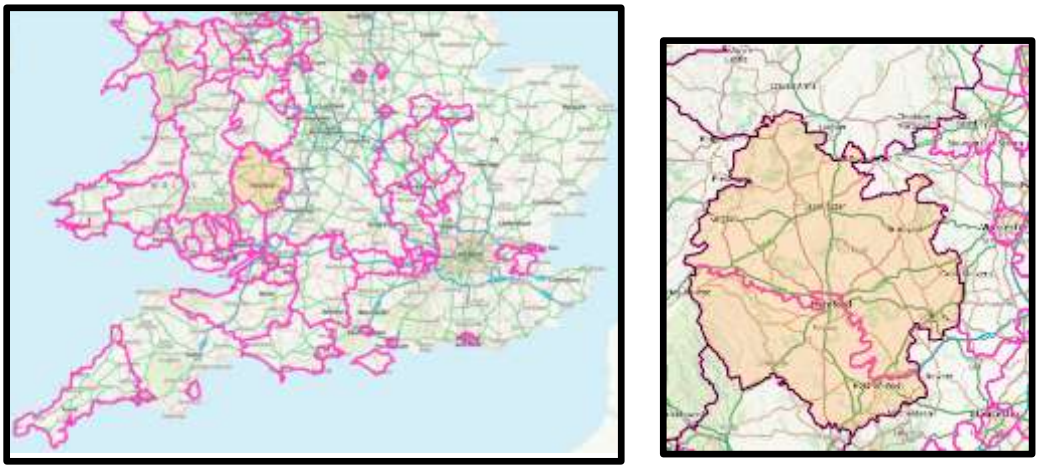


Figure 5: Maps showing location of Herefordshire (orange shading) among the Unitary Authorities of England (pink borders) and its two Parliamentary constituencies. [17]

4.2.1 Herefordshire's Parliamentary Constituency electoral history

Herefordshire's two parliamentary constituencies were slightly re-organised in 2010 but follow similar boundaries to the historic constituencies that long preceded

[17] Source: Ordnance Survey Election Maps: https://www.ordnancesurvey.co.uk/election-maps/gb/index.html

them. The North Herefordshire constituency had had a Conservative MP since 1950, with Conservative Party vote share at each election varying between 45% and 67%. Hereford & Herefordshire South is only slightly less Conservative, having returned a Conservative MP with between 39% and 61% of the vote at every election except two since 1950 (Watson et al., 2023). Recent election results had shown a strong right-of-centre skew, peaking in 2015 with a combined Conservative and UK Independence Party vote share of around 70% in both seats (BBC News, 2019a, 2019b), see also Appendix 4.1 and Footnote 2, above.

4.2.2 HCCA design and commissioning

In late 2021, Herefordshire Council commissioned a Citizens' Assembly on climate change, to be called the Herefordshire Citizens Climate Assembly (HCCA). The process ran over two evenings and two full weekends in early 2022, tasked with answering the question '*How should Herefordshire meet the challenges of climate change?*'

Herefordshire Council contracted the Sortition Foundation to recruit a panel of residents that "*represented the diversity of Herefordshire's population*" (Herefordshire Council, 2022), instructing them to use a set of criteria to represent the county's diversity, to include age, sex, ethnicity, disability status, urban/rural locations and representatives from areas across the Index of Multiple Deprivation (Sortition Foundation, 2022). A final criterion, level of concern about climate change, was measured on a 4-point scale ('not at all concerned', 'not very concerned, 'fairly concerned,' 'very concerned').

A standard two-stage Sortition process was used. In Stage One, 14,000 letters of invitation were sent to randomly selected households across the county (over-sampled in low-income areas to address recognised lower response rates from more deprived communities). In Stage two, 48 assembly participants were selected from the 'volunteer pool' of 520 people who responded to the initial invitation letter. Table 6, below shows where the target and volunteer rates differed, and also how the Sortition Foundation substantially corrected the largest skews to return an assembly with the descriptive representativeness desired by the Council.

		TARGET %	VOLUNTEERS %	SELECTED %
SEX	**Male**	49.5	44.8	48.9
	Female	50.5	54.4	51.1
AGE	**18-21**	4.2	3.4	6.4
	22-29	10.49	6.4	12.8
	30-44	20.5	16.6	19.1
	45-64	34.5	39.7	34
	65+	30.4	33.9	27.7
ETHNICITY	**White British**	91	90.2	85.1
	White non-British	7.4	6.5	10.6
	Ethnic Diverse	1.6	3.3	4.3
DISABLED	**Yes**	19	12.1	17
	No	81	87.9	83
CLIMATE CONCERN	**Very**	32.7	73.8	34
	Fairly	46.5	23.8	44.7
	Not Very	14.9	1.1	10.6
	Not at all	5.9	1.3	10.6
Index of Multiple Deprivation bracket	**1-2**	7.8	12.9	10.6
	3-4	19	19.7	19.1
	5-6	43.1	42.3	42.6
	7-8	23.2	21.2	23.4
	9-10	6.8	3.9	4.3
RURALITY	**Urban**	47.1	48.8	53.2
	Rural	52.9	51.2	46.8

Table 6: Target, volunteer and final selection proportions for the HCCA on all aspects of 'descriptive representation' used for this process. (data from Sortition Foundation, for initial 48-person group).

The volunteer rate differed most strikingly from the target proportions in relation to concern about climate change, with 73.8% of volunteers being 'Very Concerned' about climate change against a target of 32.7%, and age, with the volunteer pool skewing older than target.

Crucially, questions of political identity/party alignment *did not* form part of the selection process. This was standard practice at the time, as it was assumed that selection for a wide range of socio-demographic characteristics would deliver a suitably representative group. This chapter will go on to show that, despite

achieving the Council's targets for 'Descriptive Representation' on age, ethnicity etc, the final HCCA group was still not *politically* representative.

4.3 Data Source

Forty people participated in the Assembly[18], of whom 39 consented to participate in research after the assembly had concluded. In February 2023, I sent a survey all 39 and received survey responses from 26 people, a 65% return rate. The full survey is provided in Appendix 4.2. A summary of respondent demographics is given in Table 2, below.

SEX	
Male	13
Female	12
Not given	1
PARTY	
Conservative	6
Green	6
Labour	6
Liberal Democrat	2
UK Independence Party	1
British National Party	0
Other	5
AGE	
18-29	2
30-39	0
40-49	2
50-59	5
60-69	11
70-79	5
80-89	1

Table 7: Summary of HCCA survey respondents' socio-demographic data

[18] I do not have access to final demographic data for the 40 assembly participants, since privacy protocols meant that individual-level data on the final participants were not made available to me. This prevents assessment of whether the 26 survey respondents differ systematically from the 14 non-respondents on observable characteristics such as age, gender, or concern about climate change, because I do not have access to the information on the 8 drop-outs. However, the subsequent analysis in this chapter largely uses *a priori* knowledge of Herefordshire's wider population characteristics, rather than relying solely on comparisons within the assembly group

4.4 Methods

4.4.1 Estimating Conservative voter participation in the HCCA

To explore whether Conservatives were under-represented in the HCCA, I compare my survey group's political make up with *a priori* knowledge of Herefordshire's voting history. However, estimating the 'true' proportion of Conservative supporters in any population is not straightforward, as electoral turnout and voting behaviour provide only partial information about underlying political identity. I therefore take a cautious approach by establishing three estimates; an upper bound based on the most recent General Election results, a lower bound that accounts for non-voters, and a mid-range estimate based on historical voting patterns. For each scenario, I calculate the minimum number of Conservative supporters one would expect to find in a random sample of 40 Herefordians, and then assess whether the HCCA could plausibly have contained this many Conservatives given the observed data from my survey respondents.

As part of the survey, respondents were asked the question 'Generally speaking, do you think of yourself as most aligned with a particular party'? (*Labour, Conservative, Green, Liberal Democrat, UK Independence Party [UKIP], British National Party [BNP], other*), adapted from the standard party alignment question wording from the British Election Survey, 2019[19]. Six of the 26 respondents are Conservative, according to their responses.

General Election data (Watson, Uberoi and Loft, 2023) shows that the share of the vote that went to the Conservative party at the last General Election before the Assembly in Herefordshire (2019) was an average of 62.1% (the combined, weighted result to account for slight differences in population between the two parliamentary constituencies). On this basis, the mean number of Conservative

[19] Asking respondents for party alignment, rather than last voting decision more accurately captures underlying political party affiliation, as it is not affected by the tactical voting decisions that many voters deploy in First Past the Post Systems, which can especially mask the real level of support for minority parties.

voters in any sample of 40 people taken from the wider Herefordshire voting population would be expected to be 24.8, with a standard deviation of 3.07.

At the other extreme, with additional weighting to account for non-voters and using the most stringent bound by assuming that nobody in the non-voting population is a Conservative supporter, a weighted proportion of Conservative supporters in Herefordshire can be calculated at 43.9%. This would give a lower mean number of Conservatives in any sample of 40 Herefordians of 17.6, with a standard deviation of 3.14.

	North Herefordshire	Hereford & South Herefordshire
Turnout at General Election, 2019	72.6%	68.9%
Vote Share for Conservative party at General Election 2019	63.0%	61.2%
Eligible electors	70,252	72,085
Total Number of people who voted (all parties)	51,003	49,667
Number of people who voted CONSERVATIVE	32,132	30,396
Conservative voters as proportion of all Eligible Voters	45.7%	42.2%

Table 8: 2019 General Election results for both Herefordshire parliamentary constituencies

The true proportion of Conservative supporters in Herefordshire is more likely somewhere between the 43.9% weighted result including non-voters, and the 62.1% election result for the Conservatives at the last election, since it is *highly* unlikely that all non-voters are also not Conservative supporters. To find a mid-range estimate, I therefore examine Herefordshire's long-term election results, an average of which returns 55.7 (± 4.1)% Conservative supporters (at 95% confidence

level). [20] Subtracting the margin of error gives 51.6%, a cautious mid-range estimate[21].

This gives three possible assessments of the proportion of Conservatives in Herefordshire's population at the time of the study – an upper bound based on the most recent General Election, a lower bound based on a weighted turnout of that election, and a cautious mid-range estimate based on historical vote shares over many elections.

Using the binomial distribution (see Appendix 4.2 for full probability tables), Table 9, below gives the minimum number of Conservative voters one could expect to find in any random sample of 40 Herefordians, at 95% confidence level, using these lower, mid-range and upper bound estimates.

BINOMIAL DISTRIBUTION – Sample of 40	**Upper bound**	**Mid range est.**	**Lower bound**
Estimated proportion of Conservative supporters in Herefordshire	62.1%	51.6%	43.9%
Mean number of Conservatives in any sample of 40 Herefordians	24.8	20.7	17.6
Standard Deviation	3.07	3.14	3.14
Minimum number of Conservatives one should expect to find in any random group of 40 with 95% confidence (2 St.Dev below mean).	20	15	12

Table 9: Binomial probability of the minimum number of Conservative supporters one could expect to find in any random sample of 40 Herefordians, based on probability of each individual being a Conservative voter of 0.621 (most recent election, unweighted), 0.516 (from historical election data) or 0.439 (most recent election, weighted to include non-voters), and all participants' political views being independent of each other.

[20] Based on long-term voter history, weighted for the slight difference in population across the two constituencies, see for example Appendix 4.1, which gives election results over the past four general election cycles in both constituencies, or eight elections in total.

[21] Averaging vote share over many elections in this way allows for a better estimation of the background level of support for the party in the county, as it demonstrates the steady level of support achieved; even as members of the electorate change due to movements into and out of the area, teenagers reaching voting age, and losses due to mortality, the broad proportion of vote support remains the same.

I now turn to the specific group of 40 participants who took part in the HCCA, and assess whether it could have contained an adequate number of Conservatives to meet this minimum number under any of the three scenarios above. In simple terms, this asks the question, if there *had* been enough Conservatives in the assembly of 40, how improbable would it be to find only 6 among any 26 randomly selected members?

To answer this, I use the knowledge I have of the 26 people who responded to the survey, of whom 6 stated that they are Conservative. Using the hypergeometric probability distribution, I test the hypothesis that this subset of 26 members of the group of 40 people could contain just 6 Conservatives when there are 20, 15 or 12 Conservatives in the full group, at a confidence threshold of $\alpha = 0.05$.

In a hypergeometric distribution, items are selected from a population without replacement, and thus the probability of a successful draw of an item with the chosen characteristic changes with each selection. The hypergeometric probability is "*the probability than an n-trial hypergeometric experiment results in exactly x successes when the population consists of N items, K of which are known to be successes*" (Berman, 2023). In this case, N = 40, K = [20], [15] or [12], n = 26 and x = 6. The results are shown in Table 5 below, and a full probability table is given in Appendix 4.3.

	Upper bound	Mid-range estimate	Lower bound
Estimated proportion of Conservative supporters in Herefordshire	62.1%	51.6%	43.9%
Mean number of Conservatives in any sample of 40 Herefordians	24.8	20.7	17.6
Standard Deviation	3.07	3.14	3.14
Known number of Conservatives in HCCA from sample of 26	6	6	6
Minimum number of Conservatives one should expect to find in any random group of 40 with 95% confidence (2 St.Dev below mean).	20	15	12
Hypergeometric probability that the minimum expected number of Conservatives are present in a group of 40, if there are known to be 6 in a subset of 26.	0.0002%	1.32%	17.32%

Table 10: Hypergeometric probabilities of there being a minimum number of Conservatives in a group of 40, if a subset of 26 taken from that sample is known to contain only 6 Conservatives. Three scenarios are tested, with probability of each individual being a Conservative of 0.621 (upper bound), 0.516 (mid-range), and 0.439 (lower bound) and all participants' political views being independent of each other.

The data in Table 10 demonstrate that it is highly unlikely to see such an extremely low value of x (6 from the sample of 26) if there were either 20 or 15 Conservatives in the Assembly group of 40. Therefore, at the upper and mid-range estimates, and the data obtained can be taken as statistically significant evidence that the HCCA was not politically representative of the county as a whole. At the lower bound estimate of 43.9% Conservatives in the county, the result is non-significant. However, note that this lower bound is almost certainly too low, since it could only be derived from assuming that there are no Conservative supporters at all among the proportion of Herefordshire's population that did not turn out to vote. Indeed, if only 10% of the non-voters were Conservative supporters, even the lower bound scenario would have returned a significant result.

4.4.2 Assessing whether left-right political alignment affects participant attitude to, and perception of, a Climate Assembly.

Having established that Conservative voters were most likely numerically under-represented in the HCCA, I turned next to the follow-up survey (Appendix 4.2) to explore whether political identity also meaningfully distinguishes participants in terms of how they are likely to view the purpose and outcomes of the assembly.

4.4.2.1 Operationalisation of the variables

The full survey included multiple item batteries measuring environmental concern, open-mindedness, perceptions of assembly legitimacy and inclusion, and views on appropriate scope for future assemblies. Testing all items individually would have involved over 40 individual tests.

However, the final sample size of only 26 completed surveys, combined with corrections for multiple tests would have resulted in insufficient power to detect effects reliably across all items. I therefore focused a small amount of hypothesis testing on the batteries that were drawn from pre-tested scales (allowing me to use a single score for each), and the shortest battery of items in the set.

The small sample size also meant that analysis would be restricted to non-parametric tests, and splitting by political identity was restricted to a dichotomous grouping (left-leaning' and 'right-leaning'), rather than splitting by political party, which would have resulted in excessively small groups.

The variables used in the analysis are as follows:

Left-Right self-placement. Survey respondents were asked to place themselves on a 1-10 scale, where 1 = most left wing and 10 = most right wing. A purposeful choice was made to use a 'no-midpoint' form of the scale such that the respondents could be evenly split into '1-5' and '6-10' groups to represent broadly 'left-leaning' (LL)

and 'right-leaning' (RL) participants[22]. Research shows that "*most individuals are skilled at using their social cognition of the left-right dimension*" (Kroh, 2007), and an analysis of the Comparative Study of Electoral Systems (CSES) shows that over 90% of people in 10 European countries (including the UK) can position themselves on a L-R scale (Jou and Dalton, 2017).

Table 11, below shows the mean scores by party for the 26 respondents to the scale question and shows that, broadly speaking, the Conservative party supporters scored higher overall, with the single United Kingdom Independence Party (UKIP)[23] respondent also placing right of centre. This is largely expected and aligns with broad conceptions of Conservative parties and their offshoots being considered to be on the political right.

[22] While an 11 pt scale with midpoint is considered optimal in most large-scale political surveying because it produces the highest validity of left-right data, a 10pt scale still produces reliable data and may be suitable for particular circumstances.(Kroh, 2007)

[23] Founded in 1993 on a right-leaning, Eurosceptic platform of policies, UKIP's support has been shown to largely come from "older, white social Conservatives who had voted Conservative in the past" (Ford and Goodwin, 2017). Since the 2016 Brexit referendum's successful leave vote, UKIP's support has shrunk dramatically, initially as a result of UKIP voters defecting back to the Conservative party (Nevett, Joshua, 2023), and, since 2024, as a result of defections to Reform UK, the new party of the UK political right.

Party	Mean score on 10pt Left-Right scale
Green	3.3
Labour	3.5
Lib Dem	3.5
Conservative	7.2
UKIP	6 (single respondent)
Other	5.8

Table 11: Mean scores for participants in the HCCA, by political party, based on participant self-score on a 1-10 left-right scale. Note that although one Conservative voter placed themself at 5 on the scale, and one Green voter placed themself at 7, group means still show the strongest RL tendency for Conservative and strongest LL tendency for Green party supporters.

This dichotomous political identity variable is used as an independent variable in the remainder of the analysis. Scores on a range of other variables are compared for LL and RL participants. The dependent variables analysed are described below:

General Environmental Concern. Here, I used the long-established and widely-deployed 'New Ecological Paradigm' scale (Dunlap *et al.*, 2000), first published in 1978 and revised in 1992 and 2000. The instrument is commonly used as a unidimensional scale using 15 items (which Dunlap et al.'s initial assessment found to have a high level of internal consistency, although other researchers have found clear sub-scales within this overall set (Dunlap, 2008; Denis and Pereira, 2014; Dyr and Prusik, 2020)). Items are measured on a 5-point Likert scale, ('strongly disagree' to 'strongly agree') and reverse scored where appropriate, such that higher scores overall indicate higher levels of environmental concern, as per Dunlap's original design

NEW ECOLOGICAL PARADIGM SCALE
We are approaching the limit of the number of people the earth can support
Humans have the right to modify the natural environment to suit their needs (RS)
When humans interfere with nature, it often has disastrous consequences
Human ingenuity will ensure that we do NOT make the earth un-liveable (RS)
Humans are severely abusing the environment
The earth has plenty of natural resources if we just learn how to develop them (RS)
Plants and animals have as much right as humans to exist
The balance of nature is strong enough to cope with the impacts of modern industrial nations (RS)
Despite our special abilities, humans are still subject to the laws of nature
The so called 'ecological crisis' facing humanity has been greatly exaggerated (RS)
The earth is like a spaceship with very limited room and resources
Humans were meant to rule over the rest of nature (RS)
The balance of nature is very delicate and easily upset
Humans will eventually learn enough about how nature works to be able to control it (RS)
If things continue on their present course, we will soon experience a major ecological catastrophe

Table 12: Items in the New Ecological Paradigm Scale (Dunlap 2008)

(RS= Reverse scored) Bold items indicate those that remained after reliability analysis (see section 4.5.2)

This scale is used in the analysis to identify whether political identity has a measurable effect on underlying levels of environmental concern among sample respondents, which will obviously have been an important factor in the nature of discussions in a climate assembly.

While the NEP scale is extensively used to measure ecological worldview, research specifically examining differences in NEP scores by political orientation is surprisingly limited. However, based on cross-national research demonstrating that left-leaning individuals are generally more likely to prioritise environmental protection over economic growth and hold pro-environmental attitudes (Neumayer, 2004), *I hypothesised that right-leaning individuals in this study would have lower scores on the NEP than left-leaning individuals.*

Active Open-Mindedness. For this construct, I used a well-established scale of seven items, developed by Haran *et al*, (2013), regularly deployed in the British Election Study, which itself is based on a much longer scale by Stanovich and West, (2007).

Active Open-Minded Thinking (AOT) scale
Allowing oneself to be convinced by an opposing argument is a sign of good character
People should take into consideration evidence that goes against their beliefs
People should revise their beliefs in response to new information or evidence
Changing your mind is a sign of weakness (RS)
Intuition is the best guide in making decisions (RS)
It is important to persevere in your beliefs even when evidence is brought to bear against them (RS)
One should disregard evidence that conflicts with one's established beliefs (RS)

Table 13: Items in the Active Open-minded Thinking scale (Haran *et al*, 2013)

(RS= Reverse scored) Bold items indicate those that remained after reliability analysis (see section 4.5.3)

This scale is used in the analysis to identify whether political identity has a measurable effect on people's propensity to alter their views after encountering new information or information that contradicts existing beliefs. The responses for some items were reverse scored where appropriate, such that higher scores overall indicate higher levels of Active Open-minded Thinking.

The hypothesis is that RL voters will have lower scores than LL voters on the AOT scale, based on prior research (with weak to moderate effect sizes) suggesting correlations between RL political orientation with more rigidly-held views, and a more dogmatic adherence to existing points of view. (Jost *et al.*, 2003; Van Hiel *et al.*, 2016)

Appropriate Scope of Climate Assemblies. I also included a battery of five new items that are entirely untested as a scale, to ascertain whether participants felt that future, similar climate change assemblies should include speakers covering topics that were not covered in the Herefordshire Climate Assembly, or similar processes. Two of the items (marked *) were adapted from Blaikie (2003, p.41).

APPROPRIATE SCOPE OF CLIMATE ASSEMBLIES. "*Any future Citizens Assembly on Climate Change should always have external speakers who represent the view that...."*
Climate Change is a hoax.
Climate Change is a problem that can best be solved through the application of science and technology.*
Policies that aim to tackle Climate Change should not be so strict that they discourage industrial development.*
Policies that aim to tackle Climate Change should not radically alter established ways of farming and managing the countryside in England.
The Climate has always changed, and humanity can learn to adapt to the changes that scientists now predict.

Table 14: Items in the 'Scope of future assemblies' battery

This battery of items was included to assess whether political identity is linked to attitudes about the appropriate scope of public deliberations on climate policy. They explore, for example, whether industrial or agricultural practices should be largely protected from requirements to improve environmental standards, and question whether the fundamentals of climate science itself should be 'up for debate' in Climate Assemblies. Each item is scored on a 5-point scale, such that a high score indicates a belief that Climate Assemblies should invite speakers that provide challenge to the established climate science consensus and confine policy responses to those that operate within current agri-industrial systems. These items were included to address a theoretically important question: what perspectives should be included in climate deliberation? However, the items are not previously tested and do not necessarily form a scale that could reliably measure an underlying construct. Nor is the current sample size appropriate for EFA to determine whether such a construct might exist. Therefore, the analysis is limited to an exploration of item-by-item differences (with corrections for five simultaneous tests).

Views on the Legitimacy and Inclusivity of Deliberative Mini Publics. I had also included 20 items that were copied or adapted from the OECD's 'Evaluation Guidelines for Representative Deliberative Processes' report, Annex C (OECD, 2021a). Responses were once again given on a 5-point Likert scale from 'strongly

disagree' to 'strongly agree', and scored such that higher values indicate greater trust in the process and feelings of inclusion and respect.

However, although these items are derived from OECD guidance, well known in the deliberative democracy field, they have not previously been subjected to robust scale validation or reliability testing. Composite scores could therefore not be used, and I concluded that any analysis would have to be done at the individual item level. Given the already small sample size relative to the number of items, alongside the need for multiple test corrections, the available statistical power was insufficient for meaningful inference. Item wording is provided for reference in the full survey in Appendix 4.2, and respondent data will be stored in the final data repository, but the items are not included in the analysis that follows.

4.5 Results

4.5.1 Descriptive statistics of survey responses

As shown in Table 7, the participants had a wide but top-heavy age-range (19-80 years, skewed 60+). Men and women are roughly equally represented. Supporters of all the listed political parties bar the British National Party were in the group[24], and five participants chose the 'other' option when asked for their political party alignment, (three of whom provided additional notes to the effect that they are 'floating voters').

On the question of where they would place themselves on a left-right wing scale, the skew is to the lower end (left-leaning), with the peak under 5 and nobody placing themselves at 9 or 10 ('most right wing') on the scale. Only four of the responding participants joined the HCCA to represent the view that '*the threat of climate change is greatly over exaggerated*', with the remainder choosing the motivation '*climate change is a serious threat*'. Those motivated by the idea that the threat of climate

[24] Recall that this survey was distributed before Reform UK was a notable presence in UK politics and it was not therefore an option on the party choice list.

change is exaggerated were two Conservatives (both 8 on the L-R scale), one UKIP (6) and one 'Other' who chose L-R=5.

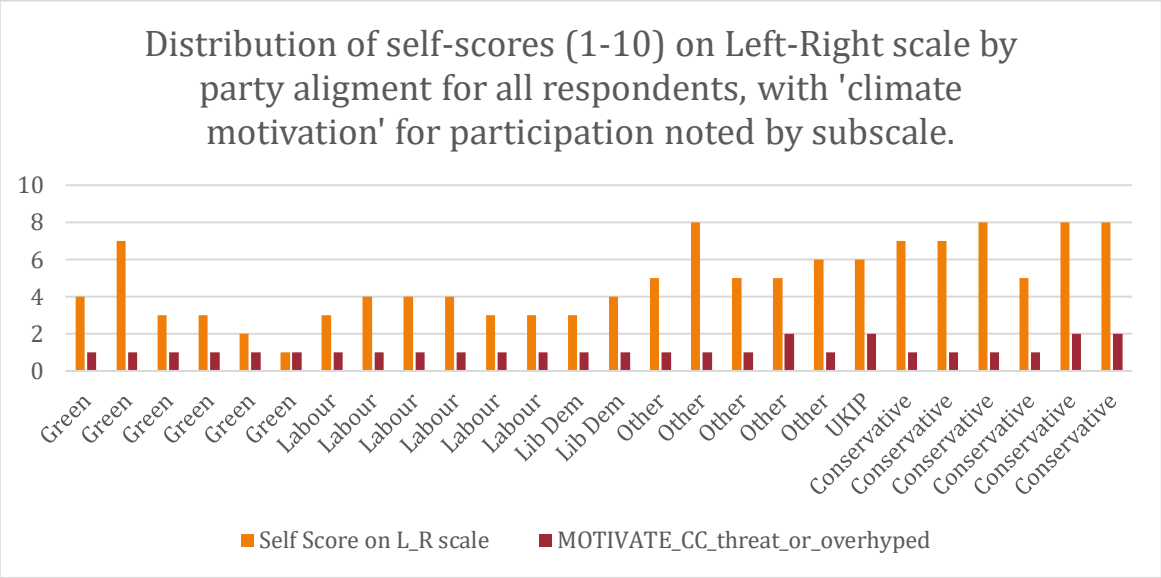


Figure 6: Distribution of L-R political scores by party alignment, and dichotomous indicator of motivation to join the HCCA to represent that the view that climate change is a serious threat ('Threat'= 1) or that the threat of climate change is greatly over exaggerated ('Exag'=2).

I next divided the full group of 26 into two sub-groups – left-leaning (LL) and right-leaning (RL) – using the 10-point political identity scale and analyse the data for differences in attitudinal responses between these groups. Participants who scored themselves 1-5 on the scale are put in the LL group (n = 17) and those scoring themselves 6-10 are put in the RL group (n = 9).

I now test null hypotheses that there are no differences in scores between the LL and RL groups, using the non-parametric Mann Whitney test, since the samples are small and fail Shapiro-Wilk normality tests, and the LL and RL groups are unequal in size.

I use a confidence threshold of $\alpha = 0.05$. The critical value of U for a one-tailed test on two groups of this size (for 0.05 significance) is 45 (Milton, 1964), thus any test result below that value suggests a statistically significant difference between the groups. The tests are set up as one-tailed, with the alternative hypotheses as follows:

- For the New Ecological Paradigm (NEP) scale mean scores, left-leaning participants will have higher scores than right-leaning participants.
- For the Active Open-minded Thinking (AOT) scale mean scores, left-leaning participants will have higher scores than right-leaning participants.
- For the five individual items in the 'Scope of Future Assemblies' battery (SCOPE), right-leaning participants will have higher scores than left-leaning participants.

4.5.2 Differences between left-leaning and right-leaning participants on the New Ecological Paradigm (NEP) scale.

A high score on the NEP indicates a respondent who rejects the notion of anthropocentric environmental management, believes there are limits to growth and that the natural world is finely balanced and easily damaged. By contrast, a low score on the NEP would indicate a participant more aligned to the idea that humanity has the right (or at least the ability) to successfully dominate nature, and that technology will ensure any eco-crisis can be averted (Dunlap *et al.*, 2000).

I first carried out a Reliability Analysis (Table 15). Both Cronbach's α and McDonald's ω were poor, suggesting the full scale in this sample was not a reliable instrument from which to extract a composite score. Sequential item deletion resulted in a 7-item version of the NEP scale with good internal consistency (Cronbach's α = 0.835, McDonald's ω = 0.843). The retained items represented four of the five known NEP subscales; limits to growth, anti-anthropocentrism, fragility of nature's balance, and possibility of eco-crisis. The Mann-Whitney analysis uses this 7-item version, with scores calculated as the mean of the 7 items, after appropriate reverse scoring.

Item Reliability Statistics			
		If item dropped	
	Item-rest correlation	**Cronbach's α**	**McDonald's ω**
EWV_Humans_right_to_modify_nature	0.475	0.833	0.840
EWV_Humans_abuse_env	0.459	0.831	0.840
EWV_Balance_of_nature_can_cope	0.716	0.794	0.800
EWV_Eco_crisis_exaggerated	0.671	0.798	0.805
EWV_Spaceship_earth	0.478	0.829	0.841
EWV_Nature_balance_easy_upset	0.682	0.797	0.812
EWV_Eco_catastrophe_soon	0.650	0.803	0.811

Table 15: Reliability analysis for stabilised 7-item NEP scale

Left-leaning participants had higher NEP scores (Median = 4.43, IQR = 4.14-4.71) than right-leaning participants (Median= 3.57, IQR = 3.57-4.14). The Mann-Whitney U test revealed that this difference was statistically significant (U = 35.0, p = 0.013, rank-biserial correlation = 0.542). (see Table 16 and Table 17, below).

Descriptives		
	LL_or_RL	NEP_7_item
N	RL	9
	LL	17
Missing	RL	0
	LL	0
Mean	RL	3.60
	LL	4.31
Median	RL	3.57
	LL	4.43
Standard deviation	RL	0.966
	LL	0.537
Minimum	RL	1.43
	LL	3.00
Maximum	RL	4.71
	LL	4.86
25th percentile	RL	3.57
	LL	4.14
50th percentile	RL	3.57
	LL	4.43
75th percentile	RL	4.14
	LL	4.71

Table 16: Descriptives - 7-item NEP subscale

		Statistic	p		Effect Size
NEP_7_item	Mann-Whitney U	35.0	0.013	Rank biserial correlation	0.542

Table 17: Mann Whitney results, 7-item NEP subscale. (H_a μRL < μLL)

The result supports the alternative hypothesis that left-leaning participants would have higher scores on the NEP scale, and I reject the null hypothesis that there is no difference between the groups.

The Rank Biserial Correlation result (0.542) is a correlation measure, which can be interpreted as a large effect size (Funder and Ozer, 2019). In practical terms, it shows that the dichotomous left/right variable has substantial predictive value scores on the 'ecological world view' NEP scale, with left-leaning participants generally ranking higher than right-leaning participants on scores.

This suggests that despite the assembly organisers' efforts to recruit participants with varying levels of specific 'concern about climate change,' selecting for underlying political identity could have better accounted for a broader conception of humanity's place with respect to the natural world, which may have repercussions for the recommendations; a mini-public that 'over-represents' citizens with pro-ecological worldviews may generate policy recommendations that appear more radical or ambitious than would be supported by a more representative sample of the macro-public, and may subsequently struggle to gain traction for the policy proposals put forward.

4.5.3 Differences between left-leaning and right-leaning participants on the Active Open-minded Thinking (AOT) scale.

A high score on the AOT scale is indicative of a cognitive style characterised by openness to new information, willingness to consider alternative viewpoints, and a readiness to revise opinions when presented with new evidence. Conversely, a low score indicates a tendency toward dogmatism, resistance to belief change, reliance on intuition, and cleaving to existing viewpoints in the face of contradictory evidence (Stanovich and West, 2007; Haran *et al*, 2013).

I first carried out a Reliability Analysis (Table 18). Both Cronbach's α and McDonald's ω were poor, suggesting the full scale in this sample was not a reliable instrument from which to extract a composite score. Sequential item deletion resulted in a 5-item version of the AOT scale with acceptable internal consistency (Cronbach's α = 0.661, McDonald's ω = 0.703). The two removed items both related to belief perseverance, while the retained items captured the core construct of openness to revising beliefs when presented with new information or contradictory

evidence, which is most relevant for the concept of a deliberative forum. I therefore proceed with the 5-item reduced scale for the analysis.

Item Reliability Statistics		
	If item dropped	
	Cronbach's α	**McDonald's ω**
OPENMIND_ConvinceMe	0.623	0.687
OPENMIND_Goes_against_beliefs	0.580	0.623
OPENMIND_Revise_belief_new_info	0.575	0.643
OPENMIND_Intuition_makes_decisions	0.619	0.665
OPENMIND_Disregard_opposing_evidence	0.653	0.687

Table 18: Reliability analysis for stabilised 5-item AOT scale

	LL_or_RL	**AOT_5_item**
N	**RL**	9
	LL	17
Missing	**RL**	0
	LL	0
Mean	**RL**	4.18
	LL	4.21
Median	**RL**	4.20
	LL	4.00
Standard deviation	**RL**	0.418
	LL	0.527
Minimum	**RL**	3.60
	LL	3.00
Maximum	**RL**	4.80
	LL	5.00
25th percentile	**RL**	4.00
	LL	3.80
50th percentile	**RL**	4.20
	LL	4.00
75th percentile	**RL**	4.40
	LL	4.60

Table 19: Descriptives - 5-item AOT subscale

Left-leaning and right-leaning participants showed very similar levels of active open-minded thinking (LL: Median = 4.00, IQR = 3.80-4.60; RL: Median = 4.2, IQR = 4.00-4.40). Table 19). The Mann-Whitney U statistic of 72, p-value of 0.414, and very small effect size (0.059) indicate that the difference between the groups is not significant. Table 20).

This result therefore does not support the alternative hypothesis that left-leaning participants would have higher scores on the AOT scale, and I do not reject the null hypothesis that there is no difference between the groups.

		Statistic	***p***		***Effect Size***
AOT_5_item	***Mann-Whitney U***	*72.0*	*0.414*	*Rank biserial correlation*	*0.0588*

Table 20: Mann Whitney results, 5-item AOT subscale (H_a μRL < μLL)

The result that both groups report similar levels of openness to revising their views when presented with new evidence is perhaps unsurprising; the assembly participants had self-selected to take part in this deliberative process, and there is a strong possibility that this group as a whole is characterised by a cognitive style that leans toward the higher scores on the AOT scale to an extent that somewhat transcends political differences that have been found in previous studies using this measure.

4.5.4 Differences between left-leaning and right-leaning participants on the items in the 'Scope of future climate assemblies' battery.

There are five items in this battery, representing alternative perspectives that are not generally incorporated into climate assemblies and were not presented at the HCCA. Since the items have not been proven via Factor Analysis to represent a latent construct, and the present sample is not of a sufficient size to do so, I therefore carried out five simultaneous Mann-Whitney comparisons on the single items, as an

exploratory study (Table 22). Descriptive statistics for the 5 items are given in **Table 21**, below, with full item wording found in Appendix 4.1.

The null hypothesis that left-leaning and right-leaning participants do not differ on these items, and the alternative hypothesis is that left-leaning participants would have lower scores than right-leaning participants. To account for the increased family-wise error risk from multiple comparisons, I applied a Bonferroni correction, adjusting the significance threshold to 0.01 (0.05/5). This approach balances controlling Type I error with maintaining reasonable power given the small sample size and exploratory nature of testing these new, unvalidated items.

	LL/RL	SCOPE_CC-Hoax	SCOPE_ technofix	SCOPE_ Industry	SCOPE_ Farming	SCOPE_ adapt
N	**LL**	17	17	17	17	17
	RL	9	9	9	9	9
Missing	**LL**	0	0	0	0	0
	RL	0	0	0	0	0
Mean	**LL**	1.82	3.00	3.00	2.24	2.59
	RL	3.00	3.56	3.89	3.00	3.11
Median	**LL**	2	3	3	2	3
	RL	4	4	4	3	4
Standard deviation	**LL**	0.809	1.00	0.935	0.903	1.00
	RL	1.73	0.726	0.782	1.00	1.36
IQR	**LL**	1.00	1.00	2.00	1.00	1.00
	RL	3.00	1.00	0.00	2.00	2.00
Minimum	**LL**	1	1	1	1	1
	RL	1	2	2	2	1
Maximum	**LL**	4	4	4	4	4
	RL	5	4	5	4	5
25th percentile	**LL**	1.00	3.00	2.00	2.00	2.00
	RL	1.00	3.00	4.00	2.00	2.00
50th percentile	**LL**	2.00	3.00	3.00	2.00	3.00
	RL	4.00	4.00	4.00	3.00	4.00
75th percentile	**LL**	2.00	4.00	4.00	3.00	3.00
	RL	4.00	4.00	4.00	4.00	4.00

Table 21: (previous page) Descriptive Statistics - items in the SCOPE battery. Scale ranges from 1 (Strongly Disagree) to 5 (Strongly Agree). Higher scores indicate greater support for limiting the scope of climate action or including climate-sceptical perspectives in Climate Assemblies.

	Statistic	p	Effect Size (rank biserial correlation)
SCOPE_CC_hoax	50.0	0.070	0.346
SCOPE_technofix	51.0	0.073	0.333
SCOPE_CC_policies_not_stop_industry	35.0	0.008	0.542
SCOPE_CC_policies_not_change_farming	45.5	0.038	0.405
SCOPE_Humans_can_adapt	57.5	0.152	0.248

Table 22: Mann-Whitney results, items in SCOPE battery. Bonferroni-corrected significance threshold: α = 0.01

One item achieved statistical significance even after alpha correction ("*Policies that aim to tackle Climate Change should not be so strict that they discourage industrial development*"). This item is also notable for having an inter-quartile range of 4-4 for the right-leaning participants (suggesting *all* RL participants gave this statement a high score). The remaining items also show small to moderate positive effect sizes, consistent with the predicted direction (that right-leaning participants would be more supportive of/have higher scores on these 'widening scope' statements). While these effects did not reach significance in the current sample and should not be over-interpreted, the consistency in effect size direction suggests the possibility of group differences that could be confirmed in larger samples.

4.6 Conclusions

The analysis in this introductory chapter has used a small sample to explore whether political identity had a statistically and practically meaningful impact on people's propensity to volunteer for a local Climate Assembly, and on some underlying attitudinal traits that may affect how they engage with these processes.

This study demonstrates that, in a political respect at least, the HCCA was not the 'diverse representation of the County' that the commissioning body hoped for. The dominant political identity in the county is likely to have been outnumbered by supporters of other parties who present radically different climate change policy proposals. In addition to under-representation of the Conservative voice, there are areas where significant differences are apparent in the attitudes of participants who self-identified as left-leaning or right-leaning more broadly. Right-leaning voters in the HCCA were:

- More likely to view environmental issues from an anthropocentric lens, and less likely to feel that there is a looming ecological catastrophe (based on differences in NEP scores),
- Just as open to changing their mind on receiving new information or evidence as the left-leaning participants in the sample,
- More likely to support inclusion of perspectives that either challenge climate science or prioritise economic/traditional concerns over environmental and economic transformation. Though not reaching statistical significance on most items (after correction for multiple tests), the consistency of this pattern (five out of five items in the predicted direction) is unlikely to be purely coincidental.

In addition, of the four people who took part from a 'defensive' point of view (because they feel that the threat of climate change is over-exaggerated) three were Conservative or UKIP voters (the final person stating this motivation did not give a party alignment).

Previous studies have suggested that politically right-leaning volunteers are less cognitively suited to deliberation (Jost *et al.*, 2003; Van Hiel *et al.*, 2016). While this *may* provide an underlying reason for lower initial volunteer rates from Conservative voters in the HCCA process (self-exclusion), for those who ultimately participated there is no evidence of a meaningful difference to the left-leaning participants in the HCCA on this measure. However, the right-leaning participants do seem to have participated in the event with fundamentally different starting

assumptions about human-nature relationships, economic priorities, and the urgency of environmental threats.

These results support the proposition that right-leaning and left-leaning individuals will hold different attitudes to participating in a climate assembly, and that selecting for a range of other socio-demographic markers such as age, ethnicity and education level does not automatically deliver a politically representative group.

4.6.1 Limitations of the study

The principal limitation was the small starting population of the HCCA (40 people) and the concomitantly small sample size of returned surveys (26 people). However, the hypergeometric probability approach taken uses a priori knowledge of the proportion of Conservative voters in the wider population from which the group of 40 was drawn and asks 'if we believe there to be a certain proportion of Conservatives in the wider population from which our 40 were drawn, what is the probability of only finding 6 in a subsample of 26?' It is therefore not a relationship between the 26 who responded to the survey and the 14 who did not. Rather, it is measuring the relationship between the 6 who are known Conservatives and a missing number of Conservatives who must be 'out there, somewhere' in our survey non-respondents, if our assumptions about proportions in the population are correct.

If the hypergeometric probability is very low, it can only mean one of two things: either there were not enough Conservatives in the group of 40 (in which case the Assembly was not representative in this regard) or the initial assumptions about the proportion of Conservatives in the wider population are wrong. Since we have robust data on past voting history for the population, and have provided upper and lower bounds and a mid-range estimate, the conclusion I draw is the former.

While the probability calculations relating to volunteering rates are less affected by this, the statistical investigation around the NEP, AOT and Scope of Future Assemblies parts of the survey was limited to non-parametric techniques using the more crude dichotomous split of left and right leaning participants. The results are

indicative of some important differences but should be treated merely as a starting point for further investigation.

The previously untested nature of some of the items in the 'Scope of future assemblies' battery also suggests caution in interpreting results. Nonetheless, use of individual items, though considered by many to be less robust than a full scale, is considered acceptable where the research is exploratory using a small sample, and where a large effect size is not expected (Diamantopoulos *et al.*, 2012). Single-item measures can have good predictive validity where both the object and the attribute of the construct being measured are easy for respondents to imagine, and where it can be reasonably assumed that most respondents will interpret them the same way. (Bergkvist and Rossiter, 2007). Since the items in the 'Scope of future assemblies' battery did not include wording that is open to wide interpretation, this may not be a significant limitation in this study.

Finally, a confounding factor arises from the fact that the HCCA was a deliberative processes *related to climate change*. The theoretical background in the literature review lays out why a right-of-centre voter may be resistant to both the process of DMPs *and* the topic of climate change.

Despite the small sample and exploratory nature of the study, parts of this work (on differential volunteering rates by Conservative voters) have already been published (Coxcoon, 2024), and have had real-world impact through increased recommendation that political identity be used as a selection variable in sortition-recruited processes like the HCCA in the future.

4.6.2 Opportunities for future work

Since Deliberative Mini Publics are, by design, limited 25-100 people, small populations like this will be a perennial issue and only by regular, consistent and comparable follow up on many DMPs could this issue be overcome.

A further topic for research could be to disentangle the deliberative democracy and climate issues from each other by exploring propensity to volunteer for DMPs on

other topics, allowing researchers to separate process-related resistance from topic-specific concerns.

5 Deliberative Mini Publics: investigating attitudes to Climate Assembly recruitment and participation

5.1 Introduction and background

This chapter expands on the findings of Chapter 4, which drew on a small sample from a single climate assembly, by introducing additional data from large-N sources. Initially, it outlines patterns that emerge from recruitment processes carried out by the Sortition Foundation for three climate-related citizens assemblies in the England. This data is provided by kind permission of the Sortition Foundation and the various commissioning organisations of the individual processes concerned. The data was secured after the findings of Chapter 4 were communicated to the Sortition Foundation, the leading practitioner organisation managing descriptively representative recruitment processes for citizens assemblies in the UK.

This assembly recruitment data is further supplemented with the findings from an additional large-N survey, designed specifically for this thesis, providing extra insight from the inclusion of the newly emergent party of the right 'Reform UK', which had not been a feature of past elections when the Sortition data were collected.

The chapter responds to Research Question 1: *Does political identity lead to differential rates of participation in climate assemblies and differences in attitudes to the legitimacy of these forums for policy-making?*

5.1.1 Study Motivation

Political change in the UK

The research presented in Chapter 4 indicated that support for Deliberative Mini Publics (DMPs) on climate may operate differentially across party political lines. However, the strength of the conclusions is limited by the small sample size, and the fact that, as the research in Chapter 4 was nearing completion, change on the political in the right in the UK was occurring. 'Reform UK' (a rebrand of the electorally unsuccessful 'Brexit Party') was not even an option offered on the party choice list for the survey used in Chapter 4, and at the time of developing the PhD research outline, the majority of political resistance to ambitious climate policy in the UK was associated with key back-bench Conservative MPs and Conservative-linked spokespersons. Understanding Conservative views on climate, as representing the bulk of right-leaning voters in the UK, was therefore the key motivating factor in the original research plan for this thesis.

Despite its relatively nascent status at the time of the survey construction for this present chapter, I did choose to include Reform UK as a party choice when designing the survey that underpins the analysis in Section 5.4.2 onwards. This transpired to be a prescient move, given the speed at which the party has moved from polling at below 5% to being the front-runner should an election be held tomorrow. (Difford, 2025).

The present Chapter builds on the emerging findings of Chapter 4 by exploring hypothetical support for the concept of climate DMPs, as well as differences in intentions and motivations to participate, among a much larger sample, taking into account political affiliation. This is a crucial lens through which to assess differential levels of support because, as detailed in Section 2.4.3 of the Literature Review, there is currently a paucity of evidence on this topic in the UK.

Moving from small-N 'real' DMPs to large-N 'hypothetical' DMPs

The 'intention-behaviour gap' is a well understood phenomenon in psychological research, describing the difference between what people say they will do when

presented with the opportunity to participate in a hypothetical activity, and what they will *actually do* if the opportunity presents itself (see Sheeran, 2002 for a meta-analytic overview). The phenomenon covers almost all forms of behaviour, from engaging in healthy eating and exercise regimes, to participating in social, relational and civic activities.

The Sortition data detailed in Section 5.4.1, below, represents real responses from invitations that were sent out to recruit for real DMPs. Those invitations included dates, times, details of commitment, and the people receiving the information will have made decisions that included trade-offs with other commitments and barriers to participation, such as work, travel and caring obligations. There is ample evidence that, although volunteering for civic engagement opportunities is influenced by psychological traits such as extraversion and open-ness to new opportunities (Weinschenk, 2013), socio-structural barriers also act to mitigate inclusion for specific groups. Younger people are less likely to participate in civic life, due to both physical barriers such as lack of transport, but also negative peer pressure experienced by peers for 'political' activities (Crocetti *et al*, 2012). Multiple studies also show that people with caring responsibilities are less likely to volunteer for civic participation opportunities, while older people's propensity for civic volunteering is a function of their combined socio-structural resources, with education, income and health intersecting to strongly predict volunteer rates (Ackermann, 2019). The data presented below from the Sortition Foundation therefore represents a *comparison of behaviours* between people of different political identities, which has already accounted for these real-life trade-offs that everyone who received an invitation will have considered.

The results presented in Sections 5.4.2 to 5.4.4, by contrast, involve data on hypothetical DMPs, from a large-N survey. Recipients were responding to a vignette describing what a Climate DMP is, and being asked 'if such a thing were to happen in your area, would you take part'? This section therefore complements the earlier parts of this chapter by allowing us to explore the *comparison in intentions* between people of different political identities, without the additional complexity of caring commitments, work demands, transport barriers, and so on.

5.2 Research Design and Data Sources

The chapter explores the relationship between political party affiliation and hypothetical attitudes toward participating in climate-focused deliberative mini-publics (DMPs). Specifically, it addresses three research questions:

1. Does political party alignment influence attitudes toward DMPs as a policy-making tool for climate issues?

2. Does political party alignment predict intention and motivation to participate in climate DMPs?

3. Do supporters of different political parties believe different demographic characteristics are more or less important when selecting DMP participants?

The results show that specific patterns with some moderate to large effect sizes do emerge, clearly distinguishing between parties on all three research questions. While these provide strong evidence of meaningful differences, this chapter is nonetheless exploratory in nature. Replication in a new, larger sample with a full urban and rural mix of participants, and pre-registered hypotheses, would be useful to provide confirmation.

5.2.1 Data

The data are drawn from two sources. Descriptive Sortition Foundation recruitment data is provided for the following processes:

- Southampton City Council Climate Assembly
- Citizens Assembly on Energy Demand Reduction
- Advertising High-Carbon Products Citizens Jury

In addition, survey data on hypothetical willingness to volunteer for climate-related DMPs comes from 710 responses to the survey detailed in Appendix 3.1.

5.2.2 Operationalisation of the survey variables

The theoretical motivations outlined in the Literature Review (Chapter 2) and Methods Overview (Chapter 3) underpinned both the survey design and the data collection strategy.

Participants responded to three questions, which were prefaced by a vignette explaining the concept of a DMP on Climate (often called a 'Climate Assembly'). The wording of the vignette is adapted from Rojon and Pilet, (2021), as is the approach of randomising the presentation of the phrases in square brackets in order that the specific characteristics of the design choices presented in the vignette do not need to be included as a control. Rojon and Pilet also offered randomised wording in relation to whether the recommendations of the assembly would be advisory or binding. I chose to offer only the wording that the recommendations would be advisory, since the 30+ UK climate assemblies (local and national) that had run up to the date of this research had been advisory in nature (Shepherd, 2024).

Vignette Wording

"Imagine that residents in your area were given the opportunity to influence political decisions on Climate Change at the local level by participating in a 'Citizens Assembly'.

The Assembly will be organised by [local politicians/ an independent organisation]. It will be composed of [25, 50, 100] randomly selected citizens from your area, ensuring a mix of different socio-economic backgrounds.

These citizens will come together for a series of weekend and evening meetings, where they will hear from a range of expert speakers. They will be paid for their time and supported with transport if they need it.

The citizen group will discuss how Climate Change should be tackled locally and will develop a list of recommendations for local policy makers.

The recommendations are advisory, which means the local government can choose whether to take account of them when making local decisions."

Three questions followed the vignette:

Support for Deliberative Mini Publics on climate change (DMP_GOODBAD). "Using the scale below, please indicate whether you think this would be a good way or a bad way of informing climate policy decisions in your local area, where 0 = this would be a very bad way of informing climate decisions for my area and 10 = this would be a very good way of informing climate policy decisions for my area."

Intention and motivation to participate in a Deliberative Mini Public on Climate Change (DMP_VOL_WHY) "And which of the following statements about a Citizens Assembly on climate policy comes closest to your views?

(1) I would volunteer to take part so that I could represent the point of view that climate change is a serious environmental threat. (CC_TP)
(2) I would volunteer to take part so that I could represent the point of view that the threat of climate change is greatly over-exaggerated. (ET_TP)
(3) I would not volunteer to take part in a process like this (NTP)"

Ranking of selection criteria for a hypothetical Deliberative Mini Public on Climate Change (DMP_RANK). "If a climate assembly were to happen in your area, which characteristics should be taken into account when picking the group of people to take part? Please rank the following options, where (1) means 'most important' and (6) means 'least important'"

1. People of different ages
2. People from different ethnic groups
3. People with different levels of income
4. People with different levels of education
5. People with different types of jobs
6. People who support different political parties[25]

[25] Presentation order of the six options was randomised for each participant

The final variable used in the analysis is **political party alignment**, from responses to the question "Generally speaking, which political party do you think best represents your views?" This was purposely worded to find the party that most closely represents a respondent's views, rather than as a 'voting intentions' or 'last vote cast' question, to avoid confounding responses from tactical voting. The party groups were Conservative (CON), Green (GRN), Labour (LAB), Liberal Democrat (LD), Reform UK (REF), and 'Other' (OTH).

5.3 Methodology

5.3.1 Validating the HCCA analysis with climate assembly recruitment data

To overcome the limitations of having data from only a single Climate Assembly for the analysis in Chapter 4, I initially approached the Sortition Foundation to explore these emerging results, who proposed that they could advise commissioning bodies for upcoming climate assembly processes to add a question on political identity during the recruitment stage, to see if any similar pattern emerged for processes they were currently recruiting for at that time (late 2022/early 2023).

As detailed in Chapter 4, questions of political identity had not normally been part of recruitment processes for DMPs, both for practical reasons (it is difficult to deliver a representative small group when trying to satisfy more than 6–7 selection variables) and data privacy reasons (political identity, like sexual orientation and religious affiliation, represents a different 'class' of data with more onerous data management responsibilities). However, following communication of the findings in Chapter 4, the Sortition Foundation suggested recommending to commissioning bodies that political identity be included as a selection variable in future processes, in order to further investigate and respond to the phenomenon of low Conservative volunteer rates identified in Chapter 4.

Table 23, below, shows the target, volunteer and selection proportions by party, for the three processes that were recruited shortly thereafter, the implications of which are discussed.

5.3.2 Survey exploration of climate DMP recruitment differences by party alignment

Using data from a survey (n=723) which investigated hypothetical support along with willingness and motivation to participate in a Climate DMP, I first explored the relationships between political party alignment and general support for the concept of climate assemblies through ANOVA with Tukey post-hoc pairwise comparisons, which control for multiple comparisons while testing all possible party pairs, revealing specific party-related patterns of support (Section 5.4.2).

I then explored the relationship between party alignment with intention and motivation to take part in a climate assembly through a simple contingency tables approach, examining the distributions across the different 'take part' categories. This established, via the use of Cramer's V coefficient, that political party alignment is significantly and reliably associated with differences in intention and motivation to participate in climate assemblies (Section 5.4.3).

Finally, the survey also collected data on respondent ranked preferences for the characteristics on which participants for a Climate DMP should be recruited. I analysed the ranked data from the variable DMP_RANK via a Friedman Repeated Measures ANOVA, a non-parametric test appropriate for analysing rankings where participants rank multiple items. This was followed by Durbin-Conover pairwise comparisons to identify which specific pairwise differences in the ranking criteria were driving the overall significant Friedman test result. Finally, I used single-variable Kruskal-Wallis ANOVAs to identify which pairwise *party affiliation* comparisons are driving the differences in rankings (Section 5.4.4).

5.4 Results

5.4.1 Examination of Sortition Foundation recruitment data for three climate-focused DMPs

Each of the three processes highlighted in Table 23 was recruited by the Sortition Foundation using a similar approach, through sending 10k-15k letters to randomly

selected addresses in the target areas, to which volunteer responses were received in the hundreds. The data lends weight to the mathematically derived findings about the Herefordshire Assembly described in Chapter 4 (where the political identity of the participants can only be estimated from post-hoc analysis as it was not used as a recruitment variable), demonstrating a 'systematic under-volunteering' from Conservative voters. The data also demonstrates how easily this under-volunteering could be (and indeed, was) substantially corrected for in the selection of the final panels, which allowed for the recruiters to return a more politically representative group in each case.

	Target proportion	Volunteer proportion	Difference in proportion (Volunteers to Target)	Selected proportion	Difference to proportion (Selected to Target)
Energy Demand Reduction Assembly[26]					
GRN	3.4%	19.3%	***567.6%***	7.3%	214.7%
LAB	27.0%	36.5%	***135.2%***	29.3%	108.5%
LiB DEM	6.1%	2.2%	**36.1%**	7.3%	119.7%
CONS	23.9%	7.2%	**30.1%**	19.5%	81.6%
OTH	7.2%	2.8%	**38.9%**	2.4%	33.3%
NONE	32.5%	32.0%	98.5%	34.1%	104.9%
Advertising High-Carbon products Jury[27]					
GRN	5.2%	13.9%	***267.3%***	26.7%	128.8%
LAB	23.5%	47.2%	***200.9%***	3.3%	113.6%
LiB DEM	6.0%	3.7%	61.7%	30.0%	55.0%
CONS	30.8%	10.2%	**33.1%**	33.3%	97.4%
OTH/None	34.4%	33.3%	96.8%		96.8%
Southampton City Council Climate Assembly[28]					
GRN	2.8%	7.0%	***250.0%***	2.4%	85.7%
LAB	28.5%	35.3%	***123.9%***	28.6%	100.4%
LiB DEM	7.3%	8.5%	***116.4%***	7.1%	97.3%
CONS	28.9%	13.9%	**48.1%**	28.6%	99.0%
OTH	2.8%	8.5%	***303.6%***	4.8%	171.4%
NONE	29.6%	26.9%	90.9%	28.6%	96.6%

Table 23: Target, volunteer and final selection proportions by political party for three climate-themed DMPs recruited by the Sortition Foundation in 2023. Bold italic type indicates volunteer rates that are more than 100% of the target, bold underlined type indicates volunteer rates less than 50% of target.

[26] https://www.edrc.ac.uk/news-blog/edrc-launches-citizens-panel-to-probe-public-opinion-on-energy-demand-reduction/

[27] https://climatecitizens.org.uk/advertising-jury/

[28] https://www.southampton.gov.uk/our-green-city/how-you-can-help/southampton-citizens-climate-assembly/

5.4.2 Support for Deliberative Mini Publics on Climate, by party alignment

Previous research has demonstrated generalised support for the use of Deliberative Mini Publics in the UK for the purpose of informing policy making (Gherghina and Geissel, 2020).

The results of my survey support those previous findings *in the aggregate* (i.e. not accounting for political affiliation). The overall skew is to the right of centre, and there is a peak at 7-8 on a 0-10 scale (Figure 7). However, there are also peaks at the neutral centre point, and at the extremities. Splitting the results by party (Figure 8) reveals that the more extreme levels of support and rejection of climate DMPs are more party-driven, though it should be noted that there is a broad spread of views within most parties.

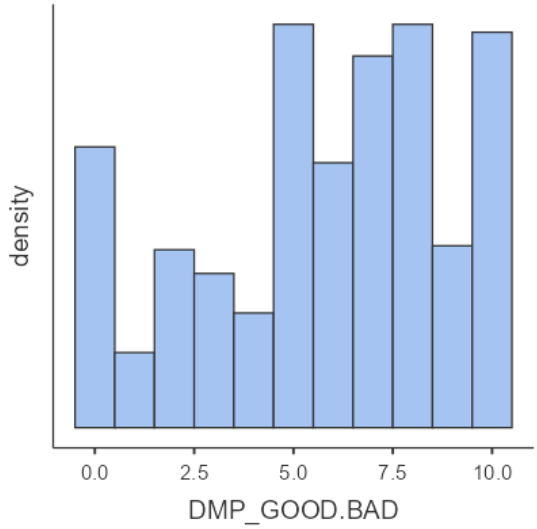


Figure 7: Support for the idea of a Climate DMP, overall

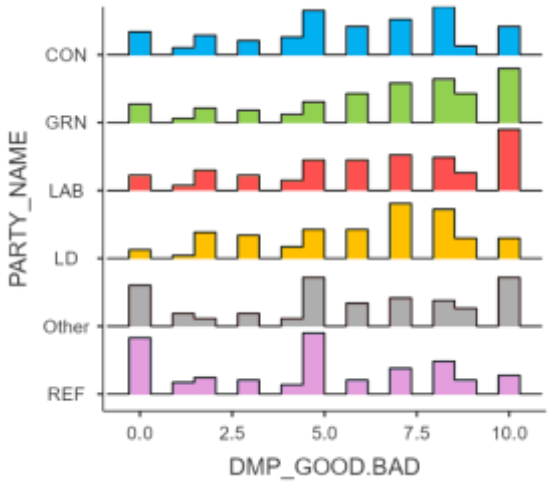


Figure 8: Support for the idea of a Climate DMP, by party

5.4.2.1 Analysis of Variance – Overall variability in Party support for Climate DMPs

I carried out a one-way ANOVA, using Welch's F to accommodate the unequal variances in the groups. The F-statistic (F=5.95, df1 = 5, df2 = 319), which represents the ratio of between-group variability to within-group variability, suggests that (despite the broad variances within the parties) there are nonetheless greater differences *between* the parties than there is variation *within* parties. The very small p value for this test (<0.001), confirms that this dataset provides strongly statistically significant evidence to support the hypothesis that there are differences between groups who align themselves with different political parties in their support for Climate Assemblies. Calculating η^2 indicates that political party alignment explains around 8.5% of the variance in the outcome[29].

5.4.2.2 Pairwise comparisons of party support

Since ANOVA identifies only that there are significant differences somewhere among the group means, I supplemented this with Tukey post-hoc pairwise comparisons (Table 24). These revealed that significant pairwise differences between Reform UK

[29] η^2 is the ANOVA equivalent of the R^2 measure of explained variance used in regression, calculated via $\eta^2 = (df1 \times F) / (df1 \times F + df2)$

and each of Labour, Green, and Liberal Democrats are the sources of the overall ANOVA result.

The size of these effects is most easily interpreted via the Common Language Effect Size, known as the Probability of Superiority (Mastrich and Hernandez, 2021). This represents the probability that a score randomly sampled from one group will exceed a score randomly sampled from another. For example, for every 100 randomly sampled pairs of Labour and Reform supporters, we could expect 72 of the higher scores to be associated with Labour rather than Reform voters (68 out of 100 pairs for Green or Liberal Democrat vs Reform).

Overall, the data suggest that support declines moving along the Left-Right political spectrum. The parties typically associated with left-leaning environmental policies (Greens, Labour, and Liberal Democrats) show higher support for Climate Assemblies compared to right-leaning parties (Figure 8). However, besides Reform UK, differences among other parties were not statistically significant, with Conservatives occupying a middle ground that, although less supportive than the left-leaning cluster, is only marginally significant ($p = 0.07$).

Interpreting Cohen's d for the significant differences between Reform UK and the Green/Labour/Lib Dem cluster indicates moderate to large effect sizes. Practically, these differences are likely to have meaningful implications for differential support for Climate Assemblies across the political spectrum in England.

		CON	GRN	LAB	LD	Other	REF
CON	Mean difference	—	-0.973	-0.754	-0.385	0.0464	0.993
	t-value	—	-2.71	-1.983	-0.973	0.122	2.67
	df	—	708	708	708	708	708
	p-value	—	0.075	0.353	0.926	1	0.082
	Cohen's d		*-0.32096*	*-0.2486*	*-0.1268*	*0.0153*	*0.327*
	Probability of Superiority		*41.0%*	*43.0%*	*46.4%*	*50.4%*	*59.1%*
GRN	Mean difference		—	0.219	0.588	1.019	1.966
	t-value		—	0.556	1.441	2.583	5.1
	df		—	708	708	708	708
	p-value		—	0.994	0.702	0.103	<.001
	Cohen's d		—	*0.0721*	*0.1939*	*0.336*	*0.6476*
	Probability of Superiority		—	*52.0%*	*55.5%*	*59.4%*	*67.6%*
LAB	Mean difference			—	0.369	0.8002	1.747
	t-value			—	0.865	1.934	4.32
	df			—	708	708	708
	p-value			—	0.955	0.382	<.001
	Cohen's d			—	*0.1217*	*0.2638*	*0.5765*
	Probability of Superiority			—	*53.4%*	*60.4%*	*71.8%*
LD	Mean difference				—	0.4311	1.378
	t-value				—	1.008	3.29
	df				—	708	708
	p-value				—	0.915	0.013
	Cohen's d					*0.1421*	*0.4544*
	Probability of Superiority					*55.6%*	*67.5%*
Other	Mean difference					—	0.947
	t-value					—	2.33
	df					—	708
	p-value					—	0.182
	Cohen's d						*0.3117*
	Probability of Superiority						*62.2%*

Table 24: Results of Tukey post-hoc pairwise comparisons, with Cohen's d and Probability of Superiority effect sizes.

5.4.3 Intention and motivation to take part in a Deliberative Mini Public on Climate, by party alignment

5.4.3.1 Measures of Association – Contingency Tables and Cramer's V

In this survey question, participants could choose from three responses which combine both intention to take part and (in the case of the first two responses) motivation for doing so. This cannot be treated as an ordinal scale, and thus the analysis here is a comparison of two categorical variables – a 6-choice 'party

alignment' question and a 3-choice 'take part' question. I therefore use a Contingency Tables approach (Table 25), which looks for deviations from expected frequencies, i.e. how many people from each political party would I expect to fall into each take part category if there were no relationship between party and intention to participate.

		DMP_VOL_WHY			
PARTY_NAME		**CC_TP**	**ET_TP**	**NTP**	**Total**
CON	Observed (n)	73	25	57	155
	(%)	*47.1%*	*16.1%*	*36.8%*	
	Expected (n)	80.1	32.1	42.8	155
	(%)	*51.7%*	*20.7%*	*27.6%*	
GRN	Observed (n)	112	2	17	131
	(%)	*85.5%*	*1.5%*	*13.0%*	
	Expected (n)	67.7	27.1	36.2	131
	(%)	*51.7%*	*20.7%*	*27.6%*	
LAB	Observed (n)	78	1	28	107
	(%)	*72.9%*	*0.9%*	*26.2%*	
	Expected (n)	55.3	22.2	29.5	107
	(%)	*51.7%*	*20.7%*	*27.6%*	
LD	Observed (n)	68	2	25	95
	(%)	*71.6%*	*2.1%*	*26.3%*	
	Expected (n)	49.1	19.7	26.2	95
	(%)	*51.7%*	*20.7%*	*27.6%*	
Other	Observed (n)	27	44	36	107
	(%)	*25.2%*	*41.1%*	*33.6%*	
	Expected (n)	55.3	22.2	29.5	107
	(%)	*51.7%*	*20.7%*	*27.6%*	
REF	Observed (n)	9	73	33	115
	(%)	*7.8%*	*63.5%*	*28.7%*	
Total	**Observed**	**367**	**147**	**196**	**710**
	(%)	*51.7%*	*20.7%*	*27.6%*	

Table 25: Contingency Table - DMP_VOL_WHY, by Party

(*DMP_VOL_WHY = 'which of the following statements is closest to your views'*

- *CC_TP = **C**oncerned about **C**limate – **T**ake **P**art*
- *ET_TP = climate change is **E**xaggerated **T**hreat – **T**ake **P**art*
- *NTP = I would **N**ot **T**ake **P**art)*

The result of a χ^2 test (χ^2=304, df=10, p<0.001) indicates a very strong departure of the observed frequencies from the expected frequencies and thus a strong

association between the two nominal variables. To test that this is not merely a by-product of a large sample size, I also derived Cramer's V, which, at 0.463, (a moderate to strong association between the variables) indicates that the association is practically meaningful, rather than of statistical relevance only.

5.4.3.2 Interpreting the Party-based departures from expected frequencies

The expected frequencies represent the distribution we would observe if each party's supporters were in line with the participation intention averages for the sample as a whole (51.7% CC_TP, 20.7% ET_TP, 27.6% NTP). Compared to the average across all parties, the following patterns emerge:.

Conservative (CON):

- Lower than expected would take part from 'climate concerned' motivation (73 vs 80.1 expected)
- Lower than expected would take part from an 'exaggerated threat' motivation (25 vs 32.1 expected)
- Higher than expected 'would not take part' (57 vs 42.8 expected)

This suggests Conservative supporters are less likely to participate than expected, a pattern that is especially pronounced among those who are concerned about climate.

Green Party (GRN):

- Much higher than expected would take part from 'climate concerned' motivation (112 vs 67.7 expected)
- Very much lower than expected would take part from an 'exaggerated threat' motivation (2 vs 27.1 expected)
- Much lower than expected non-participation (17 vs 36.2 expected)

This shows very strong pro-climate assembly participation intentions among Green supporters, with by far the lowest level of all groups in relation to the 'Not Take Part' category.

Labour (LAB):

- Higher than expected would take part from 'climate concerned' motivation (78 vs 55.3 expected)
- Much lower than expected would take part from an 'exaggerated threat' motivation (1 vs 22.2 expected)
- Similar to expected non-participation (28 vs 29.5 expected)

This is a 'lite' version of the Green party pattern – reasonably high likelihoods of participation due to climate concern. The Liberal Democrat pattern is very similar.

Reform UK (REF):

- Very much higher than expected would take part from an 'exaggerated threat' motivation (73 vs 23.8 expected)
- Much lower than expected would take part from 'climate concerned' motivation (9 vs 59.4 expected)
- Similar to expected non-participation (33 vs 31.7 expected)

Finally, the 'Other' group (OTH):

- Around half as many as expected would take part from an 'climate concerned' motivation (27 vs 55.3 expected)
- Around twice as many 'exaggerated threat' participants (44 vs 22.2 expected)
- Similar, but slightly fewer than expected non-participation (26 vs 29.5 expected)

This pattern indicates that Reform UK supporters have different motivations for taking part in Climate Assemblies. In a multinomial logistic regression (Table 26) with 'exaggerated threat–take part' as the reference outcome and Reform UK as the

reference party, supporters of the left-leaning parties are overwhelmingly more likely to report 'climate concerned–take part' rather than 'exaggerated threat–take part' compared with Reform UK supporters, with relative odds approximately 450 times higher (Green), 630 times higher (Labour), and 275 times higher (Liberal Democrat). Even Conservative supporters are 23 times more likely than Reform voters to fall into 'climate concerned–take part' rather than 'exaggerated threat–take part', while the 'Other' group also shows approximately 5 times higher odds of climate-concerned participation than exaggerated-threat participation (all $p < .001$).

Model Coefficients - DMP_VOL&WHY, CC_TP vs ET_TP							
Predictor	**Estimate**	**SE**	**Z**	**p**	**Odds ratio**	**Lower**	**Upper**
Intercept	-2.093	0.353	-5.93	<.001	0.123	0.0617	0.246
PARTY_NAME:							
CON – REF	3.165	0.423	7.49	<.001	23.685	10.3475	54.213
GRN – REF	6.119	0.796	7.69	<.001	454.234	95.4228	2162.257
LAB – REF	6.45	1.067	6.05	<.001	632.618	78.2136	5116.82
LD – REF	5.62	0.8	7.03	<.001	275.778	57.525	1322.099
Other – REF	1.605	0.43	3.74	<.001	4.977	2.1444	11.553

Table 26: Multiple Logistic Regression, odds of 'Exaggerated Threat' motivation to take part in a Climate Assembly, all other parties compared to Reform UK

5.4.3.3 Taking part vs not taking part at all

The DMP_VOL_WHY variable actually measures two things simultaneously; it offers a binary understanding of whether or not a respondent would take part in a Climate DMP, and then (for those who *would* take part), it reveals their motivation.

I further examined the simple binary contrast of 'taking part' vs 'not taking part' via a χ^2 test, which revealed significant differences ($\chi^2 = 22.76$, df = 5, $p < 0.001$). Examination of standardised residuals showed that Conservatives had significantly *higher* non-participation (37% vs 28% expected, $z = 2.17$, $p < 0.05$), while Greens

had significantly *lower* non-participation (13% vs 28% expected, $z = -3.19$, $p < 0.01$). All other parties showed non-participation rates close to the overall average of 28%.

Further analysis, through calculation of Odds Ratios, shows Conservative group members are nearly 4 times as likely to decline participation than Green members (OR = 3.90, 95% CI 2.13 - 7.14), and nearly twice as likely to decline participation than all other party group members (OR = 1.74, 95% CI =1.19, 2.54). Using Rosenthal's (1996) guidelines on effect sizes from Odds Ratios, this represents a large effect size for the comparison between Conservatives and Greens, and a small-to-medium effect size for the difference between Conservatives and all other parties.

The results demonstrate a clear and statistically significant relationship between political party support and attitudes toward participating in a Citizens Climate Assembly. Green Party supporters, followed by Labour supporters, show the strongest pro-climate assembly stance. Reform UK supporters are overwhelmingly likely to view climate threats as exaggerated; however, they still show intent to volunteer at quite high rates, albeit for different motivations.

Conservative supporters are notable, because although 'climate concern' is a more common motivator for this group than the 'exaggerated threat' motivation, overall the group shows marked tendency toward non-participation compared to all other groups, especially Green. This further supports the findings of Chapter 4, suggesting that it is possibly the process, or the perception of the democratic acceptability, of a DMP, rather than the climate content itself, that is more off-putting to them, since the 'other' and 'Reform UK' groups are less concerned about climate change but would volunteer in higher numbers.

Finally, a combination of the results of the first two questions analysed above (DMP_GOOD_BAD *and* DMP_TAKE_PART) singles out Reform UK voters as different in another way. Although they have the lowest support for the idea of DMPs overall (DMP_GOOD_BAD), they signal an intent to take part at quite a high rate, (especially when compared with, for example, Conservatives). This suggests 'defensive participation': they may be thinking, "DMPs are a bad way to make policy, but if it's happening, I want my seat at that table to make my voice heard."

As with generalised support for the principle of Climate DMPs discussed in Section 5.4.2, above, these differences are likely to have meaningful implications for differential volunteering rates for Climate Assemblies across the political spectrum in England.

5.4.4 Differential ranking of selection criteria for Deliberative Mini Publics on Climate, by party.

The final question on the survey asked participants to rank the criteria that are important in ensuring that a DMP on climate would be representative of the area that they represent. Six options were given: 'People of different ages'; 'People of different ethnicities'; 'People with different levels of education'; 'People with different levels of income'; 'People with different types of jobs'; 'People who support different political parties'. The overall rankings of the options are shown in Table 27, below.

Descriptives		
	Mean	**Median**
RANK_AGE	2.19	2.00
RANK_JOB	3.23	3.00
RANK_EDU	3.34	3.00
RANK_INC	3.55	4.00
RANK_POL	4.19	5.00
RANK_ETH	4.49	5.00

Table 27: Selection criteria rankings, all respondents (n=668)

5.4.4.1 Exploring selection criteria rank differences with Friedman ANOVA

I used a Friedman repeated measures ANOVA (non-parametric analogue to a standard repeated measures ANOVA) to understand whether these differences in rank are significantly different to each other. The initial Friedman result is highly

significant (χ^2 = 621, df = 5, p<0.001), showing that the items were indeed ranked significantly differently to each other (Mangiafico, 2025).

5.4.4.2 Pairwise selection criteria comparisons via Durbin-Conover test

However, as with all ANOVA tests, the result shows merely that the rankings are different, but does not reveal where those differences lie among the different groups. I therefore followed up the ANOVA with Durbin-Conover pairwise comparisons (which include corrections for multiple tests). The pairwise tests show that all but the JOB-EDUCATION pairings are significantly different from each other, as shown in Table 28, below. Thus, the ordering shown in Table 28, below, is statistically significant (i.e. the responses showed that including people of different ages was considered [30]most important, and so on), except that 'different types of jobs' and 'different levels of education' were considered equally important.

[30] Non-parametric test due to deviations from normality.

Pairwise Comparisons (Durbin-Conover)				
			Statistic	**p**
RANK_AGE	-	RANK_ETH	24.79	<.001
RANK_AGE	-	RANK_INC	14.71	<.001
RANK_AGE	-	RANK_EDU	12.41	<.001
RANK_AGE	-	RANK_JOB	11.23	<.001
RANK_AGE	-	RANK_POL	21.61	<.001
RANK_ETH	-	RANK_INC	10.08	<.001
RANK_ETH	-	RANK_EDU	12.38	<.001
RANK_ETH	-	RANK_JOB	13.56	<.001
RANK_ETH	-	RANK_POL	3.18	0.001
RANK_INC	-	RANK_EDU	2.30	0.022
RANK_INC	-	RANK_JOB	3.47	<.001
RANK_INC	-	RANK_POL	6.90	<.001
RANK_EDU	-	RANK_JOB	1.17	0.240
RANK_EDU	-	RANK_POL	9.20	<.001
RANK_JOB	-	RANK_POL	10.37	<.001

Table 28: Durbin-Conover pairwise comparison of ranked items

Since political party is the main lens through which variation is viewed in this exploratory study, I next carried out a one-way ANOVA (Kruskal-Wallis) for each ranked item, by party, to establish whether rankings *by party* differed significantly. Results are provided in Table 29, below.

Kruskal-Wallis				
	χ^2	**df**	**p**	ε^2
RANK_AGE	1.61	5	0.900	0.00242
RANK_ETH	106	5	<0.001	0.158
RANK_INC	6.59	5	0.253	0.00988
RANK_EDU	23.3	5	<0.001	0.0349
RANK_JOB	27.2	5	<0.001	0.0408
RANK_POL	7.96	5	0.159	0.0119

Table 29: ANOVA (Kruskall- Wallis) for each ranked characteristic, by party

The Kruskall-Wallis test results reveals that there are statistically significant party-specific differences in rankings for the variables Ethnicity, Level of Education, and

Job Type; people from different parties rank these differently. The ε^2 values give an indication of effect size, and (following Cohen, 1988), suggest that the difference in how ethnicity is ranked is a large effect, with small effects for the differences in ranking for Job Type and Education Level.

5.4.4.3 Pairwise Party comparisons via DSCF

Again, since ANOVA can only show that there are differences between *how* party groups ranked the selection variables, and not *which* party groups are driving the differences, I followed this up with pairwise comparisons (Appendix 5.1), with significant variables only shown in Table 30, below), this time using the Dwass-Steel-Critchlow-Fligner (DSCF) comparison method, again with corrections for multiple tests. The rankings and key differences by party are visually represented in Figure 9.[31]

RANK_EDU

		W	p
CON	GRN	3.083	0.247
CON	LAB	2.96	0.291
CON	LD	1.988	0.724
CON	Other	-0.81	0.993
CON	REF	-2.755	0.373
GRN	LAB	0.311	1
GRN	LD	-1.036	0.978
GRN	Other	-3.367	0.163
GRN	REF	-5.541	0.001
LAB	LD	-1.094	0.972
LAB	Other	-3.274	0.188
LAB	REF	-5.174	0.003
LD	Other	-2.446	0.512
LD	REF	-4.477	0.019
Other	REF	-1.597	0.87

RANK_JOB

		W	p
CON	GRN	4.284	0.03
CON	LAB	3.165	0.22
CON	LD	2.204	0.626
CON	Other	-0.185	1
CON	REF	-2.153	0.65
GRN	LAB	-0.986	0.982
GRN	LD	-1.748	0.819
GRN	Other	-4.146	0.04
GRN	REF	-6.265	<.001
LAB	LD	-0.831	0.992
LAB	Other	-3.174	0.218
LAB	REF	-5.217	0.003
LD	Other	-2.268	0.596
LD	REF	-4.127	0.041
Other	REF	-1.725	0.828

RANK_ETH

		W	p
CON	GRN	-6.0593	<.001
CON	LAB	-5.6462	<.001
CON	LD	-5.3699	0.002
CON	Other	-0.9019	0.988
CON	REF	6.5647	<.001
GRN	LAB	-0.0781	1
GRN	LD	-0.0702	1
GRN	Other	4.7524	0.01
GRN	REF	12.3399	<.001
LAB	LD	0.0813	1
LAB	Other	4.5017	0.018
LAB	REF	11.5172	<.001
LD	Other	4.2853	0.03
LD	REF	11.1152	<.001
Other	REF	7.156	<.001

Significant difference

Table 30: DSCF pairwise comparisons on selection criteria flagged as having significantly different rankings by party from the Kruskall Wallis ANOVA

[31] Note that the variables were ranked 1-6 where 1= most important and 6 = least important, but that these are inverted for Figure 9 to allow for more natural visual interpretation, since the 'outer spikes' are traditionally indicators of the items that are most important to people in a radar diagram.

Figure 9: Radar diagrams of selection criteria rankings, by party, with significant differences highlighted

Combining the information in Table 27 to Table 30, along with Figure 9, reveals that there are three 'tiers' of rankings. At the top, Age stands alone; it is the most important selection criteria to ensure a representative DMP for most people, and is not differentially ranked by people from different parties.

Job Type, Education Level, and Income Level form a middle tier. Income Level is ranked third most important overall, and there are no significant differences between how people from different parties rank this item. The other two 'mid-ranking' criteria do differ by party, and follow a broad left-right split in terms of party difference. 'People with different types of jobs' is ranked slightly higher by Reform UK supporters than all the left-leaning parties, while Conservative and the 'Other' group rank this significantly higher than Green voters[32].

The small effect size of the differential rankings of the item 'people with different levels of education' is driven entirely by the difference in Reform UK with the three left-leaning parties. Reform UK voters rank this item higher, on average, than all other party groups, leading to a statistically significant difference at the extremes of the left-right spectrum.

I turn now to the a 'bottom tier', the two items that are ranked lowest overall. 'People of different ethnicities' is the lowest ranked item when considering the overall mean ranking, but closer inspection of the DSCF pairwise comparisons and the visual representation in Figure 9 shows this to be the most divisive criteria. Again, there is a broad left-right split, with Reform UK ranking this significantly lower than all other groups (setting them apart even from Conservative and 'Other' groups) and, in turn, those two groups rank this item lower than the three left-leaning parties. The lowest overall mean of this variable is therefore a function of the depressing effect of the Reform UK ranking, which drags the overall mean downward, and the magnitude of the difference is also what contributes to the larger effect size.

[32] Note that another survey question asked respondents to place themselves on a left-right scale, and the 'Other' group are a right-leaning group overall on this measure.

Finally, the other lowest ranking selection variable is 'People who support different political parties.' Unlike ethnicity, this is low-ranked by all; nobody thinks it is an important selection criteria, and there is no significant difference between any party group.

5.4.4.4 Missing Data

The dropout rates for the survey questions referring to DMP_GOODBAD and DMP_VOL_WHY were minimal at 1-2%, and chi-square tests suggest no significant association with party (χ^2 = 7.23 and 6.69 respectively, both with $p>0.05$). I therefore conclude that those dropouts are Missing at Random (MAR). For the question DMP_RANK however, analysing dropouts by party resulted in χ^2 = 16.69 ($p<0.01$). The pattern of dropouts is skewed: Lib Dem, Labour and Green hover around 4%, whereas the dropout rate for Reform UK and Other is over 12%. The data for the question DMP_RANK is therefore Missing Not At Random (MNAR).

In part, it is likely that survey fatigue in general, combined with the enhanced cognitive and tactile requirements of having to 'drag and drop' multiple ranking items contributed to the sudden and substantial dropout rate at this final question. However, the pattern of missingness also appears closely tied to political affiliation, with the right-leaning groups of Reform UK and Other dropping out at 12-13% of the total sample at this point, as compared with ~3% for Green/Labour/Lib Dem, and slightly more for Conservatives.

I therefore postulate that the dropout rate may also be a function of the attitudes to Climate DMPs identified earlier. The Reform UK grouping is by far the least supportive of the idea of Climate DMPs (from the data in the question DMP_GOODBAD), with the 'Other' grouping also rating the idea of Climate DMPs lower than most. It is also likely to be a function of general beliefs about climate change (it being widely known that support for Net Zero and climate mitigation policies from Reform UK voters is much lower than it is for other parties). This may have exacerbated the general sense of survey fatigue for this group, for whom a complex ranking question on a topic they don't much care about was possibly more off-putting. Indeed, the question DMP_VOL_WHY shows this is a group that, if they

would take part in a Climate DMP at all, would overwhelmingly do so because they want to represent the view that climate change is an exaggerated threat.

This suggests that the answers to the final ranking question may be biased towards those Reform and Other participants who are, overall, *more* concerned about climate change (and therefore having more in common overall with members of other parties), and therefore the differences in rankings of some items may actually be attenuated.

5.5 Conclusions

Overall, the analysis presented in this chapter demonstrates that:

- Real-world recruitment data for Climate DMPs reveal meaningfully lower volunteer rates from *Conservative* voters. It is also clear that collecting data on political affiliation allows for the sortition processes to flex in response to this, essentially 'over-selecting' from the minimal number of Conservative voters in the volunteer pool in order to correct the imbalance to create the final assembly cohort.
- While Conservatives are not statistically significantly less supportive of the *general* idea of Climate DMPs than the parties of the left and centre-left, they are considerably less likely to volunteer for them, even in a hypothetical survey situation, and with a moderate to large effect size, depending on the comparator party. (4 times less likely than Green, and about 1.5-2 times less likely than other parties). This provides some confirmation of the real-world data from the three Sortition processes.
- The parties of the left and centre-left (Labour, Green and Liberal Democrats) are essentially indistinguishable from each other in being largely supportive of the idea of Climate DMPs, and highly likely to volunteer for one from a climate concerned perspective (in a hypothetical scenario).
- By contrast, Reform UK voters are markedly less supportive of the idea of Climate DMPs than all other party groups, but nonetheless *would* volunteer in quite large proportions if one were advertised in their area. However,

their motivation for volunteering showed a distinctive pattern of 'defensive participation,'. Reform voters are much more likely to volunteer for a climate DMP to represent the idea that the threat of climate change is exaggerated, being hundreds of times less likely (as measured by odds ratios, which have Extremely Large effect sizes) when compared to left-leaning parties (Green, Labour, Liberal Democrats), and smaller, but still notable differences to the parties of the political right.

- If a Climate DMP were to be held locally, supporters of all parties believe that 'people of different ages' is the *most* important selection criteria, and 'people who support different political parties' is the *least* important selection criteria. 'People of different incomes' is of middling importance, and not divisive. Ethnicity, job type, and education level do differ in importance though, with clear party splits and a large effect size in relation to ethnicity being a selection variable.

While the effect sizes reported above are in some cases moderate to large (for example the likelihood of Conservatives volunteering to take part at all, or the motivation for Reform UK voters volunteering), others are reasonably small, especially in relation to the ranking of selection criteria. However, it should be borne in mind that even small effects can combine to substantial impacts where a phenomenon is measurable across a large population and/or repeated across multiple events (Funder and Ozer, 2019; Mastrich and Hernandez, 2021). In the UK, the past five years have seen marked growth in the use of citizens' assemblies in general for policy making, and climate assemblies specifically, often as a result of local authority climate emergency declarations (Lewis *et al.*, 2023). The results in this and the preceding chapter suggest that increased use of participatory democracy processes may not be as welcome to Conservative voters in particular. In addition, there are clear differences in the views of Reform UK voters and most other party groups on the appropriateness of Climate Assemblies, and their reasons for volunteering.

In addition, even the 'sortition variables', by which well-meaning attempts are made to ensure a representative group is recruited, may be perceived differently by

different political groups. While some (age, income) seem non-contentious, others are more divisive. Reform UK rank 'people with different levels of education' higher than supporters of other groups. Does this reflect a sense that, to them, education in a formal sense is not important in such processes, but rather something like 'common sense' is what is needed?

Ethnicity is divisive – although it is ranked lower than other variables overall, the split between left and right is what pulls the overall mean of this item down. A cluster of left-leaning respondents feel it is more important, Conservatives a little lower, Reform UK lower still. The implications of this are hard to unpick and should be treated with great caution in terms of extrapolation beyond this study. The survey underpinning this research was distributed in rural areas of England, which were overwhelmingly white in ethnicity (95%+). The question on ranking selection variables was about a process that would run '*in your local area'*. This may reflect why, overall, ethnicity was ranked quite low by *all* respondents. But that overall ranking still masked a clear difference between the parties of the left and right, and (on the left) could be an expression of underlying, abstract values coming through (they may be thinking "this is important in an abstract way to me, and I haven't really thought about why it would be so important in such a very white area"). By contrast, it could also reflect a reverse, pragmatic logic from the Conservative and Reform UK groupings (they may be thinking "this is a very white area, so I don't think that matters *in this area*").

Political party affiliation as a recruitment variable for DMPs is ranked *right down at the bottom*. People generally think it is unimportant, and there are no significant differences on that ranking between people of different political affiliations. However, it is evident from this study overall that political affiliation affects everything, from support for DMPs as an idea, differentiation in volunteer rates, contrasting motivations for participation, and influence on what recruitment criteria people think are fair and proper to use. In light of that, this contradictory low ranking is possibly the most striking finding of all.

5.5.1 Limitations of the study and Opportunities for further research

These findings are exploratory, but reveal several patterns worthy of further investigation that warrant replication in confirmatory studies. The survey results were derived from a single large-scale sample that was used to serve different research needs within this thesis. There was not sufficient time within the PhD timetable to carry out any follow up or confirmatory work with more concrete, directional hypotheses and an independent sample. In addition, the survey was distributed only in rural areas and only in England, and so extending the study to a wider area that included urban respondents would be a natural next step.

The results should also be considered in light of the intention-behaviour gap noted in the introduction to the chapter, whereby more people will indicate an intention to take part in a hypothetical process than would actually be the case if real invitations are received. In the absence of evidence to the contrary, I also assume that this 'inflated intention' phenomenon will affect participants from all political parties equally in this study, but future work comparing real recruitment processes for Climate DMPs and a replicated survey with an independent sample could be used to explore this further.

The final limitation of the study is shared with the results of Chapter 4; it is relevant only to Climate-themed DMPs. Deliberative Mini Publics are deployed to support development of public policy across a range of themes, and it is not possible to entirely disentangle views on climate change from views on deliberative democracy more generally from the results presented here. The focus on climate DMPs was purposely done (since the focus of this thesis is firmly on *climate* policymaking) but this does mean it would be inadvisable to extrapolate these results to DMPs relating to other policy areas.

6 Resistance to Rural Climate Initiatives: scale development and testing

6.1 Introduction and background

This chapter documents the development of an attitudinal scale to address a specific policy challenge; measuring resistance to the likely landscape changes that will result from the implementation of climate mitigation and adaptation policies in rural England. While broader environmental and landscape attitude scales exist, they lack the specificity needed to understand opposition to concrete climate policy interventions like altered agricultural practices, rewilding, or renewable energy infrastructure that will change rural areas.

The chapter responds to Research Question 2: *How can resistance to rural climate policy initiatives be reliably measured?*

6.1.1 Measuring attitudes to environmental change

Understanding how to quantify people's attitudes to environmental change has long been the subject of study, with two of the best-known environmental attitude scales dating back to the 1970's (Dunlap and Van Liere's 'New Environmental Paradigm' (NEP), and Weigel and Weigel's 'Environmental Concern Scale' (ECS), both 1978). Despite the long history of their use, there remains a lack of consensus on what is meant by 'attitude' and 'environment', and what exactly such scales are measuring continues to be a lively debate. Is a 'pro-environmental attitude' a multidimensional or unidimensional construct? Are there meaningful differences between attitudes to the environment at different scales (local and global)? Is it likely that these

popular measurement instruments degrade in relevance over time? (Dunlap, 2008; Milfont and Duckitt, 2010; Cruz and Manata, 2020).

Understanding the dimensionality of environmental attitudes has become increasingly central to scale development and implementation, and the unidimensionality of the NEP in particular may be at the root of a common critique that it has often been a poor predictor of pro-environmental behaviours (Liu and Chen, 2020). Other, multidimensional scales such as the 2-MEV (Two Major Environmental Values) scale, which simultaneously measures attitudes to *conservation* and *utilisation* of environments, have grown in popularity as a result. Long-form, short-form, alternative language and adolescent-specific versions of the 2-MEV have been developed (Bogner and Wilhelm, 1996; Bogner and Wiseman, 2006; Kibbe, *et al*, 2014; Randler *et al*, 2024), though debate about what exactly an 'environmental attitude' is, remains.

The broad scope for interpretation of the term 'environment' is central to the debate, because, as detailed in the Literature Review (Sections 2.81-2.82), ample evidence exists to show that individuals can simultaneously be concerned about a global environmental issue like climate change, while holding strong attachments to their hyper-local environment.

6.1.2 Measuring attitudes to landscape

Abundant research exists on the topic of mapping and classifying 'landscape preferences' and attitudes toward specific landscape alterations, to support better involvement of people in the spatial management of the places around them (Tveit, 2009; Zoderer *et al.*, 2019). Most of these methods are situated within the conceptual framework of 'ecosystem services' (ES), an approach that categorises landscape 'benefits' into *provisioning services* (food, water, timber), *regulating services* (climate regulation, flood control), *supporting services* (soil formation, biodiversity maintenance), and *cultural services* (recreation, aesthetic value) (de Groot *et al.*, 2010; Iverson *et al.*, 2014).

Though stemming from the 1980's, the ES approach became cemented as a standard methodology for understanding and managing land use, largely as a result of the UN-initiated 'Millenium Assessment', an attempt at quantifying the role of ecosystems and landscapes in supporting human development at a global scale (Millennium Ecosystem Assessment, 2005). Though land use planning systems differ from country to country, the ES approach is now embedded in some form at a practical and policy level in most states. It has been both welcomed as a useful mechanism that helps policy makers balance competing demands on what services ecosystems and landscapes can provide (de Groot *et al.*, 2010), and criticised for representing "*the neoliberalisation of nature*" (Dempsey and Robertson, 2012, p.758). According to such critics, ES systematically marginalises the emotional, identity-based, and affective dimensions of people's relationships with their environment, and the ES framework is not well-equipped to deal with the fact that landscapes "*come into being through people's embodied practices and aspirations*", and are both "*relational and processual*" (Setten *et al.*, 2012, p.309).

Mapping and understanding landscapes in the ES paradigm includes (at the one extreme) highly technical, desk- and survey-based work covering land-cover and soil type classifications, water catchment dynamics, and climate, hydrological and habitat data. Mapping 'cultural services', at the other extreme, sits uncomfortably in this approach, and a tendency to sideline and undervalue 'intangible' cultural assets is a known weakness of ES (Chan *et al*, 2012; Plieninger *et al.*, 2013).

In part, this has been addressed by the deployment of richly qualitative, arts-based knowledge co-creation processes that centre local and traditional knowledge of landscapes and ecosystems (Galafassi *et al.*, 2018; Strand, *et al* 2022), but these are highly locally specific and costly to deliver. Public Participation GIS (PPGIS) is a broad collection of largely map-based methods for collaboratively enabling citizens to contribute local knowledge and preferences about their environments, using a range of approaches used that scale from hyperlocal participatory mapping to watershed-scale understandings of flood management. Through such methods, often incorporating a mixture of mapping, photomontage and other stimuli, via in-person meetings and (increasingly) online platforms, an understanding of the

cultural services that specific landscapes provide can be painstakingly assembled (McLain *et al.*, 2013; Brown and Fagerholm, 2015).

Whether through arts-based approaches or more formalised, semi-quantitative approaches such as PPGIS, the cultural understandings, attitudes and preferences that emerge are usually based on specified and defined landscapes, particular local planning contexts, and concrete development proposals. In a PPGIS process, respondents usually consider landscape change with reference to precise locations, specified projects, and trade-offs between alternative sites. PPGIS excels at revealing locally specific insights, which makes it well suited to development consultations.

On the other hand, relatively little in the way of measurement tools exist that address *general* attitudinal dispositions towards landscape change at a more abstract level, the results of which could be aggregated to better understand the wider social and political context within which plans for landscape change will happen. In the context of this thesis, the most relevant tools are from Park and Selman (2011), who developed and tested two broad scales that measure attitudes to rural landscape changes in England, and Williams (2011), whose scale contribution focuses on attitudes to agricultural vs. residential vs. industrial land uses in Australian landscapes.

6.1.3 Motivation for development of a new measurement instrument (RRCI)

The wider motivations for development of the Resistance to Rural Climate Interventions (RRCI) scale outlined in this chapter are detailed in the Literature Review and are summarised again here as:

- 'Industrial scale' solutions to both climate change mitigation and adaptation require the countryside for their successful execution (such as wind farms, solar farms, plantations for carbon capture).
- At the same time, the wider social and environmental challenges facing rural areas do not necessarily attract the same level of policy focus or funding (e.g. poor transport links, older and less thermally efficient homes, and knock-on

effects such as purchase of land for carbon capture competing with established but economically precarious land uses such as hill farming).

- Rural areas are widely seen as unchanging and as the embodiment of national identity, particularly cultural/banal nationalisms, increasing the sense that change is inappropriate or that protecting this intangible but important characteristic needs to be balanced with other priorities (such as climate response).
- There is a long history of rural/urban conflict driven by conceptions of 'rural exploitation', in which energy/climate solutions are a new chapter.

More specifically, the prescriptions of the Climate Change Committee's 6th Carbon Budget Sector Report on Agriculture, Land Use Change and Forestry (Climate Change Committee, 2020)[33] gives a good overview of the broad changes that will have to occur in rural areas if the UK's climate policy commitments are to be met:

- Changed agricultural land uses, in particular novel crops (including energy crops), agroforestry practices (mixing crops with trees in managed plantations), and a visible reduction in livestock numbers.
- Emergence/re-establishment of ecosystems that are unfamiliar to the general public, through re-foresting, re-wilding and re-wetting of previously farmed or drained land, and the deployment of agro-forestry systems.
- Development of distributed energy generation systems, principally wind and solar power, replacing the UK's post-WWII highly centralised power generation system based on coal and gas.

While public opinion surveys regularly show that support for robust climate policies remains high for the UK public (DESNZ, 2025), this masks differences that are both spatial and ideological in nature (Climate Barometer, 2025; Gillreath-Brown *et al.*, 2025). Given the reality that so much of the large-scale climate policy impact will be seen in rural areas, I set out to develop a policy-relevant measurement tool that can be used to help understand the patterns of demographic support for and resistance

[33] The CCC's Seventh Carbon Budget was published during the course of this research and after the survey had been piloted and issued in full form, but the broad prescriptions remain the same.

to the types of changes that will be specifically driven by climate policies. Note that these are not the same as the changes that climate change itself (droughts, increased intensity of rainfall etc) will cause.

In the development of the item pool, I aimed to include items that measure resistance to the specific types of landscape changes that will occur as a result of climate policy, at the same time as considering emotional attachments to the land. My initial assumptions were that a set of scales would emerge that could be used in tandem, measuring both higher-order emotional/affect based attitudes to landscapes and their links to identity, and lower-order attitudes, tied to progressively more concrete and specific attitudes about specific, physical changes (in line with the advice of Cruz and Manata, 2020). However, as detailed in the method and results that follow, the final scale proved to be surprisingly, but solidly, unidimensional, suggesting that the more abstract and more concrete attitudes being measured are more closely intertwined than I had expected.

6.2 Development of the item set

6.2.1 Developing an initial item pool

I began by developing a broad list of items to be used in a Likert-style survey, which would cover the types of land use change that would result from the provisions of the aforementioned CCC Sixth Carbon Budget Report.

Items 1,18, 22, 28 and 31 of the pilot scale in Table 31 below were slightly modified versions of items from Park and Selman's 'Rural Landscape Attitude Scale'. Items 15 & 16 of the pilot scale were adapted from two items in their 'Landscape Change Attitude Scale'.

More broadly, the development of the pilot items was particularly inspired by the work of Williams (2011), and also drew on the work of Devine-Wright (2005); Ellis and Robinson, (2007); Sharp and Adua, (2009); Duenckmann, (2010); and Anderson, Ford et al., (2017) who, between them, provided useful stimuli for items on the appropriateness of productive infrastructure in rural landscapes, anti-

conservationist narratives in agricultural communities, and the evolving relationship between rural and urban places.

6.2.2 Content validity

As insurance against substantial item wastage during the stages of scale refinement, I initially developed a large item pool. The pool was then reviewed for content validity and language accessibility by a team of three academics from Lancaster Environment Centre (Professor, Senior Research Associate, and PhD researcher in associated fields). The resulting pilot item pool consisted of 35 items, (Table 31, below).

1	It doesn't matter to me what the English countryside looks like, as long as I know that changes we make are directly tackling climate change
2	The English countryside is no place for industrial scale renewable energy installations like wind turbines or solar farms.
3	The English countryside would be changed for the better if there were far fewer cows in the fields
4	The English countryside would be changed for the better if there were far fewer sheep in the fields
5	One downside of people eating a more plant-based diet is that we will see fewer cows in England's countryside
6	One downside of people eating a more plant-based diet is that we will see fewer sheep in England's countryside
7	Rural areas in England should produce as much renewable energy as they can and export spare to urban areas
8	It is not the role of England's rural areas to provide renewable energy for towns and cities
9	If we are to successfully tackle climate change, England must have a countryside management strategy based on science, not tradition.
10	The people who manage England's countryside now are best-placed to decide how we use rural areas to tackle climate change
11	I would find it upsetting if large areas of English farmland were returned to a wild and un-managed state
12	Reducing the amount of meat in our diets would be a good thing for this country, because it would allow us to re-wild and re-forest large areas of England's countryside
13	Renewable energy systems like solar farms and wind turbines are only acceptable when they are directly owned by the communities where they are sited
14	The government should establish a national energy company that will build renewable energy in the English countryside for all of us
15	It saddens me to think of English cities changing

16	It saddens me to think of the English countryside changing
17	The real heart of English identity is found in our cities and towns
18	Rural landscapes are more important to English identity than urban places
19	Preserving traditional rural English ways of life is vital, even if it means doing less than we otherwise could to tackle climate change
20	I don't mind taxpayers' money being used to help farmers do all they can to tackle climate change, even if it means the English landscape will look very different
21	Tackling climate change offers a great opportunity to transform English towns and cities for the better
22	Tackling climate change offers a great opportunity to transform England's countryside for the better
23	I am excited by the idea that, as our diets change to tackle climate change, so will the English landscape
24	I find it encouraging to see new types of crops and plants growing in the English countryside
25	If the English landscape were radically different, it would change who we are as a nation
26	The English countryside is beautiful to me largely because it has been shaped by many generations of my countrypeople
27	The English countryside would be improved by large areas of new forestry
28	The English countryside would be improved by large areas of new woodland
29	We should encourage the planting of fast-growing trees in the English countryside to tackle climate change, even if they are non-native species
30	We should focus our efforts to tackle climate change in English towns and cities, and leave the countryside alone
31	I would rather that English rural landscapes are preserved as they are now
32	Renewable energy should never be built on farmland where food could be grown instead
33	I see no reason why farmers shouldn't generate renewable energy on their land, so long as they can still produce food around it.
34	I think that wind turbines add interest to the English countryside
35	I think that solar farms in England's countryside are a welcome development

Table 31: Initial item pool for the pilot stage.

I included three sets of almost identical statements, to differentiate livestock and tree cover preferences:

- Item 3. The English countryside would be changed for the better if there were far fewer **cows** in the fields.

- Item 4. The English countryside would be changed for the better if there were far fewer **sheep** in the fields
- Item 5. One downside of people eating a more plant-based diet is that we will see fewer **cows** in England's countryside
- Item 6. One downside of people eating a more plant-based diet is that we will see fewer **sheep** in England's countryside
- Item 27. The English countryside would be improved by large areas of new **forestry**
- Item 28. The English countryside would be improved by large areas of new **woodland**

The first two pairs were designed to investigate whether meaningful differences exist in respondent preferences for the presence of different livestock species in the English countryside. Finally, items 27 & 28 referred to woodland *or* forestry since 'woodland' evokes a more natural, unmanaged wooded ecosystem, whereas 'forestry' evokes managed timber crops.

6.2.3 Statement valence

The valence of around half of the items relates to *resistance* to the sorts of change that climate policy may bring, whereas the valence of the remainder represents *openness* to such changes. Interpretation of mean scores in the descriptive statistics therefore requires attention to the meanings implied by 'double-negative' or 'double positive' effects.

- Resistant valence item + high mean score = Resistance to change
- Resistant valence statement + low mean score = Openness to change
- Openness valence statement + high mean score = Openness to change
- Openness valence statement + low mean score = Resistance to change

I avoided simple 'negated-pair' versions of the same statement (in the vein of "I am often happy" vs "I am often sad"), as these have been shown to both induce a method effect in factor analysis (where all negatively worded statements load onto a separate factor that simply reflects 'negative affect') (Zeng *et al*, 2020; Tang *et al*,

2024) and to have low correlations, (suggesting that they are not interpreted as exact opposites of each other) (Krosnick and Presser, 2009; DeVellis, 2017; Paap *et al.*, 2024).

By contrast, the opposite-valence statements in the pilot scale represent genuinely different attitudinal positions that are framed from either the point of opposition to climate policy in rural areas (e.g. "*The English countryside is no place for industrial scale renewable energy*") or those that represent openness to such policies (e.g. "*Rural areas should produce as much renewable energy as they can to export the excess to urban areas"*). As insurance, I tested for negative-affect method effects on the final scale and demonstrated that the scale is not impacted by this phenomenon.

6.3 Pilot survey

Respondents were invited to complete a pilot survey containing the full 35-item pool shown in Table 31 via a public message on the 'Nextdoor' localised social media network, covering fourteen villages and one small rural town in Gloucestershire and Oxfordshire.

The invitation message presented the survey as part of a PhD study into attitudes to rural change as a result of climate policy. Respondents were made aware that the survey was in pilot form, and that their responses would be used to refine and shorten the survey for use in a wider, national study. At several points throughout the survey the respondents were reminded that its length was related to the pilot nature and encouraged to complete it to aid the ongoing research. No payment or other incentive was offered.

The survey was open for four weeks and accrued 95 responses with no missing data in the scale items. In addition to the scale items, demographic and identity information was collected on age, sex, and people's self-perception of whether they view themselves as 'rural or urban'.

All items in the scale were measured on an 11-point Likert scale. From the participant's point of view, this was represented as 0 = Strongly Disagree through to

10 = Strongly Agree (though results below present this as 1-11, due to the software settings). A free text comment field was provided for general feedback, specifically asking for commentary on accessibility and comprehension of the items and their relevance to the topic.

6.3.1 Descriptive Statistics – Pilot cases

Appendix 6.1 shows the descriptive statistics for the 35 items, based on the 95 pilot responses.

Item means range from 3.76 to 8.82, with a standard deviation of 1.85 to 3.87 on the 11-point Likert scales.

Maximum and minimum scores range from 1-11 on almost all items (31 of 35), with the remaining four items using the scales from 3-11 (items 24, 27 and 28), and from 2-11 (item 35), suggesting good item discrimination which can effectively distinguish between respondents with different attitudes.

Skewness ranges from -0.98 to 0.790, and kurtosis from -1.17 to 1.09. Both are well within the range considered acceptable for assumptions of normality for further analysis (within +/- 2 for skewness and less than 7 for kurtosis).

The most skewed items are Item 33 ('*I see no reason why farmers shouldn't generate renewable energy on their land, so long as they can still produce food around it*'), with a mean score of 8.82 and skew of -0.98 (skewed negatively; high agreement), and item 19 ('*Preserving traditional rural English ways of life is vital, even if it means doing less than we otherwise could to tackle climate change'*), mean 4.14, skew 0.708 (skewed positively; high disagreement). Note however that the effect of the double-negative in interpretation of item 19 means that both of these most highly skewed items in the set suggest that overall, the pilot respondent group leans towards *support* for changed countryside practices in relation to climate policy. This may be a reflection of the relatively small sample, drawn from a geographically restricted area.

6.3.2 Correlations

I first examined **Item-to-item** correlations using Excel's CORREL function (which returns the Pearson's product-moment simple linear correlation coefficient, r), to identify any items that have low correlation coefficients with all or most of the other items, an early indication that they are not reliably measuring the same underlying construct. This could be a result of wording that is too broad (allowing multiple interpretations), or simply because they do not measure the underlying construct well (Blaikie, 2003).

Items 10, 13, 17 and 24 had the lowest item-to-item correlations across the range.

- 10: '*The people who manage England's countryside now are best-placed to decide how we use rural areas to tackle climate change*'
- 13: '*Renewable energy systems like solar farms and wind turbines are only acceptable when they are directly owned by the communities where they are sited*'
- 17: *'The real heart of English identity is found in our cities and towns*'
- 24: '*I find it encouraging to see new types of crops and plants growing in the English countryside*'

The highest correlations related to the items where sheep/cows and forest/woodland had been used in otherwise identically worded items. Items 3 & 4 ('*The English countryside would be changed for the better if there were far fewer COWS/SHEEP in the fields'*) correlate at r = 0.8, items 5 & 6 ('*One downside of people eating a more plant-based diet is that we will see fewer COWS/SHEEP in England's countryside'*) correlate at r = 0.7 and items 2 & 28 ('*The English countryside would be improved by large areas of new FORESTRY/WOODLAND'*) correlated at r = 0.6, suggesting the pairs could conveniently be combined into more generally worded items, reducing the overall item total.

I next examined **Item-to-total** correlations using Jamovi's Item Reliability Statistics output, as an initial test of unidimensionality. Correlation coefficients ranged from 0.102 to 0.737, with the lowest four items being the four already identified as weak

through the item-to-item correlations, above. Of the 35 items, 25 have moderate to strong item-to-total correlations (r = 0.40 to 0.74). (see Table 32, below), suggesting a reasonable scale.

6.3.3 Reliability coefficients

Initially, Cronbach's alpha and McDonald's omega for the 35-item scale were very low (α = 0.424, ω=0.593). Reverse-scoring some items to account for the resistance and openness valence of item wordings resulted in 16 reverse scored items (resistant valence) and 19 originally scored items (openness valence) with excellent overall alpha (0.923) and omega (0.924) scores.

Software outputs indicated that both scale reliability coefficients could be further improved by removal of three of the items already flagged as weak through the correlation analyses (10, 13 and 17), while the fourth (item 24) remained just within limits. I removed the three weakest one by one (with the coefficients re-assessed between rounds to ensure that the solution did not re-stabilise, allowing any of them to be retained).

With these three items removed, alpha and omega stabilised at 0.928 and 0.929 respectively, generally considered excellent scores (though possibly slightly inflated due to the very long item list).

Scale Reliability Statistics

	SD	Cronbach's α	McDonald's ω
scale	1.34	0.923	0.924

Item Reliability Statistics		If item dropped	
	Item-rest correlation	**Cronbach's α**	**McDonald's ω**
1_ChangeNotMatterIfTackleCC	0.620	0.919	0.920
2_NoREinCountrysides [a]	0.455	0.921	0.922
4_betterNoSheep	0.505	0.920	0.922
3_betterNoCows	0.542	0.920	0.921
6_worseNoSheep [a]	0.544	0.920	0.921
5_worseNoCows [a]	0.737	0.917	0.919
7_ruralExportRE	0.583	0.919	0.921
8_ruralNoREforTowns [a]	0.446	0.921	0.922
9_ruralScienceStrategy	0.557	0.920	0.921
11_rewildingUpsetting [a]	0.624	0.919	0.920
12_rewildingGood	0.698	0.918	0.919
14_RE_Nationalised	0.401	0.922	0.923
15_sadCityChange [a]	0.355	0.922	0.923
16_sadRuralChange [a]	0.524	0.920	0.921
18_IdentityInRural [a]	0.300	0.923	0.924
19_TradMoreImportantthanCC [a]	0.594	0.919	0.920
20_FundFarmersToTackleCC	0.656	0.918	0.920
21_CC_policyChangeCitiesForBetter	0.578	0.920	0.921
22_CC_policyChangeRuralForBetter	0.653	0.918	0.920
23_dietChangeLandscapeChangeGood	0.589	0.919	0.920
24_newCropsGood	0.259	0.923	0.924
25_changeLandscape=changeNation [a]	0.472	0.921	0.922
26_ruralBeautyInWorkOfPast [a]	0.470	0.921	0.922
27_ForestryImprovesCountryside	0.395	0.921	0.923
28_WoodlandImprovesCountryside	0.360	0.922	0.923
29_WelcomeNonNativeTrees4CCS	0.386	0.922	0.923
30_FocusCCPolicyCities [a]	0.470	0.921	0.922
31_PreserveRuralLandscapes [a]	0.694	0.918	0.919
32_NoRE_OnFoodLand [a]	0.517	0.920	0.921
33_EncourageFarmersRE	0.371	0.922	0.923
34_WindTurbinesInteresting	0.543	0.920	0.921
35_SolarFarmsWelcome	0.507	0.920	0.921
10_ruralTraditionStrategy [a]	0.131	0.924	0.925
13_REownedCommunity [a]	0.203	0.924	0.925
17_IdentityInCities [a]	0.102	0.924	0.926

[a] reverse scaled item

Table 32 (previous page): Reliability Analysis and Item-to-Total Correlations for 35-item pilot scale

6.3.4 Pilot scale rationalisation

I had hoped to carry out an Exploratory Factor Analysis (EFA) on the pilot data to identify emerging subscales, but with a sample of 95 for 35 items, the item-to-case ratio was only 2.7:1, which I considered likely to result in unstable or misleading solutions, since recommendations generally range from a minimum of 5:1 to 10:1 for stable EFA solutions. (Mundfrom, Shaw and Ke, 2005; Tavakol and Wetzel, 2020; Whittaker and Schumacker, 2022). Rather than relying on potentially unstable EFA solutions, I instead used the correlation and reliability analysis results, along with a review of participant feedback comments in the free-text fields, to refine and shorten the scale before using it in a wider survey.

The main aim of this refinement was to reduce the number of items in the scale, while still leaving sufficient items for the inevitable further item losses that would result from EFA after circulation of the survey to a larger sample. Table 33 below shows the amendments. Items used in the full survey are given in bold italic text.

Pilot No.	Pilot Item wording	Treatment and new item code	Rationale for removal/rewording
1	***It doesn't matter to me what the English countryside looks like, as long as I know that changes we make are directly tackling climate change***	Retain **(LS1.1)**	
2	***The English countryside is no place for industrial scale renewable energy installations like wind turbines or solar farms.***	Retain **(LS1.2)**	
3	The English countryside would be changed for the better if there were far fewer COWS in the fields	Combine items 3 and 4. "***The English countryside would be changed for the better if there were far fewer sheep and cows in the fields.***" **(LS1.3)**	Very high correlation between items 3 & 4 suggests no meaningful distinction between livestock species for these items
4	The English countryside would be changed for the better if there were far fewer SHEEP in the fields		
5	One downside of people eating a more plant-based diet is that we will see fewer COWS in England's countryside	Retain (reworded) "***It will negatively affect the English landscape if people reduce the amount of beef and dairy that they eat.***" **(LS3.1)**	Participant feedback – confusingly worded item. Retain separately (reworded) in case confusion was partly the cause of the high correlation with item 6.
6	One downside of people eating a more plant-based diet is that we will see fewer SHEEP in England's countryside	Retain (reworded) "***It will damage the beauty of the English countryside if fields of grazing sheep are replaced with fields of crops instead.***" **(LS2.4)**	Participant feedback – confusingly worded item. Retain separately (reworded) in case confusion was partly the cause of the high correlation with item 5.
7	***Rural areas in England should produce as much renewable energy as they can and export spare to urban areas***	Retain **(LS1.5)**	
8	***It is not the role of England's rural areas to provide renewable energy for towns and cities***	Retain **(LS2.1)**	
9	If we are to successfully tackle climate change, England must have a countryside management strategy based on science, not tradition.	Retain (reworded) ***"If we are to successfully tackle climate change, England's countryside management strategy must be led by scientists, not farmers"*** **(LS2.3)**	Reword to centre the actors (scientists or farmers) which is a clearer distinction than 'science' or 'tradition'.
10	The people who manage England's countryside now are best-placed to decide how we use rural areas to tackle climate change	Retain (reworded) ***"The farmers and landowners who manage England's countryside now are best-placed to decide how we use rural areas to tackle climate change"*** **(LS3.2)**	Participant feedback – 'people' too vague. Reworded 'actor' focus with more specific roles.
11	***I would find it upsetting if large areas of English farmland were returned to a wild and un-managed state***	Retain **(LS2.2)**	
12	***Reducing the amount of meat in our diets would be a good thing for this country, because it would allow us to re-wild and re-forest***	Retain **(LS2.5)**	

Pilot No.	Pilot Item wording	Treatment and new item code	Rationale for removal/rewording
	large areas of England's countryside		
13	Renewable energy systems like solar farms and wind turbines are only acceptable when they are directly owned by the communities where they are sited	Remove	Item high uniqueness, and item more related to infrastructure ownership structures than rural change in general.
14	The government should establish a national energy company that will build renewable energy in the English countryside for all of us	Remove	As per item 14, Item 15 is unlikely to be a stable item in a wider survey as it is more clearly measuring attitudes to state/communal ownership of infrastructure.
15	It saddens me to think of English cities changing	Remove	Low item to item correlations across the board suggest this is not meaningfully part of a rural change scale.
16	It saddens me to think of the English countryside changing	Remove	Originally included as a partner to item 15. Removal of item 15 and retention of similar item 31 suggest removal of this item for parsimony.
17	The real heart of English identity is found in our cities and towns	Partially retain by combining with 18 (see new wording in next row) **(LS3.3)**	Low item to item correlations across the board suggest this is not meaningfully part of a rural change scale.
18	Rural landscapes are more important to English identity than urban places	Retain (reworded) ***"The real heart of English identity is found in our rural landscapes and places, not in our cities and towns."*** **(LS3.3) (with above item)**	Allows partial retention of item 17, without needing an additional item.
19	***Preserving traditional rural English ways of life is vital, even if it means doing less than we otherwise could to tackle climate change***	Retain **(LS3.4)**	
20	***I don't mind taxpayers' money being used to help farmers do all they can to tackle climate change, even if it means the English landscape will look very different***	Retain **(LS2.6)**	
21	Tackling climate change offers a great opportunity to transform English towns and cities for the better	Remove	Participant feedback – too vague
22	Tackling climate change offers a great opportunity to transform England's countryside for the better	Remove	Participant feedback – too vague
23	I am excited by the idea that, as our diets change to tackle climate change, so will the English landscape	Reword ***"I am happy with the fact that, as our diets change to tackle climate change, so will the English landscape*** **(LS3.5)**	Participant feedback – original phrasing felt a bit forced.

Pilot No.	Pilot Item wording	Treatment and new item code	Rationale for removal/rewording
24	I find it encouraging to see new types of crops and plants growing in the English countryside	Remove	Low item to item correlations across the board
25	***If the English landscape were radically different, it would change who we are as a nation***	Retain **(LS3.6)**	
26	***The English countryside is beautiful to me largely because it has been shaped by many generations of my countrypeople***	Retain **(LS4.1)**	
27	The English countryside would be improved by large areas of new FORESTRY	Combine items 27 and 28, incorporate both terms. ***"The English countryside would be improved by large areas of new forestry and woodland"*** **(LS4.2)**	High correlation between items 27 & 28 suggests no meaningful distinction between terminology
28	The English countryside would be improved by large areas of new WOODLAND		
29	***We should encourage the planting of fast-growing trees in the English countryside to tackle climate change, even if they are non-native species***	Retain **(LS4.4)**	
30	***We should focus our efforts to tackle climate change in English towns and cities, and leave the countryside alone***	Retain **(LS4.5)**	
31	***I would rather that English rural landscapes are preserved as they are now***	Retain **(LS4.6)**	
32	***Renewable energy should never be built on farmland where food could be grown instead***	Retain **(LS4.3)**	
33	***I see no reason why farmers shouldn't generate renewable energy on their land, so long as they can still produce food around it.***	Retain **(LS4.7)**	
34	I think that wind turbines add interest to the English countryside	Remove both	No meaningful difference in strength of responses between item specifying wind and item specifying solar (had included both to investigate technology preferences). Removed for the sake of parsimony, given there are several other items referring to 'renewable energy' in general.
35	I think that solar farms in England's countryside are a welcome development		
-	***Farmers should be supported to turn some of their drained fields back into natural wetlands***	New **(LS1.4)**	This new item introduced a land management change not previously separated from 'rewilding' in the pilot scale, but which I considered on reflection to be materially different enough to warrant inclusion, and should ideally have been included in the pilot

Table 33: Item rationalisation from pilot to full survey. Retained item wording in italics

This item review thus resulted in a shortened list of 23 items from the pilot, to which I added a new item covering peat/wetland restoration.

6.4 Main survey

The refined 24-item pool was distributed as part of a wider survey, (see Methodology chapter for full details of the sample distribution, promotional methods etc). The same survey collected data for research in Chapter 5 and Chapter 8 of this thesis and therefore was longer than just the landscape scale tested here. Including items on demographic data, political ideology (populism and nationalism), and a set of questions on attitudes to climate policy-making (which came at the end of the survey, after the Landscape Scale), the full survey consisted of 56 items in six blocks. Data were cleaned and missing data dealt with as described in Section 3.2.7.1 of the Methodology (Chapter 3), leaving a sample of 723 cases.

6.4.1 Split-sample process

I randomly assigned the 723 cases with completed landscape scales to two groups, using Excel (RANDBETWEEN 0,1) to allow for a split-sample EFA followed by a CFA. The resulting EFA group size (n=345) improved the item-to-case ratio to 14.4:1.

Though this ratio, along with a total sample size in excess of 200, is considered broadly adequate for EFA by various sources (Whittaker and Schumacker, 2022; Howard and Henderson, 2023), Mundfrom *et al.*'s (2005) empirical simulation study provides a more nuanced approach which suggests that neither absolute nor item-to-case sample size rules are entirely reliable, as complex interactions between the communality of the items on the final factors and the item-to-factor ratio affect the appropriate sample size. Since neither the communalities nor the ratios can be known in advance, given the exploratory nature of the process, I therefore also carried out an *ex post* analysis of the sample size once the factor structure had emerged, results of which are given in Section 6.5.6.

Before proceeding to EFA, I also carried out a MANOVA to compare the means of the EFA split-half (n=345) and the split-half sample retained for the CFA analysis (n=378). Bonferroni correction (adjusted $\alpha = 0.00208$, (0.05/24)) was applied to account for the effects of 24 simultaneous tests. The analysis showed that the group assignment process resulted in equivalent groups across all items, with no significant differences between the groups on any item.

6.5 Exploratory Factor Analysis

6.5.1 Descriptive statistics – EFA cases

Appendix 6.2 shows the descriptive statistics for the 24 items, based on the 345 cases to be used for EFA.

Item means ranged from 3.3 to 8.2, with a standard deviation of 2.62 to 3.49 on the 11-point Likert scales. Every item had responses across the full 11 points, suggesting good item discrimination which effectively distinguishes between respondents with different attitudes.

Skewness ranged from -0.94 to 0.85, and kurtosis from -1.32 to 0.4. Both are well within the range considered acceptable for assumptions of normality for further analysis (within +/- 2 for skewness and less than 7 for kurtosis). Most items had negative kurtosis, suggesting flatter peaks than a standard normal distribution, but well within limits.

As with the pilot, the most skewed item is LS4.7 (item 33 from the pilot: '*I see no reason why farmers shouldn't generate renewable energy on their land, so long as they can still produce food around it*'), with a mean score of 8.2 and skew of -0.94 (skewed negatively; high agreement). This conditional support for renewable energy *so long as it doesn't displace food production* is an interesting early observation, since the 'renewable energy vs food production' debate is central to some opposition to renewable energy production (Torma and Aschemann-Witzel, 2023; Cunningham and Seidman, 2024).

6.5.2 Reliability analysis and EFA Assumption checks

Cronbach's Alpha and McDonald's Omega were initially poor for the 24-item scale, but after reverse-scoring the opposite-valence items, both improved to 0.946.

The following two items were removed in consecutive rounds, at which point both alpha and omega stabilised at 0.948 and could not be improved by removal of further items:

- LS4.4_NON_NATIVE_TREE_OK ("*We should encourage the planting of fast-growing trees in the English countryside to tackle climate change, even if they are non-native species*")
- LS2.4_DAMAGE_IF_CROP_no_SHEEP ("*It will damage the beauty of the English countryside if fields of grazing sheep are replaced with fields of crops instead*")

Item-to-total correlations ranged from moderate to excellent for the remaining items (0.446 to 0.841). The full, stabilised list of 22 items is shown in Table 34, below.

Scale Reliability Statistics

	Mean	SD	Cronbach's α	McDonald's ω
scale	6.18	2.26	0.948	0.948

Item Reliability Statistics

		If item dropped	
	Item-rest correlation	Cronbach's α	McDonald's ω
LS1.1_CHANGES_OK_4_CC [a]	0.655	0.946	0.946
LS1.2_NO_RE_IN_RURAL	0.654	0.946	0.946
LS1.3_BETTER_NO_LIVESTOCK [a]	0.648	0.946	0.946
LS1.4_NEW_WETLANDS [a]	0.561	0.947	0.947
LS1.5_RURAL_EXPORT_RE [a]	0.626	0.946	0.946
LS2.1_RURAL_NOEXPORT_RE	0.577	0.947	0.947
LS2.2_UPSET_REWILD	0.544	0.947	0.947
LS2.3_RURAL_SCIENTIST_MGMNT [a]	0.716	0.945	0.945
LS2.5_NOMEAT_REWILD_IS_GOOD [a]	0.743	0.944	0.945
LS2.6_TAXPAY_FARMCHANGE_FOR_CC_GOOD [a]	0.720	0.945	0.945
LS3.1_LESS_MEAT_LANDSC_DAMG	0.687	0.945	0.946
LS3.2_RURAL_FARMER_MGMNT	0.694	0.945	0.945
LS3.3_ENG_ID_IN_RURAL	0.547	0.947	0.947
LS3.4_TRAD_MGMT_BEATS_CC	0.754	0.944	0.944
LS3.5_DIET_CHNG_LS_OK [a]	0.841	0.943	0.943
LS3.6_LANSDC_IS_NAT.ID	0.717	0.945	0.945
LS4.1_LANDSC_BEAUTY_PAST_PPL	0.601	0.946	0.947
LS4.2_NEW_FORESTS_GOOD [a]	0.489	0.948	0.948
LS4.3_NO_RE_ON_FOOD_LAND	0.681	0.945	0.946
LS4.5_DO_CC_POLICY_IN_TOWN	0.708	0.945	0.945
LS4.6_PREFER_LANDSC_NOW	0.756	0.944	0.945
LS4.7_RE_MIX_FOOD_OK [a]	0.446	0.948	0.949

[a] reverse scaled item

Table 34:(previous page): Stabilised Reliability Analysis and Item-to-Total Correlations for 22-item scale (split-sample, n=345).

Bartlett's Test of Sphericity was significant (χ^2: 4687, df: 231, p<0.001), and KMO values for all 22 remaining items were between 0.931 and 0.973, indicating that the

item set is 'marvellous' (as per Kaiser's original naming scheme) and likely to have a good level of shared variance between items, and thus suitable for Factor Analysis.

I summarise the rounds of EFA testing below.

6.5.3 EFA: Round 1 (unrotated)

I first generated an unrotated solution using Maximum Likelihood estimation and Parallel Analysis to guide the number of factors to extract. (Table 35)

The unrotated solution shows all 22 items loading on a single primary factor, explaining between 21% and 77% of the variance in each item, derived from the squared loadings (ignoring sign (Blaikie, 2003)). There are two additional factors, with four and two items respectively, though in each case the item cross-loads more heavily on the primary factor than on its second factor.

The model fit indices are broadly acceptable: RMSEA = 0.052 (CI 0.044 to 0.061), TLI = 0.950. While the model χ^2 is significant, the χ^2/df ratio is low, at ~2, suggesting any misfit is trivial.

The unrotated result with a single primary factor onto which all items load convincingly suggests that the entire scale may represent a generalised construct of resistance to change from climate-related rural policies. In this unrotated form however, the solution has limited additional interpretability.

Factor Loadings

	Factor			
	1	**2**	**3**	**Uniqueness**
LS3.5_DIET_CHNG_LS_OK	-0.875			*0.214*
LS2.5_NOMEAT_REWILD_IS_GOOD	-0.788	0.384		*0.213*
LS3.4_TRAD_MGMT_BEATS_CC	0.780			*0.357*
LS4.6_PREFER_LANDSC_NOW	0.772			*0.340*
LS2.6_TAXPAY_FARMCHANGE_FOR_CC_GOOD	-0.747			*0.377*
LS3.6_LANSDC_IS_NAT.ID	0.735			*0.405*
LS2.3_RURAL_SCIENTIST_MGMNT	-0.730			*0.457*
LS4.5_DO_CC_POLICY_IN_TOWN	0.726			*0.376*
LS3.1_LESS_MEAT_LANDSC_DAMG	0.717			*0.423*

Factor Loadings

	Factor			
	1	**2**	**3**	**Uniqueness**
LS3.2_RURAL_FARMER_MGMNT	0.704			*0.472*
LS4.3_NO_RE_ON_FOOD_LAND	0.691			*0.494*
LS1.2_NO_RE_IN_RURAL	0.681	0.451		*0.322*
LS1.3_BETTER_NO_LIVESTOCK	-0.677			*0.476*
LS1.1_CHANGES_OK_4_CC	-0.675			*0.527*
LS1.5_RURAL_EXPORT_RE	-0.640	-0.301		*0.421*
LS4.1_LANDSC_BEAUTY_PAST_PPL	0.615		0.324	*0.517*
LS2.1_RURAL_NOEXPORT_RE	0.602	0.499		*0.368*
LS1.4_NEW_WETLANDS	-0.574			*0.577*
LS3.3_ENG_ID_IN_RURAL	0.561		0.371	*0.530*
LS2.2_UPSET_REWILD	0.554			*0.645*
LS4.2_NEW_FORESTS_GOOD	-0.509	0.408		*0.569*
LS4.7_RE_MIX_FOOD_OK	-0.462			*0.641*

Table 35: EFA round 1 (unrotated solution)

Useful insight can be gained from the negatively loaded items (which are interpreted as correlating negatively with the underlying causal factor). This suggests that the overall scale does indeed measure *resistance* to rural climate initiatives, since the negatively loaded items are the ten items for which higher agreement means *openness* to change in the landscape, and *accepting* a move away from traditional management approaches, as detailed in Table 36, below:

LS1.1	It doesn't matter to me what the English countryside looks like, as long as I know that changes we make are directly tackling climate change
LS1.3	The English countryside would be changed for the better if there were far fewer sheep and cows in the fields
LS1.4	Farmers should be supported to turn some of their drained fields back into natural wetlands
LS1.5	Rural areas in England should produce as much renewable energy as they can and export spare to urban areas
LS2.3	If we are to successfully tackle climate change, England's countryside management strategy must be led by scientists, not farmers
LS2.5	Reducing the amount of meat in our diets would be a good thing for this country, because it would allow us to re-wild and re-forest large areas of England's countryside

LS2.6	I don't mind taxpayers' money being used to help farmers do all they can to tackle climate change, even if it means the English landscape will look very different
LS3.5	I am excited by the idea that, as our diets change to tackle climate change, so will the English landscape
LS4.2	The English countryside would be improved by large areas of new forestry and woodlands
LS4.7	I see no reason why farmers shouldn't generate renewable energy on their land, so long as they can still produce food around it.

Table 36: Items loading negatively in the unrotated solution ('openness to change' valence)

Cumulatively, this three-factor solution explained 55.8% of the variance in the 24 items. Explanatory value loaded heavily on the primary factor (Table 37).

Factor	SS Loadings	% of Variance	Cumulative %
1	10.187	46.30	46.3
2	1.315	5.98	52.3
3	0.779	3.54	55.8

Table 37: Per factor and cumulative variance explained, unrotated solution

I turned next to a rotated solution to see if a more easily interpreted solution with fewer items could be found, with equal or better explanatory value.

6.5.4 EFA: Round 2 (oblique rotation)

An obliquely-rotated solution (Direct Oblimin), again using Maximum Likelihood estimation and Parallel Analysis to guide the number of factors to extract, produced a more interpretable structure. (Table 38).

In this solution, Factor 1 represents a scale that is broadly concerned with acceptance of the change in landscapes and rural places that will come with climate-policy implementation. Note that eight of the ten items that negatively loaded onto the General Factor in the unrotated solution are now located (positively loaded) on this first factor; it represents openness to or acceptance of changed rural management practices.

Factor 2 can be interpreted as broadly concerned with the maintenance of rural traditions, rural landscapes as markers of national identity, and a concomitant resistance to rural change.

Factor 3 is strongly linked to beliefs about the appropriateness of renewable energy in rural places, viz. siting, export relationships with urban areas, and displacement of food production.

Cumulatively, this three-factor solution still explained 55.8% of the variance in the items, but the explanatory value was split more evenly across the three factors. Thus, while the fit measures and proportion of variance explained remained the same as in Round 1, interpretability was greatly improved. (Table 39).

Factor Loadings

	Factor			
	1	**2**	**3**	**Uniqueness**
LS2.5_NOMEAT_REWILD_IS_GOOD	0.872			*0.213*
LS4.2_NEW_FORESTS_GOOD	0.716			*0.569*
LS1.4_NEW_WETLANDS	0.652			*0.577*
LS3.5_DIET_CHNG_LS_OK	0.606			*0.214*
LS3.1_LESS_MEAT_LANDSC_DAMG	-0.601			*0.423*
LS1.3_BETTER_NO_LIVESTOCK	0.594			*0.476*
LS2.6_TAXPAY_FARMCHANGE_FOR_CC_GOOD	0.503		0.462	*0.377*
LS2.3_RURAL_SCIENTIST_MGMNT	0.469			*0.457*
LS2.2_UPSET_REWILD	-0.436			*0.645*
LS1.1_CHANGES_OK_4_CC	0.362		0.352	*0.527*
LS3.3_ENG_ID_IN_RURAL		0.746		*0.530*
LS4.1_LANDSC_BEAUTY_PAST_PPL		0.668		*0.517*
LS4.6_PREFER_LANDSC_NOW		0.639		*0.340*
LS4.5_DO_CC_POLICY_IN_TOWN		0.612		*0.376*
LS3.6_LANSDC_IS_NAT.ID		0.598		*0.405*
LS3.4_TRAD_MGMT_BEATS_CC		0.545		*0.357*
LS3.2_RURAL_FARMER_MGMNT	-0.336	0.457		*0.472*
LS2.1_RURAL_NOEXPORT_RE			-0.754	*0.368*
LS1.2_NO_RE_IN_RURAL			-0.703	*0.322*
LS1.5_RURAL_EXPORT_RE			0.699	*0.421*
LS4.7_RE_MIX_FOOD_OK			0.608	*0.641*
LS4.3_NO_RE_ON_FOOD_LAND		0.311	-0.361	*0.494*

Table 38: EFA Round 2. Initial 3-factor solution

Summary

Factor	SS Loadings	% of Variance	Cumulative %
1	4.84	22.0	22.0
2	4.13	18.8	40.8
3	3.31	15.0	55.8

Table 39: Per factor and cumulative variance explained, initial rotated solution

6.5.5 EFA: Rounds 3-6

Despite the improved interpretability of the solution after Round 2, problematic cross-loading remained. The items in Table 40 cross-loaded at above 70% (meaning the weakest loading represents more than 70% of the value of the strongest loading for this item, making it hard to distinguish which factor it is truly part of):

LS1.1	It doesn't matter to me what the English countryside looks like, as long as I know that changes we make are directly tackling climate change
LS2.6	I don't mind taxpayers' money being used to help farmers do all they can to tackle climate change, even if it means the English landscape will look very different
LS3.2	The farmers and landowners who manage England's countryside now are best-placed to decide how we use rural areas to tackle climate change
LS4.3	Renewable energy should never be built on farmland where food could be grown instead

Table 40: Highly cross-loaded items from initial 3-factor solution

I therefore removed these items stepwise, starting with the item with the highest cross-loading that had the lowest total loading across all factors.

ROUND 3: Item LS4.3 ('*Renewable energy should never be built on farmland where food could be grown instead'*) loaded weakly at <0.4 on both Factors 2 and 3 in Round 2. The cross loading was 86%, and its absolute total loading was the lowest of all items. This item was therefore removed in Round 3. Fit measures overall improved slightly, but cross-loading of other items remained (and worsened in some cases).

ROUND 4: After the change in Round 3, item LS1.1 ('*It doesn't matter to me what the English countryside looks like, as long as I know that changes we make are directly tackling climate change'*) loaded weakly at <0.4 on both Factors 2 and 3. The item's cross loading was now 90%, and its absolute total loading was the lowest of all remaining cross-loaded items. This item was therefore removed in Round 4. Fit measures again improved slightly, but cross-loading of other items remained.

ROUND 5: After the change in Round 4, item LS3.2 ('*The farmers and landowners who manage England's countryside now are best-placed to decide how we use rural areas to tackle climate change'*) loaded at <0.4 on Factor 1 and was still cross-loaded at 75%. This was removed in Round 5. Fit measures again improved marginally, but item LS2.6 (though higher loading overall than LS3.2 at the start of this round) remained cross-loaded at 85% even after the removal of LS3.2.

ROUND 6: Item LS2.6 ('*I don't mind taxpayers' money being used to help farmers do all they can to tackle climate change, even if it means the English landscape will look very different'*) was removed in this round.

The solution at this point stabilised into broadly the same three factors that began to emerge in Round 2. All cross-loading had been eliminated, most items loaded well above 0.4 (with the exception of LS2.3 and LS2.2, though even those loadings were still acceptable), leaving a clean three-factor structure.

Fit Measures were also slightly improved: RMSEA = 0.046 (CI 0.035 to 0.058), TLI = 0.967. The Model χ^2 remained significant (suggesting that the 3-factor solution from Parallel Analysis was close, but not an *extremely* close fit to the data), but the χ^2/df ratio reduced to 1.74, which is good (Carmines and McIver, 1983). Noting that model χ^2 very rarely reaches non significance in EFA, (since it is an exploratory rather than confirmatory method), I considered this to be the optimum structure to take into CFA for further assessment.

The three correlated (obliquely rotated) factors at this point cumulatively explained 56.3% of the variance in the item set. (Table 41), an increase on the initial unrotated solution, achieved with a more parsimonious set of 18 rather than 24 items.

Factor	SS Loadings	% of Variance	% Cumulative variance
1	4.06	22.6	22.6
2	3.51	19.5	42.1
3	2.56	14.2	56.3

Table 41: Per factor and cumulative variance explained, stable solution after 6 rounds of EFA

Factor Loadings

	Factor			
	1	**2**	**3**	**Uniqueness**
LS2.5_NOMEAT_REWILD_IS_GOOD	0.926			*0.181*
LS4.2_NEW_FORESTS_GOOD	0.700			*0.582*
LS1.4_NEW_WETLANDS	0.641			*0.598*
LS3.1_LESS_MEAT_LANDSC_DAMG	-0.635			*0.410*
LS3.5_DIET_CHNG_LS_OK	0.611			*0.215*
LS1.3_BETTER_NO_LIVESTOCK	0.590			*0.482*
LS2.3_RURAL_SCIENTIST_MGMNT	0.479			*0.473*
LS2.2_UPSET_REWILD	-0.445			*0.647*
LS3.3_ENG_ID_IN_RURAL		0.748		*0.539*
LS4.1_LANDSC_BEAUTY_PAST_PPL		0.694		*0.520*
LS4.6_PREFER_LANDSC_NOW		0.677		*0.335*
LS3.6_LANSDC_IS_NAT.ID		0.607		*0.397*
LS4.5_DO_CC_POLICY_IN_TOWN		0.604		*0.377*
LS3.4_TRAD_MGMT_BEATS_CC		0.586		*0.349*
LS2.1_RURAL_NOEXPORT_RE			0.813	*0.320*
LS1.2_NO_RE_IN_RURAL			0.715	*0.322*
LS1.5_RURAL_EXPORT_RE			-0.662	*0.459*
LS4.7_RE_MIX_FOOD_OK			-0.606	*0.652*

Note. 'Maximum likelihood' extraction method was used in combination with 'oblimin' rotation and Parallel Analysis

Table 42: Item loadings on 3-factor solution after 6 rounds of EFA

6.5.6 Sample size adequacy check

To ensure the replicability and stability of the solution, I evaluated the result against the empirically derived recommendations from Mundfrom et al, (2005), whose simulation study provides minimum sample size guidelines based on certain data and factor structure characteristics.

The final EFA solution comprised 3 factors with 8, 6, and 4 items respectively, giving an average 6:1 item to factor ratio. The communalities (which are one minus the Uniqueness values for each item shown in Table 42, above) range from 0.348 to

0.819, which aligns with Mundfrom *et al's* 'wide' communality class. For 'wide' communalities and a 3-Factor structure with an item:factor ratio of 6:1, Mundfrom *et al* report that a sample size of 75 is sufficient for 'good' agreement and 180 is sufficient for 'excellent' agreement between the sample factor solution and that which would exist in the population. With a sample size of 345 for the EFA, I therefore conclude that the solution is likely to be robust.

6.5.7 Naming the factors

The three factors that emerged from the EFA cluster around three constructs:

Resisting Land Use Change (RLUC), 8 items: These items broadly represent resistance to changing the way that land is managed, including reducing livestock numbers and a general move towards rewilding and reforestation.

- LS2.5RV: Reducing the amount of meat in our diets would be a good thing for this country, because it would allow us to re-wild and re-forest large areas of England's countryside
- LS1.4RV: Farmers should be supported to turn some of their drained fields back into natural wetlands
- LS3.1 It will negatively affect the English landscape if people reduce the amount of beef and dairy that they eat.
- LS1.3RV: The English countryside would be changed for the better if there were far fewer sheep and cows in the fields
- LS2.2: I would find it upsetting if large areas of English farmland were returned to a wild and un-managed state
- LS3.5RV: I am happy with the fact that, as our diets change to tackle climate change, so will the English landscape
- LS2.3RV: If we are to successfully tackle climate change, England's countryside management strategy must be led by scientists, not farmers
- LS4.2RV: The English countryside would be improved by large areas of new forestry and woodland

Valuing Landscape, Tradition and Identity (VLTI), 6 items: These items represent an attachment to land and landscapes because of its link to traditional management, the practical and cultural role of past fellow-citizens in shaping the land, and the sense that land and landscapes are inherently part of national identity.

- LS3.3: The real heart of English identity is found in our rural landscapes and places, not in our cities and towns
- LS4.6: I would rather that English rural landscapes are preserved as they are now
- LS4.1: The English countryside is beautiful to me largely because it has been shaped by many generations of my countrypeople
- LS3.6: If the English landscape were radically different, it would change who we are as a nation
- LS4.5: We should focus our efforts to tackle climate change in English towns and cities, and leave the countryside alone
- LS3.4: Preserving traditional rural English ways of life is vital, even if it means doing less than we otherwise could to tackle climate change

Resisting Rural Renewables (RRR), 4 items: These items broadly represent resistance to the idea of renewable energy generation in rural areas, and the idea that rural areas should supply urban areas with energy. Though the use of land for generating energy represents a form of 'land use change', these items have consistently factored separately from those items that make up the RLUC factor.

- LS2.1: It is not the role of England's rural areas to provide renewable energy for towns and cities
- LS1.2: The English countryside is no place for industrial scale renewable energy installations like wind turbines or solar farms.
- LS1.5RV: Rural areas in England should produce as much renewable energy as they can and export spare to urban areas
- LS4.7RV: I see no reason why farmers shouldn't generate renewable energy on their land, so long as they can still produce food around it.

6.6 Confirmatory Factor Analysis

The 18 remaining items were then used in a CFA (with the other half of the split sample, n=378) to further interrogate the 3-factor structure and investigate the possibility that a General Factor of 'Resistance to Rural Climate Interventions' (as suggested by the unrotated solution) exists as part of a more complex hierarchical scale structure.

The final 3-factor solution from the EFA contained both positively and negatively loaded items (due to the mix of wording valence across the items). I therefore reverse-scored the items in Table 43, below, at this stage to aid interpretation of the scales during the CFA, and in order that all final scales (whether simple 3-factor or a more complex hierarchical structure) could be intuitively used as an indicator of *resistance* to rural climate initiatives. Reverse scored items are distinguished via the suffix 'RV' after their item number in the subsequent CFA analysis rounds.

LS1.3	The English countryside would be changed for the better if there were far fewer sheep and cows in the fields
LS1.4	Farmers should be supported to turn some of their drained fields back into natural wetlands
LS1.5	Rural areas in England should produce as much renewable energy as they can and export spare to urban areas
LS2.3	If we are to successfully tackle climate change, England's countryside management strategy must be led by scientists, not farmers
LS2.5	Reducing the amount of meat in our diets would be a good thing for this country, because it would allow us to re-wild and re-forest large areas of England's countryside
LS3.5	I am happy with the idea that, as our diets change to tackle climate change, so will the English landscape
LS4.2	The English countryside would be improved by large areas of new forestry and woodlands
LS4.7	I see no reason why farmers shouldn't generate renewable energy on their land, so long as they can still produce food around it.

Table 43: Items that are reverse scored in the CFA

6.6.1 Descriptive Statistics – CFA cases

Appendix 6.3 shows the descriptive statistics for the 18 items, based on the 378 cases used in the CFA.

Item means ranged from 4.08 to 8.82 (with the reverse scoring accounted for, or 3.18 to 7.92 without), with a standard deviation of 2.89 to 3.64 on the 11-point Likert scales. Every item had responses across the full 11 points available, suggesting good item discrimination which effectively distinguishes between respondents with different attitudes.

Before reverse scoring, item skewness ranged from -0.85 to +1.20. After reverse scoring eight items to ensure consistent interpretation, the skewness range became -1.20 to +0.85. This simple reversal is a result of the two most highly skewed items both being part of the reverse scored group; reverse scoring effectively flips the sign of skewness while preserving its magnitude, maintaining the same overall distributional characteristics.

Kurtosis, which is unaffected by the reverse scoring, ranged from -1.28 to 0.28. Most items had negative kurtosis, suggesting flatter peaks than a standard normal distribution.

6.6.2 Reliability Analysis

Given MANOVA analysis had already shown that the EFA and CFA split-samples were not significantly different across any item, I expected the reliability of this split-half sample to be similar but carried out the tests again for surety. This returned Cronbach's alpha of 0.937 and McDonald's Omega of 0.938. Neither score could be improved by removal of further items. The CFA was conducted in Jamovi, using the Structural Equation Modelling plugin (SEMlj) rather than the basic confirmatory factor analysis tools in the standard software package. This provides a wider range of fit measures and Modification Indices tables that are only provided in the full SEM module.

6.6.3 Choice of estimator and scaling

It is common practice to treat ordinal scales with more than 5 or 7 items as essentially continuous data. In addition, both the skewness and kurtosis are within the bounds of what many consider acceptable for Maximum Likelihood Estimation.

However, using the wrong estimator can lead to biased results and incorrect conclusions about model fit, potentially rejecting a good model or accepting a poor one. Li, (2016), building on the work of Muthen & Kaplan (1992) and Beauducel & Herzberg, 2006), maintains that "*In general, it is not advisable to use normal theory-based ML in an SEM model with ordinal observed variables.*", and also demonstrates that ML estimation in a SEM environment with ordinal data is more likely to lead to incorrect rejection of an acceptable model. Fitriyati and Wijaya, (2022) also recommend the use of DWLS over ML in CFA, even where Likert scales with higher numbers of scale points are used because although the parameter bias in scales with >5 points is trivial when using ML, "*the drawback is that it is very unlikely to achieve a satisfactory fit based on the Chi-square test*", which creates issues when drawing inferences in empirical work since "*the estimated parameters can only be interpreted and be trusted once the model shows no lack of fit*".

Since the wider aim is to use extracted Factor Scores from this scale for further analysis, I therefore used DWLS estimation with robust mean and variance adjustments applied (WLSMV) for the CFA work outlined below. Using this approach, fit measures are scaled and adjusted to suit the ordinal and non-normally-distributed characteristics of the data.

Residual variances of latent variables are fixed to 1, rather than fixing the scale of the latent variables to the scale of the first indicator. This allows covariances between factors to be interpreted as correlations (Curran and Bauer, 2023).

6.7 Confirmatory Factor Analysis – iterative refinement

The CFA was completed over 10 rounds of model specification, modification, and re-specification. Appendix 6.4 gives details of the range of Measures of Fit used to assess the models. Appendix 6.5 details the model structure and the results for the Measures of Fit assessment for each round of model testing.

Sections 6.7.1 to 6.7.10, below provide narrative detail and justification for the re-specifications. The final model comparison tests that resulted in adoption of Model 10 as the final scale are detailed in section 6.7.11 and 6.7.12.

6.7.1 CFA Round 1

The CFA process began with a single-factor solution, to test the fit of the full list of 18 items with no sub-factors. Although the EFA suggested a three-factor solution (with correlations, since the best fitting model used an oblique rotation), I used this single-factor approach to create a baseline set of fit indices for comparison with future rounds.

The Measurement Model showed moderate to strong loadings for each item onto the factor (ranging from 0.497 to 0.873), with narrow confidence intervals, very high z-scores and p-values that demonstrated a strongly significant relationship between the items and the factor. (See Appendix 6.5, Table title 'CFA Round 1, Single Factor Solution').

However, overall, the model fit indices for this Single Factor structure were poor, with the exception of SRMR, which was just acceptable. Large Modification Indices suggested items would need to correlate more closely with other items than this single factor structure allowed, for the model to closely match the data structure.

6.7.2 CFA Round 2

In Round 2, I moved away from the single-factor structure to three separate factors. Unlike the EFA, which used an oblique rotation and therefore allowed the factors to correlate, here the factors were prevented from correlating, which allowed for an assessment of model fit with forced orthogonality.

Factor residual variances were set to 1 (rather than taking the scale of an item within them). In future rounds, this allowed for any covariances between the Factors to be interpreted as correlations.

Round 2 again showed statistically significant loadings of moderate to high strength, slightly better than the previous round (0.574 to 0.897). Overall though, the fit indices of this model were much worse than the single-factor model, and there were almost 150 suggested Modification Indices >10, many with very large values, suggesting that the correlations between the three factors are substantial

contributors to the global fit of the model, possibly more so than the distribution of items between each factor. (See Appendix 6.5, Table title 'CFA Round 2, Three Uncorrelated Factors').

6.7.3 CFA Round 3

In this round, I allowed the three factors to correlate, aligning with the structure that emerged from the EFA.

Round 3 again showed statistically significant loadings of moderate to high strength for all items (0.524 to 0.908). The measures of fit overall were also greatly improved. SRMR was 'good', and RMSEA would meet the 'acceptable' level of many published studies. The χ^2/df ratio was <3, which would be considered acceptable by some, and both TLI and CFI were good. However, the overall Model χ^2 test remained significant, along with the RMSEA pClose[34]. In addition, there were still nine substantial modification indices. Taken together, these suggested that relationships in the data were still not adequately represented by the model. (See Appendix 6.5, Table title 'CFA Round 3, Three Correlated Factors').

While most Modification Indices made little theoretical sense, three suggested that items within the first factor (Resisting Land Use Change) should be allowed to correlate with each other. These were theoretically plausible modifications and I therefore applied them one at a time in rounds 4, 5, and 6, below, based on the largest MI. The items in question are:

- LS4.2RV_NEW_FORESTS_GOOD – "*The English countryside would be improved by large areas of new forestry and woodlands*"

[34] In CFA, as in other forms of Structural Equation Modelling, the use of p-values is counter-intuitive. Unlike standard hypothesis testing, here we look for a 'notable null hypothesis'. We hope that our goodness-of-fit tests are *non-significant*. This indicates that there is *no* significant difference between the model-implied data structure and the structure of the data in our sample. The closer the sample data is to true random sampling and the larger the sample, the more we can make at least tentative inferences that the model structure we have proposed would also generalise to the population. (Peugh and Feldon, 2020; Curran and Bauer, 2023).

- LS2.2_UPSET_REWILD – "*I would find it upsetting if large areas of English farmland were returned to a wild and un-managed state*"
- LS1.4RV_NEW_WETLANDS – "*Farmers should be supported to turn some of their drained fields back into natural wetlands*".

6.7.4 CFA Round 4

The item pair LS4.2RV_NEW_FORESTS_GOOD and LS2.2_UPSET_REWILD were allowed to correlate in this round (See Appendix 6.5, Table title 'CFA Round 4, Three correlated factors, one within-factor covariance on RLUC').

Loadings remained statistically significant and in the moderate to strong range (0.502 to 0.908). All measures of fit were marginally improved, but theoretically plausible Modification Indices remained for the items:

LS4.2RV_NEW_FORESTS_GOOD with LS1.4RV_NEW_WETLANDS, and
LS1.4RV_NEW_WETLANDS with LS2.2_UPSET_REWILD.

6.7.5 CFA Round 5

Here the next highest MI for a theoretically plausible modification was to allow LS4.2RV_NEW_FORESTS_GOOD to correlate with LS1.4RV_NEW_WETLANDS.

All loadings remained statistically significant, ranging from 0.478 to 0.909. Once again, fit measures improved marginally. RMSEA pClose reached non-significance (for alpha = 0.05). However, the Model χ^2 test remained significant, the χ^2 /df ratio remained above 2, and the final MI (to allow the last of the three pairs of land-use items to correlate) remained above 10. (See Appendix 6.5, Table title 'CFA Round 5, Three correlated factors, two within-factor covariances on RLUC').

6.7.6 CFA Round 6

Here, the final pair of land use items flagged by the MI table was also allowed to correlate. (See Appendix 6.5, Table title 'CFA Round 6, Three correlated factors, three within-factor covariances on RLUC').

Loadings remained statistically significant for all items, in the same range as the previous round. Most fit indices looked very good at this point, with the exception of the Model χ^2 test, which was still significant. According to many standard guidelines (and a great many published papers), using standard rules-of-thumb for fit measures, this would be acceptable model. However, Modification Indices of some magnitude remained (range 13.44 to 17.72), all of which indicated cross-loadings between factors that were theoretically indefensible, meaning no further legitimate modification within the correlated-factors structure was appropriate.

Given that no further theoretically justifiable modifications to the three-factor correlated structure could be made, and following the guidance of several authors (Barrett, 2007; Xia and Yang, 2019; Lai, 2020; and McNeish and Wolf, 2022, 2023), who between them urge a more nuanced approach than merely relying on standardised 'rule-of-thumb' cutoffs for measures of fit, I therefore moved beyond a straightforward correlated-factors structure, to a more hierarchical structure, introducing a Bifactor Model structure in Round 7. This theoretically-informed decision built on the knowledge that the single-factor model tested in Round 1 of the CFA was shown to have moderate to strong correlations between *all* the items. Despite this, measures of fit demonstrated that this single factor structure was a wholly inadequate fit for the data. The aim of testing a bifactor structure was therefore to test whether partitioning the *specific* variance of the three factors from the *shared* variance of all items, could better capture that broad structure of correlated resistance.

6.7.7 CFA Round 7

A bifactor structure can be understood as "*modelling the general commonality between all items on the test/survey and the residual variance for each [topic] area beyond that [of the General Factor] with equal weight*." (Dunn and McCray, 2020). If no meaningful General Factor exists, the primary loadings will be weak.

For Round 7, I retained the same item distribution among three Specific Factors that were present in previous rounds, along with the item covariances between the three

items on Wetlands, Forests, and Rewilding (LS1.4, LS4.2 and LS2.2), and the covariances between the Specific Factors. (See Appendix 6.5, Table title 'CFA Round 7 – Bifactor Model, Specific factor covariances and item covariances retained).

The substantive structural change in this round was therefore the introduction of the General Factor, onto which all items primarily load.

The structure produced a highly non-significant RMSEA pClose and very low chi square to df ratio, with no modification indices above 10 remaining. CFI, TLI and RMSEA were all good and Round 7 therefore represented a better fitting model than the correlated factors approach.

However, the Model χ^2 result remained significant, and the Measurement Model tables showed that the covariances between the Specific Factors had become non-significant for RLUC~~VLTI (p=0.254) and for RRR~~VLTI (p=0.143) once the General Factor had been introduced. I therefore removed those correlations sequentially in rounds 8 and 9, below.

6.7.8 CFA Round 8

In this round, I removed the weakest of the two factor covariances (RLUC~~VLTI). Once again, although the fit measures all looked exceptionally good, and even the overall Model χ^2 result became highly non-significant, Measurement Model still showed a non-significant covariance between RRR~~VLTI. (See Appendix 6.5, Table title 'CFA Round 8 – Bifactor Model, Covariance RLUC~~VLTI removed).

6.7.9 CFA Round 9

In this round I removed the remaining non-significant factor covariance (RRR~~VLTI). SRMR and RMSEA marginally improved, and the overall Model χ^2 result remained highly non-significant. (See Appendix 6.5, Table title 'CFA Round 9 – Bifactor Model, Covariance RRR~~VLTI also removed).

Examination of the Measurement Model loadings showed that the items on the VLTI Specific Factor now had very low loadings (with the exception of LS3.3). The vast

majority of the variance in the items in this Specific Factor were now accounted for by the General Factor itself.

ITEM	Loading on VLTI SF	z	p
LS3.3_ENG_ID_IN_RURAL	0.606	4.115	<0.001
LS4.6_PREFER_LANDSC_NOW	0.141	2.503	0.012
LS4.1_LAND_BEAUT_PAST_PPL	0.171	2.459	0.014
LS3.6_LAND_IS_NAT_ID	0.123	2.340	0.019
LS4.5_DO_CC_POLICY_IN_TOWNS	0.184	2.741	0.006
LS3.4_TRAD_MGMNT_BEATS_CC	0.009	0.106	0.859

Table 44: VLTI specific factor item loadings at end of Round 9

I considered that the variance of the items on this scale may be so heavily accounted for by the General Factor that there may be utility in constraining the VLTI Specific Factor paths to zero, in order to increase the parsimony of the model further, without creating a detrimental reduction in fit.

6.7.10 CFA Round 10

In Round 10, I removed the VLTI Specific Factor altogether, allowing the items detailed in Table 44, above, to load only onto the General Factor. (See Appendix 6.5, Table title 'CFA Round 10 – Bifactor Model, VLTI Specific Factor removed altogether).

Fit measures worsened slightly compared to Model R9, although overall, they remain excellent. The slight worsening of fit created a conundrum; Model R10 represented a theoretically neater structure with more practical interpretability than Model R9, but on fit measures alone, Model R9 was the superior model.

6.7.11 Model Comparison Tests – Model 9 and Model 10

I carried out model comparison tests using the LRT, AIC and BIC, to explore whether the increase in parsimony and interpretability gained by losing the VLTI Specific Factor in Model 10 had created a meaningfully worse model by comparison to Model 9.

6.7.11.1 LRT test

The Comparative Likelihood Ratio Test (LRT) is a hypothesis test for which the null hypothesis is that both models fit the data equally well. Thus, if the LRT result is non-significant, then the additional parameters in Model 9 (the loadings on the Specific Factor VLTI) are not needed, and the simpler Model 10 can be accepted.

$$LRT = \chi^2_{Model\ 10} - \chi^2_{Model\ 9}, \text{ with } df = df_{Model\ 10} - df_{Model\ 9}$$

Thus: LRT = 233 - 207.3 = 25.7 df = 119 - 113 = 6. For a test statistic value of 25.7 within a χ^2 distribution with df=6, the p-value =0.0003.

This significant result suggested that, despite being less parsimonious, Model R9 *was* statistically significantly better than the reduced form (R10) model.

6.7.11.2 AIC test

The Akaike Information Criterion (AIC) is a model selection test that balances model fit against model complexity. AIC does not involve hypothesis testing but rather provides a relative measure of model quality. Lower AIC values indicate better models, with the AIC difference used to compare models. A difference of 0-2 suggests substantial support for both models, 4-7 indicates considerably less support for the model with higher AIC (but not rejecting the 'worse' model is still a methodologically defensible choice (Burnham and Anderson, 2002), and >10 indicates that the model with the higher score is, statistically speaking, objectively the worse model.

$$AIC = \chi^2 + 2k, \text{ where } k = \text{number of free parameters}$$

Thus:

AIC Model 9 = 207.3 + 2(220) = **647.3**
AIC Model 10 = 233 + 2(214) = **661.0**
AIC difference = 529.0 - 525.3 = 1**3.7**

This result suggested that Model 9 is also better than Model 10.

6.7.11.3 BIC test

Like the AIC, the Bayesian Information Criterion (BIC) also balances model fit against model complexity, and does not include hypothesis testing. BIC penalises complexity more heavily than AIC, especially with larger sample sizes. Lower BIC values indicate better models, and again a series of bands is used to interpret the result. A difference of 0-2 is not meaningful. A value 2-6 lower provides slight evidence of a better model, 6-10 provides strong evidence of a better model, and a difference >10 indicates that a model with the lower score is, in a statistical sense, objectively better than the other. (Symonds and Moussalli, 2011).

***BIC* = χ^2 + *k* × *ln(N)*, where *k* = number of free parameters and *N* = sample size**

Thus:

BIC Model 9 = 207.3 + 220 × ln(378) = 207.3 + 220 × 5.935 = **1513.0**
BIC Model 10 = 233 + 214 × ln(378) = 233 + 214 × 5.935 = **1503.1**
BIC difference = 1513.0 - 1503.1 = **9.9**

Unlike the LRT and AIC, which favoured Model 9, the BIC result (which penalises model complexity) favours Model 10. This leaves an interpretation conundrum, since fit measures for both models are excellent, and the comparison tests are not in agreement.

6.7.12 Justification for accepting Model 10 as the final model

I re-considered the items that load onto the VLTI Specific Factor in Model 9. Only item LS3.3 has a substantial loading; the VLTI Specific Factor explains 37% of its variance, which is substantial. Once common variance due to the General Factor is taken into account, the other items load onto the VLTI Specific Factor at levels between 0.000081% (essentially zero) to 0.033% (negligible in any practical sense).

I concluded that the statistical significance of the LRT model comparison test is almost certainly driven entirely by item LS3.3. Removing the VLTI Specific Factor in Model 10 forces this item to load only on the General Factor, which creates a significant misspecification for that single item.

Item LS3.3's loading on the General Factor in both Model 9 and Model 10 is 0.52038 (27% of variance explained). In Model 9 it also loads on the VLTI Specific Factor at 0.60626 (37% of variance explained, *orthogonal to the variance explained by the General Factor*). Thus around 64% of its variance is explained in Model 9 (General + VLTI) down to just 27% in Model 10 (General only). This substantial loss of explained variance for that single item most likely drives the comparison test results.

I next reconsidered the full item wordings for the VLTI items:

- LS3.3 - The real heart of English identity is found in our rural landscapes and places, not in our cities and towns
- LS4.6 - I would rather that English rural landscapes are preserved as they are now
- LS4.1 - The English countryside is beautiful to me largely because it has been shaped by many generations of my country-people
- LS3.6 - If the English landscape were radically different, it would change who we are as a nation
- LS4.5 - We should focus our efforts to tackle climate change in English towns and cities, and leave the countryside alone
- LS3.4 - Preserving traditional rural English ways of life is vital, even if it means doing less than we otherwise could to tackle climate change

If the broad, abstract issues around identity and landscape are now accounted for by the General Factor, I concluded that the weakness of the VLTI Specific Factor, with LS3.3 as its stand-alone anchor item, is driven by the content difference in the items. *LS3.3 is the only item making an absolute, definitional statement about English*

identity itself. The other items are still related to policy preferences or trade-offs, and, though they are at a more abstract level than the concrete agricultural or energy infrastructure items in the other Specific Factors (RLUC and RRR), they still are grounded in policy-preferences in the same way:

- LS4.6: a preference for preservation versus change
- LS4.1: a measure of aesthetic appreciation with identity undertones
- LS3.6: a conditional identity claim (*if* landscape changed, *then* identity would change)
- LS4.5: a protective identity claim - spatial targeting of climate policy
- LS3.4: an explicit policy trade-off (tradition versus climate action)

Since item LS3.3 maintained its position as a core element of the scale through EFA and CFA, I conclude that it may in fact be a strong anchor item for the underlying, identity-based attitudinal dimension from which other resistances flow, since it articulates *a foundational belief that rural landscapes are definitional of English identity itself.*

The parsimony and interpretability gains of Model 10, combined with a reasonably compelling BIC comparison test, and consideration of the core role of item LS3.3 are therefore justification for accepting the simpler structure and dispensing with the VLTI Specific Factor, i.e. allowing the items in this subscale to load only onto the General Factor, thus forming the core of the scale.

The full Measurement Model table for Model 10 is shown in Table 45, below. Item loadings on the General Factor range from 0.419 to 0.850, with an average loading of 0.69. The 'identity/affect' items that previously made up the VLTI subscale have become the core of the General Factor. The strength of the loadings of all other items on the General Factor demonstrate that resistance to specific landscape changes due to climate policy is closely intertwined with these more 'affect-based' items that formerly made up the VLTI Specific Factor.

Taken together, the fit measures and model comparison tests provide empirical evidence that this structure produces an overall correlation matrix that is not significantly different from the original sample correlation matrix.

Latent	Observed	Estimate	SE	95% CI Lower	95% CI Upper	β	β 95% CI Lower	β 95% CI Upper	z	p
Specific Factor (RLUC)	LS2.5RV_NOMEAT_REWILD_IS_GOOD	0.537	0.044	0.451	0.624	0.537	0.451	0.624	12.22	< .001
	LS1.4RV_NEW_WETLANDS	0.373	0.051	0.273	0.472	0.373	0.273	0.472	7.36	< .001
	LS3.1_LESS_MEAT_LANDSC_DAMG	0.334	0.039	0.257	0.411	0.334	0.257	0.411	8.52	< .001
	LS1.3RV_BETTER_NO_LIVESTOCK	0.376	0.043	0.291	0.461	0.376	0.291	0.461	8.67	< .001
	LS2.2_UPSET_REWILD	0.307	0.045	0.219	0.396	0.307	0.219	0.396	6.79	< .001
	LS3.5RV_DIET_CHNG_LS_OK	0.246	0.032	0.183	0.309	0.246	0.183	0.309	7.62	< .001
	LS2.3RV_RURAL_SCIENTIST_MGMNT	0.206	0.048	0.113	0.299	0.206	0.113	0.299	4.33	< .001
	LS4.2RV_NEW_FORESTS_GOOD	0.281	0.059	0.167	0.396	0.281	0.167	0.396	4.81	< .001
Specific Factor (RRR)	LS2.1_RURAL_NOEXPORT_RE	0.544	0.032	0.482	0.606	0.544	0.482	0.606	17.21	< .001
	LS1.2_NO_RE_IN_RURAL	0.552	0.037	0.480	0.624	0.552	0.480	0.624	15.01	< .001
	LS1.5RV_RURAL_EXPORT_RE	0.468	0.039	0.391	0.545	0.468	0.391	0.545	11.94	< .001
	LS4.7RV_RE_MIX_FOOD_OK	0.389	0.044	0.302	0.475	0.389	0.302	0.475	8.81	< .001
General_Factor (RRCI)	LS2.5RV_NOMEAT_REWILD_IS_GOOD	0.755	0.027	0.702	0.807	0.755	0.702	0.807	28.10	< .001
	LS1.4RV_NEW_WETLANDS	0.593	0.036	0.522	0.664	0.593	0.522	0.664	16.43	< .001
	LS3.1_LESS_MEAT_LANDSC_DAMG	0.755	0.026	0.704	0.806	0.755	0.704	0.806	29.07	< .001
	LS1.3RV_BETTER_NO_LIVESTOCK	0.675	0.033	0.611	0.740	0.675	0.611	0.740	20.59	< .001
	LS2.2_UPSET_REWILD	0.624	0.035	0.555	0.693	0.624	0.555	0.693	17.69	< .001
	LS3.5RV_DIET_CHNG_LS_OK	0.850	0.019	0.814	0.887	0.850	0.814	0.887	45.73	< .001
	LS2.3RV_RURAL_SCIENTIST_MGMNT	0.718	0.029	0.661	0.775	0.718	0.661	0.775	24.69	< .001
	LS4.2RV_NEW_FORESTS_GOOD	0.419	0.041	0.339	0.500	0.419	0.339	0.500	10.18	< .001
	LS3.3_ENG_ID_IN_RURAL	0.563	0.035	0.494	0.632	0.563	0.494	0.632	16.03	< .001
	LS4.6_PREFER_LANDSC_NOW	0.826	0.019	0.789	0.862	0.826	0.789	0.862	43.97	< .001
	LS4.1_LANDSC_BEAUTY_PAST_PPL	0.689	0.030	0.631	0.747	0.689	0.631	0.747	23.15	< .001
	LS3.6_LANSDC_IS_NAT.ID	0.808	0.019	0.770	0.846	0.808	0.770	0.846	41.70	< .001
	LS4.5_DO_CC_POLICY_IN_TOWN	0.732	0.026	0.680	0.783	0.732	0.680	0.783	27.88	< .001
	LS3.4_TRAD_MGMT_BEATS_CC	0.850	0.019	0.813	0.887	0.850	0.813	0.887	44.99	< .001
	LS2.1_RURAL_NOEXPORT_RE	0.645	0.030	0.586	0.704	0.645	0.586	0.704	21.38	< .001
	LS1.2_NO_RE_IN_RURAL	0.670	0.030	0.611	0.730	0.670	0.611	0.730	22.19	< .001
	LS1.5RV_RURAL_EXPORT_RE	0.645	0.031	0.585	0.705	0.645	0.585	0.705	20.96	< .001
	LS4.7RV_RE_MIX_FOOD_OK	0.539	0.039	0.463	0.614	0.539	0.463	0.614	13.97	< .001

Table 45: Measurement Model (Model 10), final structure (bifactor model with two specific factors)

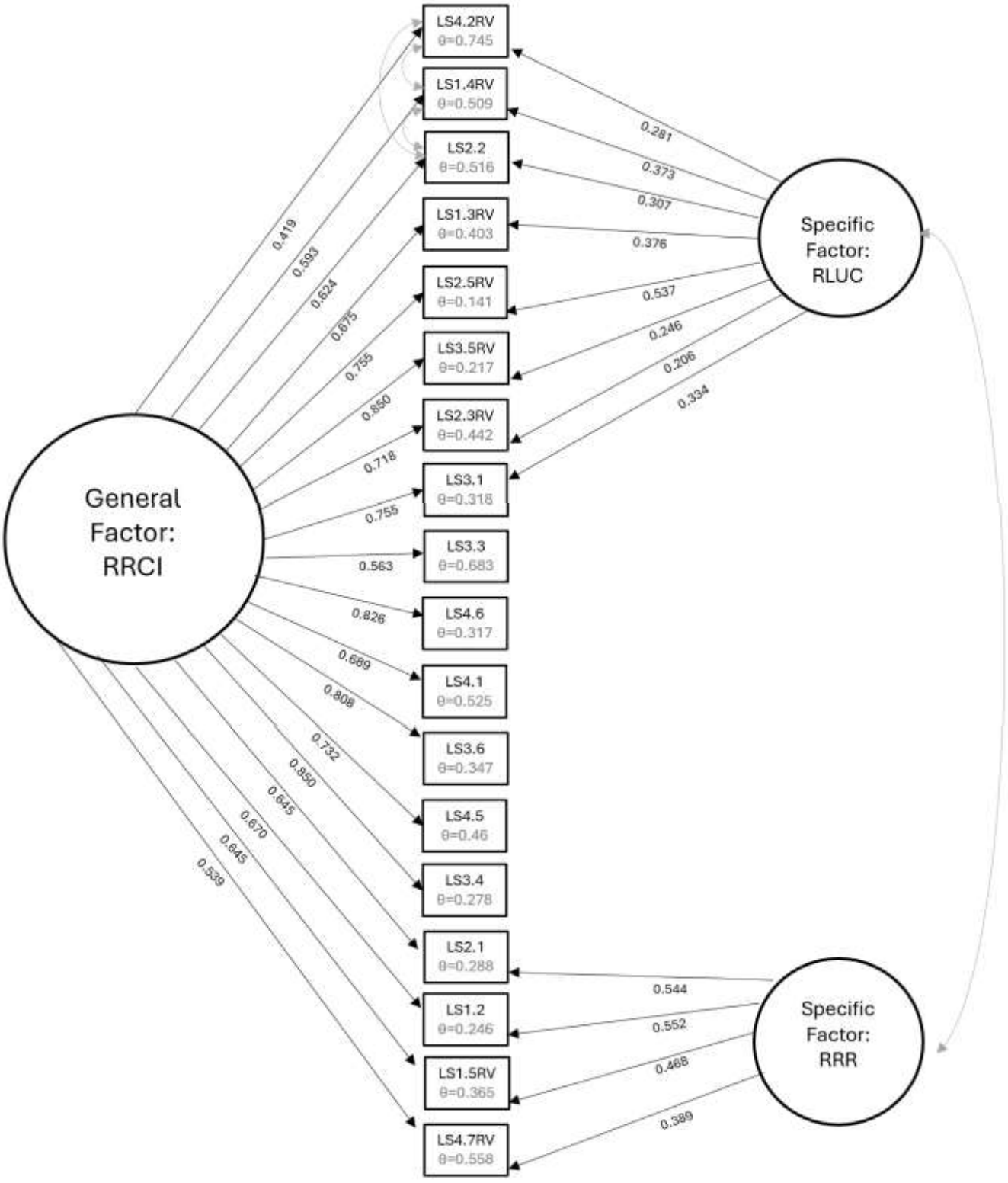


Figure 10: Path Diagram for final measurement model

Figure 10, above shows the path diagram of the final bifactor measurement model with two Specific Factors. Standardised loadings are shown on the regression arrows for each item on both the General and Specific Factors. Each item's unique variance (θ) is shown in grey text. The loadings can be squared to give the variance of each item accounted for by the factors. General, Specific and Unique variances sum to 1 for each item.

6.8 Tests of robustness of the final scale

A long-standing debate in the development of measurement models is to what extent multi-dimensional models could or should be treated as unidimensional for practical purposes (even though the truly unidimensional model may seem to have poorer fit), and what statistical criteria can be used to determine this. (Reise, 2012).

Reise proposed a simple technique for estimating whether a scale is essentially unidimensional, which is to calculate the Explained Common Variance (ECV), which "*can be defined as the ratio of variance explained by the general factor, divided by the variance explained by the general plus the group factors*". Data that is completely unidimensional (i.e. from a set of measurement items that measure one and only one latent trait), would have an ECV score of 1.0, (though in practice such a score would never be achieved).

The crucial question, therefore, is how high should an ECV score be for a researcher to be confident that they can treat data gathered from responses to a set of items as essentially unidimensional? And by contrast, how low should an ECV score be for a researcher to be confident that they should definitely treat data gathered from responses to a set of items as essentially a set of multidimensional (though possibly correlated) sub-factors? If a scale is essentially unidimensional, researchers can use a single total score to represent the overall position (in this case, resistance to rural change) of respondents. If the scale is truly multidimensional, researchers must generate and analyse separate subscale scores to capture meaningful differences in how people respond to different types of interventions.

Quinn (2014) was among the first to consider whether a benchmark or cutoff could be derived to answer these questions, and though she concludes that a single cutoff point remains elusive, her work does provide a useful lower and upper bound. ECVs greater than 0.9 indicate essentially unidimensional models, and ECVs lower than 0.7 indicate essentially multidimensional models. The area between those scores remains a grey area, where researcher interpretation becomes more important.

In a similar vein, Rodriguez et al (2016), state that "*when ECV is greater than, say, .70 to .80, the factor loadings obtained from a unidimensional model might approximate well (i.e., be unbiased) to the factor loadings on the general factor obtained from a bifactor solution.*"

	ECV/ ECV_S	Omega/ OmegaS	OmegaH/ OmegaHS	Relative Omega	H	FD	PUC	ARPB
GF_RRCI	0.819	0.957	0.893	0.933	0.953	0.967	0.778	0.073
SF_RRR	0.382	0.873	0.331	0.379	0.568	0.836	N/A	N/A
SF_RLUC	0.203	0.916	0.180	0.196	0.536	0.811	N/A	N/A

Table 46: Factor and Model level results, Deuber's Bifactor Calculator

Item Name	IECV	Relative Parameter Bias	Absolute Relative Parameter Bias
LS2.5RV_NOMEAT_REWILD_IS_GOOD	0.664	-0.114	0.114
LS1.4RV_NEW_WETLANDS	0.717	-0.143	0.143
LS3.1_LESS_MEAT_LANDSC_DAMG	0.836	-0.061	0.061
LS1.3RV_BETTER_NO_LIVESTOCK	0.763	-0.080	0.080
LS2.2_UPSET_REWILD	0.805	-0.111	0.111
LS3.5RV_DIET_CHNG_LS_OK	0.923	-0.027	0.027
LS2.3RV_RURAL_SCIENTIST_MGMNT	0.924	-0.017	0.017
LS4.2RV_NEW_FORESTS_GOOD	0.690	-0.186	0.186
LS3.3_ENG_ID_IN_RURAL	1.000	0.037	0.037
LS4.6_PREFER_LANDSC_NOW	1.000	0.035	0.035
LS4.1_LANDSC_BEAUTY_PAST_PPL	1.000	0.035	0.035
LS3.6_LANSDC_IS_NAT.ID	1.000	0.035	0.035
LS4.5_DO_CC_POLICY_IN_TOWN	1.000	0.034	0.034
LS3.4_TRAD_MGMT_BEATS_CC	1.000	0.035	0.035
LS2.1_RURAL_NOEXPORT_RE	0.584	-0.112	0.112
LS1.2_NO_RE_IN_RURAL	0.596	-0.107	0.107
LS1.5RV_RURAL_EXPORT_RE	0.655	-0.084	0.084
LS4.7RV_RE_MIX_FOOD_OK	0.658	-0.065	0.065

Table 47: Item level results, Dueber's Bifactor Calculator

6.8.1 Assessment of scale unidimensionality

Table 46, above shows that the ECV of the General Factor is 0.819. This falls in what Quinn (2014) empirically demonstrated to be a 'grey area' between 0.7-0.9 where unidimensionality cannot be automatically assumed nor rejected, though it does meet the less stringent guidance laid out by Rodriguez, et al (2016), being in excess of 0.8.

The PUC represents the percentage of covariance items which only reflect variance from the General Factor. Along with ECV, the PUC influences whether the unidimensional solution will have excessive or acceptable parameter bias, (Deuber, 2017), who also reports that "*Rodriguez, Reise, and Haviland (2016a) indicate that "when ECV is > .70 and PUC > .70 relative bias will be slight and the common variance can be regarded as essentially unidimensional*" (p. 232).

In addition, Reise et al (2013) report that "*When Percent of Uncontaminated Correlations (PUC) values are higher than .80, general ECV values are less important in predicting bias; when PUC values are lower than .80, general ECV values greater than .60 and OmegaH > .70 suggest that the presence of some multidimensionality is not severe enough to disqualify the interpretation of the instrument as primarily unidimensional.*"

The General Factor scale has a PUC of 0.778, OmegaH is 0.893 and the ARPB is 7.3%, well below the threshold of 10-15% that would begin to pose concern.

Assessing the individual IECVs at item level in Table 47 provides further confirmation that the scale can be used as a unidimensional measure; the *majority* of each item's common variance (the variance shared with other items) is explained by the general factor versus the specific factors. For the items that load onto the RLUC Specific Factor, only half of them have Specific Factor explained variance of over 30%, with two items having less than 10% of their variance explained by the Specific Factor. The RRR Specific Factor items hover around 55-65% variance explained by the General Factor.

6.8.2 Assessment of Scale Reliability and Factor Determinacy

The H value of the scale is 0.953, well in excess of the threshold of >0.8 which suggests a well-defined latent variable that is more likely to be stable when measured across multiple studies (Hancock and Mueller, 2001).

Finally, the General Factor has very high Factor Determinacy (FD), the correlation between factor scores on the scale and the 'true' score for any given participant on the underlying factor. High factor determinacy allows researchers to confidently estimate respondents' true scores on the underlying construct, making the scale practically useful for research applications. At 0.967, the RRCI scale's FD is above the 0.90 threshold above which extracted factor scores for participants can be reliably used (Gorsuch, 1983; Dueber, 2017).

6.9 Discussion and next steps

In this chapter I have documented the process of item development, piloting, full survey, EFA and CFA analysis to produce a policy-specific measure that can assess levels of Resistance to Rural Climate Initiatives (RRCI).

6.9.1 Technical summary

The refinement process has produced a robust, novel scale of 18 items that I have demonstrated can be used as a measure of broad Resistance to Rural Climate Initiatives, which:

- is likely to remain stable across future studies and can provide researchers with an easily administered way to measure attitudes toward climate policy in rural areas
- provides a high level of confidence that a respondent's score on the scale is a true reflection of their true resistance to rural climate initiatives
- accounts for both a more abstract resistance to landscape change as an 'assault on identity and tradition', alongside more concrete resistance to specific physical changes and management practices that would materially alter the landscape.

- Has a nuanced underlying bifactor structure, allowing researchers with access to good statistical software to extract only the General Factor score, as a 'purer' measure of the underlying general dimension, with the specific factor variance statistically partitioned out. This will result in a more theoretically precise measure per participant, for use in further analysis.

The scale development process goes well beyond the standard accepted in many published papers. I have deployed a robust process for item development, piloting, item refinement, factor exploration and structural confirmation, avoiding the use of rules-of-thumb, maximising the parsimony and explanatory value of the scale, providing additional model comparison statistics and proof of the unidimensional nature of the scale, and determining that there are no negative-affect method effects resulting from the difference valence of item wording.

6.9.2 Reflection on potential for model overfitting

Compared to many published papers on scale development, this Chapter contains a relatively high number modification rounds. As described in some detail in Sections 1.6 and 1.7 of the Methods Annex, the field of Structural Equation Modelling (which the techniques used here are a part of) is plagued by the common but methodologically problematic approach of testing a model until the point that a set of approximate fit indices meet standard cutoffs (principally those defined by Hu and Bentler, (1999), and declaring the model final.

However, despite its widespread application, leading to many models in published papers that have undergone only 2 or 3 rounds of modification, this approach is widely criticised, leading to "*journals littered with…a plethora of forgettable, non-replicable, and largely 'of no actual measurable consequence' models*." (Barrett, 2007). It persists due to the availability of user-friendly software packages that tend to codify these approaches via pre-selected settings, leading to widespread poor practice (Cortina, 2002). Hu and Bentler's cutoffs were derived under a limited range of model and data conditions and have been shown to be inappropriate when applied uncritically across different model structures (McNeish and Wolf, 2022; Ximénez et al., 2022). Meeting a standard cutoff is not the same as establishing that

a model is the best available explanation of the data. As Xia and Yang, (2019) note, achieving acceptable fit indices is only one part of demonstrating a well fitted model. The researcher must demonstrate that the structure, and any modifications made, were theoretically justified and make practical sense.

The iterative model development process documented here guards against overfitting through a theoretically grounded process culminating in a comparison of models using LRT, AIC, and BIC tests, reflecting on whether additional complexity was both statistically worthwhile and theoretically grounded. Modification indices were not blindly used to guide structural changes; all modifications were driven by theoretical interpretation of item content, avoiding the risk of capitalising on chance sample characteristics (a risk identified by (MacCallum et al, 1992) and discussed further in the Methods Annex (Section 1.7). The final model's degrees of freedom (df=119) are well in excess of the minimum 10 recommended by Kenny et al, (2015) for a sample of this size, indicating a model structure that remains falsifiable rather than being tightly tailored to the sample. Finally, the approach had additional overfitting safeguards from the outset, through the use of a split-sample approach. The emergent model structure from the EFA used one half of the data, and retained its core features when confirmed on the other half that had not been interrogated via EFA.

Notably, the final accepted model (Model 10) is more parsimonious than the model that preceded it, having fewer estimated parameters. Thus, the iterative process ultimately resulted in a reduction in complexity, which provides a final contra-indication against the likelihood of overfitting.

6.9.3 Substantive applicability

The RRCI scale makes a novel contribution to research on climate policy implementation in England.

I had expected the more abstract, emotional, national identity and affect-driven items in the pilot set to form a separate and distinct measure to those that reference the more tangible, visible or quantifiable changes in rural England that will happen

as a result of climate policy. However, the emergence of a strong General Factor onto which all items primarily load, alongside the eventual redundancy of the 'Valuing Landscape, Traditions and Identity' Specific Factor during the process of model refinement demonstrates that identity and affect are likely to be in the foreground of landscape attitude measurement in relation to changes driven by climate policy.

The scale measures a hierarchical attitude structure (as summarised by Cruz and Manata, 2020). The General Factor is anchored on six items about national identity and traditional landscape preservation, which represent the higher-order attitudinal foundation. These foundational attitudes create a general predisposition toward resistance, which then manifests in the specific domains of opposition to renewable energy infrastructure or land use changes.

Rather than treating rural residents' concerns about climate-driven landscape change simply as preferences for particular aesthetic concerns or familiar practical land uses, the RRCI scale reveals that attitudes toward specific policy interventions (wind farms, rewilding, agricultural changes etc.) are fundamentally intertwined with identity-based attachments to place, in particular, those that define English national identity. The scale's unidimensional structure suggests that, especially for respondents who will have a high score on the RRCI scale, it may not be possible to separate concerns about specific landscape changes from a respondent's broader sense of place-based identity. For respondents with a high score on the scale, it is unlikely that there are discrete preferences for land-uses that can simply be traded off against each other; rather, some respondents' attitudes of high resistance will constitute a holistic response to perceived threats to valued landscapes, national identities, and ways of life. This work therefore offers a more psychologically grounded foundation for understanding and potentially addressing rural resistance to planned climate policies.

6.9.4 Limitations of the study and opportunities for future work

The focus of this thesis is rural populations in England, and the sample was drawn only from rural places. The structure of the scale, though shown to be robust and likely to remain stable across future studies, may have been influenced by this.

Beyond the scope of this thesis, further items could be added to test whether additional features of climate policy will factor together with existing items. For example, the current scale does not include items relating to energy transmission infrastructure. However, as the national consciousness of the need for grid upgrades is increasingly linked to the rollout of renewable energy in the popular narrative, it would be useful to understand if new items on this theme would factor with renewable energy, would stand alone, or would be considered too general to factor into the scale at all.

Similarly, the scale does not include other contested land uses that have carbon emissions implications that are also tied to traditional rural leisure pursuits, such as the burning of peat-rich grouse-moors. An additional 'rural sport' item set could possibly be developed that may sit apart from the original VLTI items as a stronger measure of rural, rather than national identity.

The RRCI scale could also be tested in the other UK subnations, as well as in other countries outside the UK, and with larger and more heterogenous samples, including urban and suburban populations, to establish whether the scale structure remains reliable. It is likely that alternative item wording and locality-specific items may need to be added for other national contexts. Nonetheless, the core of the scale represents a solid tool for other researchers to adapt.

Item LS3.3, "*The real heart of English identity is found in our rural landscapes and places, not in our cities and towns*" emerged as an interesting anchor item around the pure link between landscape and identity. While it has factored meaningfully into the full scale throughout the process, its standalone status on the VLTI Specific Factor suggests that further scale development work on 'pure' attitudes about the role of places in the formation of national identities could also be fruitful.

In the next chapter of this thesis, the predictive validity of the RRCI scale is tested via linear regression and path analysis models, to determine whether it can meaningfully differentiate between different socio-demographic groupings and political identities.

7 A Path Model Analysis of Resistance to Rural Climate Policy

7.1 Introduction

Having developed and tested an instrument to measure Resistance to Rural Climate Initiatives (RRCI) in the previous chapter, the aim of this chapter is to use the General Factor scores on that scale (RRCI_GF) from a large-n survey to explore the relationships between deeply-held markers of identity (Populism, Rural Identity, and English National Identity), political alignment, and people's attitudes to changes in the countryside that will be brought about by climate policies such as renewable energy infrastructure, and changed agricultural practices.

The chapter responds to Research Question 3: *What are the pathways by which political identity, populism, and rural identity shape resistance to rural climate policy?*

7.1.1 Study Motivation

The motivating question for the thesis as a whole, ('How can climate policy making be made more inclusive of the views and concerns of rural, politically right-leaning communities in England?') focuses on right-of-centre voters because, as detailed in the Literature Review, there is a substantial body of research suggesting that right-leaning individuals are less supportive of climate action. However, as also detailed in the Literature Review (Section 2.5.3), this phenomenon is likely exaggerated by the proportion of evidence emanating from the USA. Many US-based studies are limited (due to highly restrictive ballot access rules), to assessing the influence of

party-political alignment on policy attitudes at the level of three crude groupings; conservative/right-wing, liberal/left-wing and 'independent' (the latter of which does not even translate into a meaningful party choice at national level in the USA).

Until very recently the UK Conservative Party represented the single distinctly right-leaning party with any significant electoral presence in England. As a result, the terms 'right-wing' and 'Conservative' have also been largely conflated in UK political discourse, a phenomenon that has likely been exacerbated by the influence of US political life on the political language of the UK, particularly around 'culture-war' issues since 2016 (Duffy *et al.*, 2021).

With no meaningful challenger party on the right, the UK Conservative party has for many years benefitted from vote-splitting on the left (as Labour, the Green Party, and the Liberal Democrats offer overlapping policy positions). But the party has also tussled for decades with the problems that come with being a 'Big Tent' party, attempting to accommodate the views of everyone from 'small-c' cultural conservatives to radical economic libertarians. The recent rise of Reform UK as a major presence in UK politics generally, and English politics especially, has offered a home for many who felt frustrated by the Conservative policy offer, but unable to align themselves with any of the parties of the left. For this thesis, this has presented an extraordinarily timely opportunity to probe the views of right-leaning rural voters on climate in a more segmented way.

This chapter explores, and confirms as plausible, some key causal mechanisms that could underpin resistance to rural climate policy on the political right in England. It is already known that 'one-size-fits-all' policy messaging is inadequate on climate, especially since so much of it is underpinned by left-of-centre ideological imperatives around global social justice. This chapter exposes that addressing this inadequacy through the application of crude 'right-wing-friendly' policy framings that do not segment the political right in any meaningful way, is also likely to be insufficient.

This chapter first investigates relationships between the identity and attitude variables through Linear and Logistic Regression models, to establish what

meaningful relationships exist. A variable that appears to have substantial predictive power on an outcome can fade into insignificance when another predictor, with which it shares substantial variance, is added to the model. By adding variables to Linear and Logistic Regression models in hierarchical blocks, the unique contributions of individual variables (once the effect of others is controlled for) are revealed.

However, regression models can only represent the empirical association between two or more variables. To diagnose plausible causality requires more advanced methods, such as Structural Equation Modelling (SEM). (Goldberger, 1972; Bollen and Pearl, 2013). The latter part of the chapter therefore details the development of a Path Model (a restricted form of SEM), to fully test the hypotheses that:

- The core identity markers Populism, Relative English Nationalism and Objective Rurality are meaningfully transmitted via Party Alignment to significantly impact on Resistance to Rural Climate Initiatives (RRCI), and
- These core identity variables will operate differently on parties of the political right vs parties of the political left.

The identity traits are operationalised via a set of variables, detailed in Section 0, below.

A brief introduction to the Path analysis techniques is given in Section 7.4.1, and a full 'Methods Tutorial' is provided in Annex 1 for the reader who has limited background in either regression models or SEM and wishes to have more detail (but it is not necessary to read the Annex to follow this Chapter).

7.2 Research Design and Methodology

7.2.1 Data

The data are drawn from the survey in Appendix 3.1. From 723 complete surveys, 16 are discounted for the full modelling in this chapter because the respondents do not have any UK national identity, a crucial variable in the model.

7.2.2 Operationalisation of variables

The following variables are used in the models. In the explanatory text the long-form name is used to aid interpretation. The short variable names in brackets are found in some tables and figures where space is limited:

Resistance to Rural Climate Initiatives. (RRCI_GF). (Endogenous[35], dependent only). The General Factor (GF) score from the measurement model, developed and tested in Chapter 6 of this thesis (derived from 18 Likert items on a 0-10 scale). RRCI_GF is a measure of resistance to rural climate initiatives, anchored on six items about national identity and traditional landscape preservation, representing a higher-order attitudinal foundation. These foundational attitudes create a general predisposition toward resistance, which then manifests in the specific domains of opposition to renewable energy infrastructure or land use changes covered by the remaining 12 items. A higher factor score equals more resistance to rural climate policy. This is the final outcome (endogenous) variable in the Path Models. (Factor Score, zero-centred, range -2.57 to +2.68 [5.26]).

Rejection of Climate Science (CC_CAUSE_NCEN). (Endogenous, mediator). Initially a three-level ordinal variable representing increasing rejection of climate science, where 1= '*The world's climate is changing, largely due to human activity*', 2 = '*The world's climate is changing, largely due to natural causes'*, and 3 = '*The world's climate is not changing'*. Since software limitations prevented the use of the 3-level variable, this was converted to a pseudo-continuous variable by adding or subtracting tiny

[35] Endogenous/Exogenous role is relevant only in Path Modelling, and is explained in Section 7.4.1

amounts of random noise to each data point, while preserving the overall mean and distribution. The resulting variable was then mean-centred to aid interpretation of models, ensuring that the intercept corresponds to the predicted outcome when the predictor CC_CAUSE is average, (in relation to the baseline reference party where the PAR_NAME variable is used).

Left-Right Alignment (LR_CEN). (Endogenous, mediator). Self-placement on 1-10 scale where 1= '*most left wing*' and 10= '*most right wing'*. (Mean-centred to aid model interpretation).

Populism (POP). (Exogenous). Factor Score comprised of five Likert items, tested by regular deployment in the British Election Study (Fieldhouse et al., 2023a, p. 642) (see Appendix 3.1, items 19-23 for wording). Higher score equals higher levels of populism. (Factor score, zero-centred, range -3.19 to +1.79).

Relative English National ID (ENG_REL). (Exogenous). In multi-state nations such as the UK, or contested sub-regional identities such as the Basque or Catalan region of Spain, people often feel more than one national or subnational identity, or have exclusively strong attachment to only one of the nationalities available to them (Moreno, 2006, Henderson, 2017). The Relative English National ID variable reflects this complexity, using a 'Moreno Scale' approach that compares the relative strength of one national ID to another.

Respondents provided a measure of their strength for each UK national identity (British, English, Scottish, Irish, Welsh) using a 0-7 scale, again taken from the British Election Study (Fieldhouse et al., 2023b, pg 261), where 0 = '*I do not feel this sense of national identity at all*' and 7 = '*I have a very strong sense of this national identity*'. Since English national identity is the focus of the study, scores were then combined to create a bipolar Moreno scale with the following categories, following the scale conventions in Fieldhouse et al., 2023b (p.254-265):

- Other UK national ID but no English national ID (-2)
- More of another UK national ID than English ID (-1)
- Equally another UK national ID and English ID (0)

- More English than another UK national ID (+1)
- English but no other UK National ID (+2)

The scale has the benefit of capturing the characteristic of 'Exclusive Englishness' (being English without feeling any association with other UK identities), in the +2 category. This 'exclusively English' identity has been shown to have policy relevance in other areas such as the Brexit vote in 2015 (Henderson, 2017). This variable is not mean-centred for use in the analysis, since the mid-point 'equally English with another UK nationality' is a natural centre point.

Objective Rural Identity (RUR_CEN). (Exogenous) - Composite index score made from responses to two ordinal items on place of current and childhood residence, and four binary items, indicating whether respondents live in a 'rurally employed household', whether they are a member of rural trade bodies, rural shooting associations, and rural hunting with hounds associations. (Weightings for Rural Index items were derived through both empirical work and theory and its structure is described in Appendix 7.1). Possible Rural Index scores range from 0 to 21. (Mean-centred to aid model interpretation).

Subjective Rural Identity (RUR_URB). (Exogenous). Binary variable representing self-perception as a 'rural person', via the question "*Regardless of where you live now, the kind of work you do, or where you grew up, which of these two phrases do you think most accurately reflects the kind of person you are?"* to which available responses are *"I am very much a country sort of person, not really comfortable in big towns and cities*" (1) or "*I feel most at home in an urban or suburban environment*" (0).

Political Party Alignment (PAR_NAME [categorical], or *PAR*_EFF [effect coded form]). (Endogenous, Mediator). The original categorical political party alignment variable (PAR_NAME) contained six categories: Green Party, Labour, Liberal Democrat, Conservative, Reform UK, and Other. This was used in its original form for the early Linear and Logistic Regression models, but was then converted with Effect Coding for the Path Models, following established procedures (Alkharusi, 2013; te Grotenhuis et al., 2017), which are elaborated on further in Section 7.5.1

Appendix 7.2 presents raw descriptive statistics for the sample, broken down by political party alignment, which is treated as a 'prism' through which the effect of predictor variables is seen to be transmitted to the outcome in the Path Modelling process.

The mean score distributions are also visualised in Figure 11, below, using standardised scores, to give an initial picture of the party alignment 'attitude landscape' under investigation.

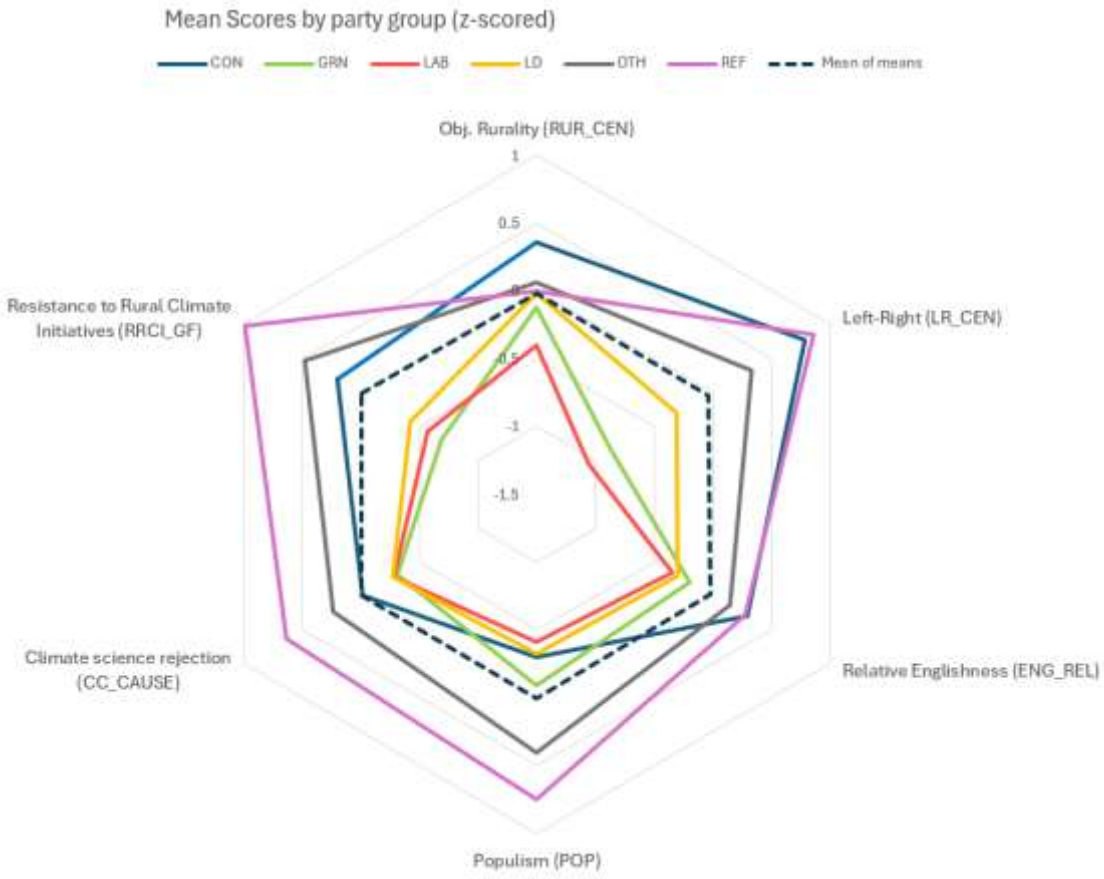


Figure 11: Distribution of standardised mean scores by party

Mean scores imply a largely predictable distribution on the left-right scale, with Green/Labour/Liberal Democrats creating a left-of-centre grouping, and Conservative/Reform/'Other' groups placing themselves right of centre. However, the mean scores across all variables also suggest the left-leaning party groups are more closely related to one another on most measures, particularly Green Party and

Labour group members, who are not easily distinguished from each other than on the populism measure. By contrast, the right-leaning party groups display more varied profiles. The 'Other' group presents as a less extreme version of Reform UK on most measures (though slightly more rural), while Conservatives have a distinctly different profile, distinguished from the other right-leaning groups by low populism and the highest rurality scores of all.

7.2.3 Research hypothesis and informing the Path Model specification

A broad hypothesis is postulated, drawn from the literature review, that there is a causal path that runs from the 'core identity markers' of populism, rurality and nationalism, which first expresses itself through political alignments, and from there on to levels of rejection of climate science and ultimately, rejection of climate policies, represented in Figure 12, below:

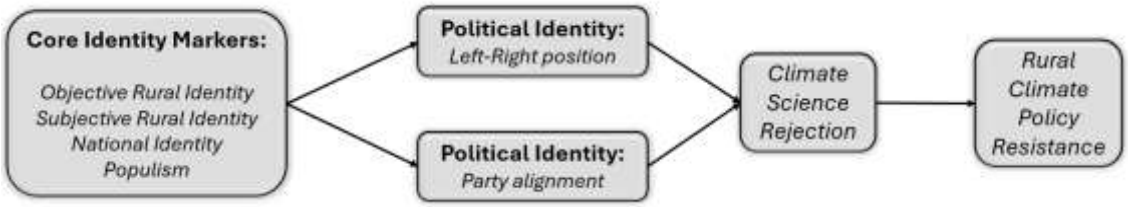


Figure 12: Initially hypothesised causal paths

Political Identity takes the form of both an abstract sense of an individual's personal placement on a political spectrum from left to right, and (at a more concrete level), choice of the political party that they feel best represents their views. Since political group loyalty is expressed and remade through cleavage to particular viewpoints, and climate policy is among the more politically divisive areas of public policy making, I theorise that Party Alignment (PAR_NAME) will form a crucial 'refractive lens' that reveals different paths to the final outcome variables.

Before developing the more nuanced Path Model structure, I first tested the broad relationship blocks represented in Figure 12 above, through linear and logistic regression models to refine the structure.

7.3 Informing the Path Model structure

7.3.1 Linear Regression 1- Predictors of Left-Right political position

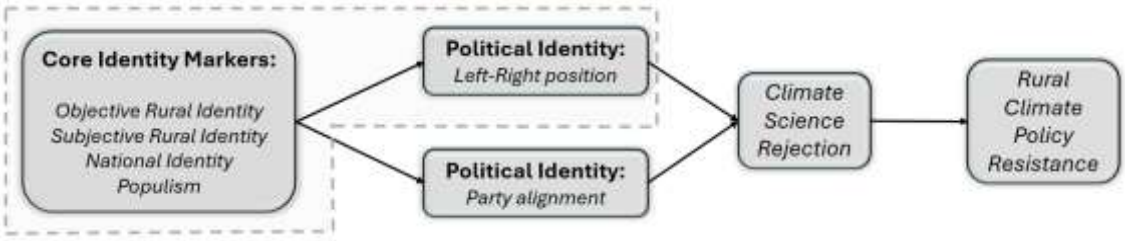


Figure 13: Schematic indicating relationships being tested in this section

I first test the theoretical assumptions that deeper markers of identity (nationalism, populism and rurality) are precursors to Left-Right positioning. Figure 13 Each predictor was initially tested in a simple regression. Since Subjective Rural Identity (RUR_URB) was not significant as a single predictor (r=0.0595, p=0.114), only the three other predictors were carried forward into the hierarchical linear regression model.

Results are presented in Table 48 and Table 49, below. Table 48 shows the overall model fit statistics and the additional explanatory value added at each step of the hierarchical regression, and demonstrates that each additional predictor does contribute statistically meaningful explanatory power to the model. Table 49 shows the coefficients for the final fully-specified three-predictor model. Full hierarchical results for all three models are given in Appendix 7.3

Model Fit Measures

				Overall Model Test			
Model	R	R^2	Adjusted R^2	F	df1	df2	p
1	0.176	0.0309	0.0295	22.4	1	705	< .001
2	0.304	0.0926	0.0900	35.9	2	704	< .001
3	0.342	0.1170	0.1133	31.1	3	703	< .001

Note. Models estimated using sample size of N=707

Model Comparisons

Comparison							
Model		Model	ΔR^2	F	df1	df2	p
1	-	2	0.0617	47.9	1	704	< .001
2	-	3	0.0244	19.5	1	703	< .001

Table 48: Model Fit measures and Model Comparison for hierarchical model with Objective Rural Identity, Relative English Identity, and Populism variables added

Model Coefficients - LR_CEN

			95% Confidence Interval					95% Confidence Interval	
Predictor	Estimate	SE	Lower	Upper	t	p	Stand. Estimate	Lower	Upper
Intercept	0.0619	0.0706	−0.0767	0.200	0.877	0.381			
RUR_CEN	0.0916	0.0195	0.0533	0.130	4.694	< .001	0.166	0.0968	0.236
ENG_REL	0.5075	0.0809	0.3487	0.666	6.273	< .001	0.225	0.1545	0.295
POP	0.3137	0.0711	0.1741	0.453	4.412	< .001	0.158	0.0878	0.229

Table 49: Model Coefficients for Model 3 (all predictors)

I use Funder and Ozer's 2019 guidelines on effect size, reporting r/R coefficients directly (superseding the more commonly used Cohen guidelines based on r^2/R^2). Funder and Ozer's highly cited work, building on Abelson, (1985), demonstrates that although small standardised effects (such as correlations between an individual's score on a predictor and a behavioural or attitudinal outcome) may appear inconsequential at the level of a single event or person, when these small effect sizes operate across large populations or over many instances, their cumulative impact can be substantial, as exemplified by examples provided in Weston *et al*, (2019).

Effect Sizes are thus reported against Funder and Ozer's guidelines, such that r for single variable models (or R, in multivariate models), indicate the following effect sizes:

- 0.05 indicates "*an effect that is **very small** for the explanation of single events but potentially consequential in the not-very-long run*",
- 0.10 indicates "*an effect that is still **small** at the level of single events but potentially more ultimately consequential*",
- 0 .20 indicates "*a **medium** effect that is of some explanatory and practical use even in the short run and therefore even more important*"
- 0.30 indicates "*a **large** effect that is potentially powerful in both the short and the long run*"; and
- 0.40 indicates "*a **very large** effect size, which, in the context of psychological research is likely to be a gross overestimate that will rarely be found in a large sample or in a replication*".

In the multivariate models, I use the standardised regression coefficients (β) for each predictor, representing the change in the outcome variable per SD increase in the predictor, after adjusting for the other variables, for effect size interpretation in SD units.

The results of multivariate linear regression models testing the predictors Objective Rural Identity, Relative English National ID, and Populism as predictors of Left-Right Alignment (presented in Table 48 and Table 49, above and in Appendix 7.3), demonstrate that all three predictors:

- have statistically and practically significant variance with Left-Right Alignment
- are correlated positively with the outcome, (an increase each predictor is associated with a more right-leaning placement on the Left-Right Alignment scale).

- Produce stable coefficients that change only minimally with order of entry, suggesting their contributions to outcome variance are largely independent of each other. (Interaction effects were tested for, and were not present).

Objective Rural Identity: For each 1 SD increase in Objective Rural Identity, there is a 0.166 standard deviation increase in Left-Right Alignment (0.35 points), controlling for the other predictors. In practical terms, this means that every 3.58 increase in the (21-point) Rural Index predicts a 0.33 move to the right on the (10-point) left-right political placement scale.

Populism: For each 1 SD increase in Populism, there is a 0.158 standard deviation increase in Left-Right Alignment (0.35 points), controlling for the other predictors. In practical terms, this means that every 0.998 increase in the (5-point) Populism scale predicts a 0.31 move to the right on the (10-point) left-right political placement scale.

Using Funder and Ozer (2019) guidelines, these represent small effect sizes at the level of single events, which are potentially more consequential over repeat events or at the population level.

Relative English National ID : For each 1 SD increase in Relative English National ID, there is a 0.225 standard deviation increase in Left-Right Alignment (0.45 points), controlling for the other predictors. In practical terms, this means that every 0.878 increase in the (5-point) Relative English Nationalism scale predicts a 0.45 move to the right on the (10-point) left-right political placement scale. Using Funder and Ozer (2019) guidelines, this represents a medium effect size which is of explanatory and practical use, even in the short run or at the individual level.

The aggregate R-value for the combined predictors (R=0.342) is a large effect size, therefore potentially powerful in both the short and long run, reflecting the substantial joint contribution of these predictors to political positioning. This supports the theoretical model that Objective Rurality, Relative English Nationalism, and Populism are distinct but related constructs that each separately influence political spectrum placement, tending to push people toward the political right.

7.3.2 Linear Regression 2: Party and climate science beliefs as predictors of Resistance to Rural Climate Initiatives

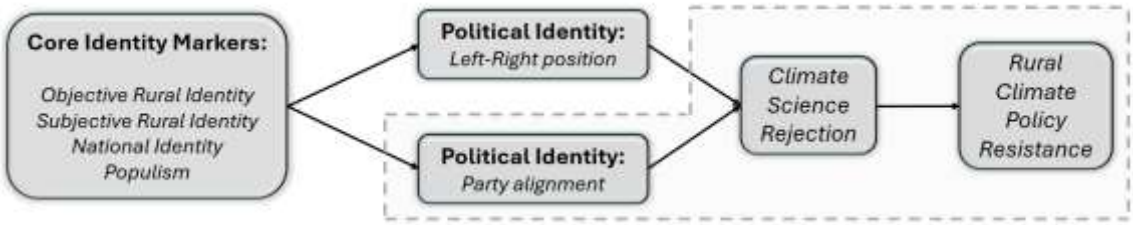


Figure 14: Schematic indicating relationships being tested in this section

I next test the impact of level of Rejection of Climate Science (CC_CAUSE_NCEN , Model 1), and choice of Party Alignment (PAR_NAME, Model 2) on Resistance to Rural Climate Initiatives (RRCI_GF), the final outcome variable. I include an interaction term to determine whether the effect of Rejection of Climate Science on RRCI_GF is affected *by* alignment with different political parties (Model 3). See Table 50 and Table 51, below, which present the results with Party Alignment entered first, reflecting the theoretically hypothesised causal order in Figure 14. Appendix 7.4 contains full results with each different party as the baseline.

Model Fit Measures

			Overall Model Test			
Model	R	R^2	F	df1	df2	p
1	0.636	0.404	97.3	5	717	< .001
2	0.681	0.464	103.2	6	716	< .001
3	0.691	0.478	59.1	11	711	< .001

Note. Models estimated using sample size of N=723

Model Comparisons

Comparison						
Model	Model	ΔR^2	F	df1	df2	p
1	- 2	0.0595	79.44	1	716	< .001
2	- 3	0.0139	3.79	5	711	0.002

Table 50: Model Fit measures and Model Comparison for hierarchical model with Party Alignment, and Rejection of Climate Science variables added, plus interaction term

Omnibus ANOVA Test

	Sum of Squares	df	Mean Square	F	p
PAR_NAME	50.14	5	10.029	21.03	< .001
CC_CAUSE_NCEN	11.68	1	11.676	24.49	< .001
CC_CAUSE_NCEN ✻ PAR_NAME	9.04	5	1.808	3.79	0.002
Residuals	339.01	711	0.477		

Note. Type 3 sum of squares

Table 51: Model Coefficients for model with all predictors

Each predictor was initially tested in a simple regression, producing very large effect sizes (Rejection of Climate Science r=0.583, F 372(df1), p<0.001, and Party Alignment r=0.636, F97.3(df5), p<0.001). Subsequent hierarchical testing (Models 1,2,3) in a multivariate model showed substantial shared variance in relation to the outcome (RRCI), with a combined R for both predictors of 0.681.

When Rejection of Climate Science is entered first, r=0.583, and subsequent addition of Party Alignment raises the association to R=0.681, a notable improvement (ΔR=0.098) that is statistically significant (F(5,716)=32.93,p<.001). Including their interaction further increases overall association to r=0.691, a modest but nonetheless statistically significant rise (ΔR=0.01, F(5,711)=3.79,p=.002[36].

When Party Alignment is entered first, however, r=0.636 (as shown in Table 50, above). Subsequent addition of Rejection of Climate Science again raises the association to R=0.681, (ΔR=0.045). This smaller ΔR when Rejection of Climate Science is added second suggests that, once party membership is accounted for, Rejection of Climate Science has less unique variance left to explain, although it is still a statistically and practically meaningful direct predictor of increased RRCI score. The high level of shared variance and nuance revealed by order of model entry is consistent with party exerting influence 'upstream' of climate science beliefs, as hypothesised in the schematic in Figure 14. However, the strong influence of Party Alignment directly on RRCI_GF, controlling for the other variables, suggests

[36] TablesTable 50 andTable 51present results with *Party Alignment* entered first, reflecting the theoretically hypothesised causal order. The alternative entry order is discussed in the text above.

that resistance to climate policy does not run *wholly* via rejection of climate science, as per the hypothesised structure.

Per Funder and Ozer, effect sizes of this magnitude should be treated with caution. I posit that the cause is likely to be the highly 'proximal' nature of both predictors to the outcome. Climate science beliefs (CC_CAUSE_NCEN) are likely to directly inform attitudes toward climate-related policies. Political party affiliation (PAR_NAME) captures ideological positioning that encompasses environmental policy preferences, and often acts as a core component that divides parties by policy. This contrasts with psychological research where predictors such as personality traits and attitudes to abstract concepts are more distal to final outcomes, often operating through multiple mediating pathways that attenuate effect sizes.

As a categorical variable, the effect of Party Alignment on RRCI demonstrates varying predictive power by party, revealed clearly by changing the baseline reference party in the model, see Appendix 7.4 and the summary in Table 52, below, which summarises the pairwise differences in predicted RRCI score between any two parties (raw estimates), controlling for climate science beliefs and the interaction term.

This contextualises the predictive power and very large effect size of the combined Party Alignment variable on the outcome, demonstrating where the largest party contrasts lie. The largest contrasts are between Reform UK and Green Party supporters, representing 27% of the outcome scale's range.

- Reform UK being the only party that is significantly different to all others, higher (by at least 12% of the scale's range than any other party)
- Green Party mean scores are the lowest, although do not differ significantly from Labour scores
- In turn, the gap between Labour and Liberal Democrats is also not significantly different.
- Conservative and 'Other' also form a pairing with no significant difference in the predictive power of party membership on RRCI score.

Political Party Contrasts in RRCI (Adjusted Means)

		BASELINE IN MODEL					
		CON	GRN	LAB	LD	OTH	REF
CONTRAST	CON		0.705	0.538	0.358	-0.085	-0.702
	GRN	-0.705		-0.167	-0.347	-0.79	-1.407
	LAB	-0.538	0.167		-0.18	-0.623	-1.24
	LD	-0.358	0.347	0.18		-0.443	-1.06
	OTH	0.085	0.79	0.623	0.443		-0.617
	REF	0.702	1.407	1.24	1.06	0.617	

Contrast party mean significantly higher than baseline party
Contrast party mean significantly lower than baseline party
Not significantly different

Table 52: Pairwise differences – predictors of RRCI by political party (marginal means)

7.3.2.1 Interaction Effects – does the effect of Rejection of Climate Science on RRCI differ by Party Alignment?

The omnibus test for the interaction term (F=3.79, p=0.002) indicates significant differences in how climate science beliefs relate to rural climate policy resistance across parties (Table 53, below). However, interpretation of these effects is substantially constrained by the distinctive distribution of climate science beliefs within party groups also shown in the table.

CC_CAUSE	CON	GRN	LAB	LD	OTH	REF
Score 1	107	130	106	90	57	17
Score 2	49	3	3	5	47	90
Score 3	0	0	0	0	7	12
TOTAL	***156***	***133***	***109***	***95***	***111***	***119***
% score 1 (climate change real, and manmade)	69%	98%	97%	95%	51%	14%
% score 2 (climate change real, but natural)	31%	2%	3%	5%	42%	76%
% score 3 (climate change not real)	0%	0%	0%	0%	6%	10%

Table 53: Distribution of climate science beliefs by party (CC_CAUSE, original 3pt ordinal variable before mean centred).

The data in Table 53, above, reveal substantial party-based differences in climate science acceptance. Although Reform UK respondents are distributed across all levels of climate science belief, and the majority accept that climate change *is* happening, most of those respondents attribute it to natural causes. 10% of Reform UK respondents reject the idea that the climate is changing at all. Supporters of the Green Party, Labour and the Liberal Democrats overwhelmingly accept anthropogenic climate change (95-98%). 'Other' and Conservative supporters show considerably more acceptance of the 'natural causes' hypothesis than Green Party, Labour and Liberal Democrats, though still much lower than Reform UK. There are zero instances of belief that the climate is not changing at all among Conservative, Labour, Liberal Democrat and Green Party supporters, meaning outright rejection of climate change as a phenomenon is limited to Reform UK and 'Other' respondents in the sample.

The data in Table 53, above, and the linear regression interaction results in Appendix 7.4 also demonstrate that climate science rejection does not have the same predictive ability for each party. Although the interaction term between Rejection of Climate Science and Party Alignment is significant for the model as a whole, Reform UK supporters are distinctive in maintaining consistently elevated resistance scores on RRCI regardless of their climate science beliefs (which are elevated compared to all other groups). For this group, climate science rejection is somewhat 'decoupled' from RRCI scores (see for example the high intercept value in Appendix 7.4, when using Reform UK as the reference party).

7.3.3 Logistic Regression 1 – Objective Rural Identity, English Nationalism, Populism and Left-Right position as predictors of party alignment

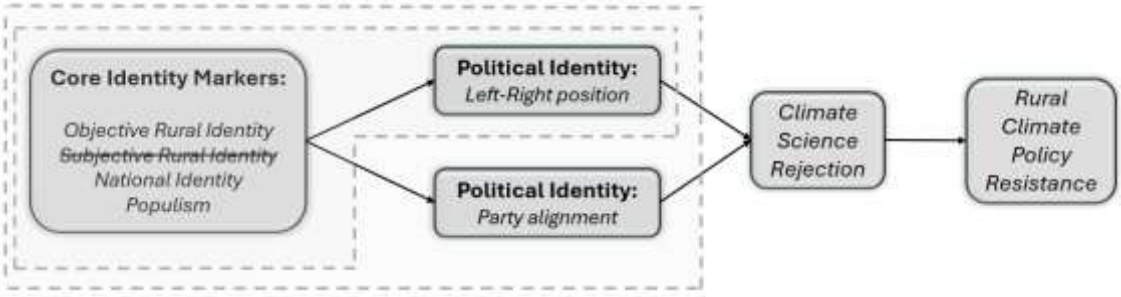


Figure 15: Schematic indicating relationships being tested in this section

Having examined the role of Party Alignment as a *predictor*, I turn next to the more complex task of logistic regression, now using this categorical variable as an *outcome*, testing the hypothesised relationship between the core predictors of Objective Rural Identity, Relative English National ID, Populism and Subjective Rural Identity and also Left-Right Alignment, and using Party Alignment as the outcome variable. (Figure 15).

Multivariate Multinomial Logistic Regression (Appendix 7.5) revealed that all variables are statistically significant predictors of Party Alignment (when controlling for the effect of all other variables in the model). However, despite being statistically significant, Subjective Rural Identity's predictive value was very minimal in practical terms, and it did not add significantly to the explanatory power of the model, sharing much of its variance with other predictors. I therefore excluded it from further analysis in the logistic regression model.

For the remaining predictors, I determined optimal entry order (Relative English National ID → Objective Rural Identity → Populism → Left-Right Alignment), providing maximum explanatory value and aligning with the theoretical hypothesis that the three 'core variables' of Objective Rurality, Relative English Nationalism, and Populism are precursors to Left-Right Alignment, which all, in turn, meaningfully predict Party Alignment. (Table 54).

I then systematically tested the model with each party as baseline (full results in Appendix 7.5) and extracted only statistically significant odds ratios ($p < 0.05$) for

further analysis, which are considered further in Figure 17, Figure 18, and Figure 20, below.

Model Fit Measures

				Overall Model Test		
Model	Deviance	AIC	R^2_{McF}	χ^2	df	p
1	2462	2482	0.0210	52.8	5	< .001
2	2419	2449	0.0381	95.7	10	< .001
3	2291	2331	0.0888	223.3	15	< .001
4	1766	1816	0.2974	747.9	20	< .001

Note. Models estimated using sample size of N=707

Model Comparisons

Comparison					
Model		Model	χ^2	df	p
1	-	2	42.9	5	< .001
2	-	3	127.6	5	< .001
3	-	4	524.6	5	< .001

Table 54: Model Fit measures and Model Comparison for hierarchical model with Relative English National Identity, Objective Rural Identity, Populism and Left-Right Alignment as predictors of Party Alignment

I use Rosenthal's, (1996) guidance on effect sizes in logistic regression, results of which are most interpretable when expressed as naturalised Odds Ratios. For representing odds ratios in natural language this way, ORs > 1 already represent the naturalised form (e.g. OR 12.05 = 'twelve times higher odds'). For ORs < 1, a more intuitive form is $^1/_{OR}$ with the comparison *reversed*; for example, an OR of 0.045 corresponds to the *comparison group* having about twenty-two times higher odds.

Rosenthal's Effect Sizes are:

- 1.5 to 1 - small effect/weak association (equivalent to 1.5 times higher/lower odds).
- 2.5 to 1 – medium effect/moderate association (equivalent to 2.5 times higher/lower odds).

- 4 to 1 – large effect/strong association (equivalent to 4 times higher/lower odds).
- >10 to 1 – very large effect/very strong association (equivalent to 10 times higher/lower odds).

In addition, I use z-scored versions of the predictor variables to 'pre-standardise' the variables for easier comparison, since Logistic Regression does not provide standardised betas. The odds ratios therefore represent the higher or lower odds of a survey respondent being in one party compared to the baseline party in the model, for a one 1SD increase in the predictor score, holding all other variables constant.

7.3.3.1 Objective Rural Identity as a predictor of party alignment

The variable Objective Rural Identity[37] appears to operate largely to distinguish Labour supporters (lowest rurality) from everyone else apart from Reform UK, and to additionally distinguish Reform UK (lower rurality) from Conservative (highest rurality). All other parties are not statistically distinguishable from each other on this predictor, controlling for the impact of other predictors in the model. This may partly be a result of the different variances in the party groups; The Conservative cases have a very high variance and the highest mean, suggesting that while Conservative voters are spread widely across the index scores, they also dominate the highest (most rural) levels. By contrast the Labour supporters' variance and mean are the lowest, indicating that Labour supporters are clustered tightly at lower rurality levels. It is this tight clustering that allows Objective Rural Identity to strongly distinguish Labour from almost all others in the multivariate model, apart from Reform UK, who have similarly low rurality probabilities as Labour.

[37] Recall that the survey was distributed in rural areas and this variable thus serves to distinguish levels of 'rural embeddedness' *between* people living in rural areas, rather than simply comparing urban and rural dwellers.

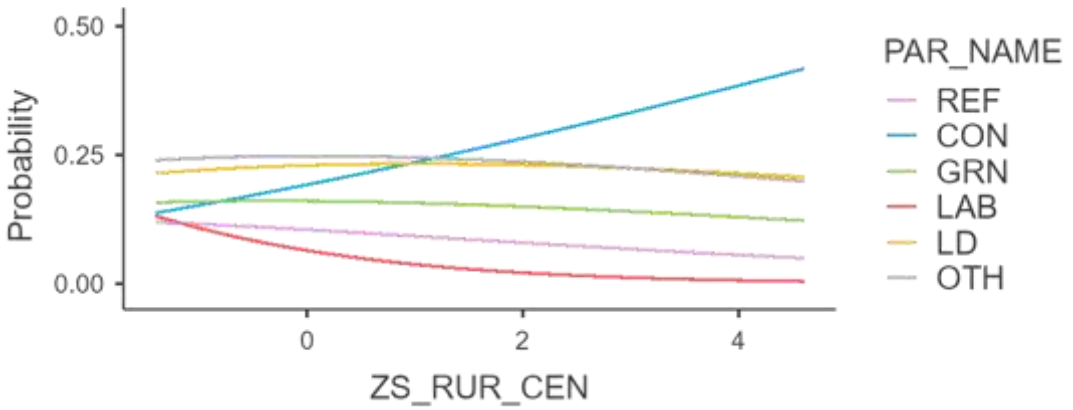


Figure 16: Probability Distribution - Objective rurality (Objective Rural Identity) as a predictor of political party alignment

The estimated marginal means plot (Figure 16, above) also reveals the probability of being Conservative rising linearly, reaching substantially higher predicted probabilities at the high end of rurality compared to all other parties. Since the Reform UK and Labour lines remain consistently low across rurality values, the contrast between those groups and the most rural Conservative voters is clear and large. However, less consistent differences in other party groups reduce Objective Rural Identity's statistical power to distinguish Conservatives significantly from Green Party, Liberal Democrat, or 'Other' supporters, especially once other predictors in the model are accounted for.

In practical terms, the results reveal that every 1 SD (3.58 point) increase in the (21-point) Objective Rural Identity index predicts odds of being aligned with Labour that are 1.7-2.1 times lower than for all other party groupings, other than Reform UK, a small to medium effect size that is likely to create meaningful differences at whole-population level. (see Figure 17, below).

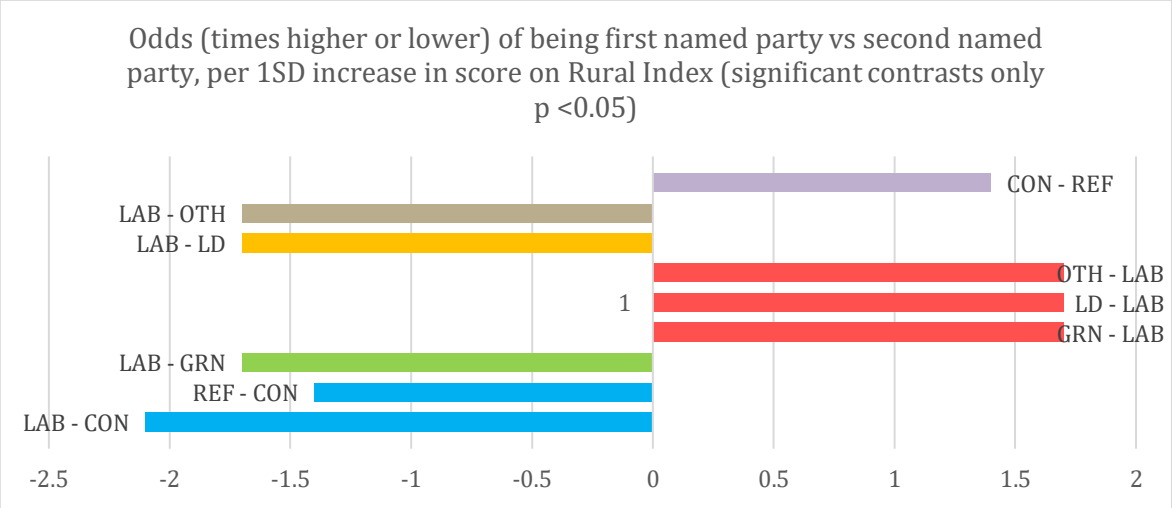


Figure 17: Significant Odds Ratios, Objective Rurality (Objective Rural Identity) as predictor of party alignment

7.3.3.2 Populism as a predictor of party alignment

Controlling for strength of English Nationalism, Objective Rural Identity, and position on the Left-Right scale, Populism's effects clearly distinguish between the established mainstream parties (Conservative, Liberal Democrat and Labour) and the challenger parties Reform UK and the Green Party, and the non-aligned 'Other' group, who form a higher populism trio. Generally, effect sizes are small to medium, although the pairwise contrast between Reform UK and Conservative approaches a large effect size.

Figure 18, below, shows that survey respondents with higher populism scores have substantially higher odds of being Reform UK aligned than any other party. A 1SD increase in Populism (equating to a 0.998 increase in the (5-point) scale) predicts odds of being aligned with Reform UK that are 1.4 to 3.5 times higher than for any other party. For the 'Other' group, higher populism scores predict higher odds of membership than for any other party apart from Reform UK. The Green Party group also sit on the higher end of the populism odds ratios; the odds of being Green Party rather than Liberal Democrat, Labour or Conservative are around 1.5 times higher for every 1SD increase in the Populism score. The pattern on the right-hand-side of the clustered bar chart in Figure 18 demonstrates the markedly similar (and low) populism profile of Liberal Democrat, Labour and Conservative supporters, all of

which contrast most strongly with Reform UK, followed by 'Other', followed by Green Party. Notably, the biggest contrast of all on populism is between Conservative and Reform UK (3.5 x lower odds of being Conservative than Reform UK for each 1SD increase in Populism). This runs counter to common narratives that describe Conservative voters as populist; on this measure they are indistinguishable from the other mainstream parties of the left and centre-left and indeed, once other predictors are controlled for, populism's predictive effect on the Conservative group is the lowest of all.

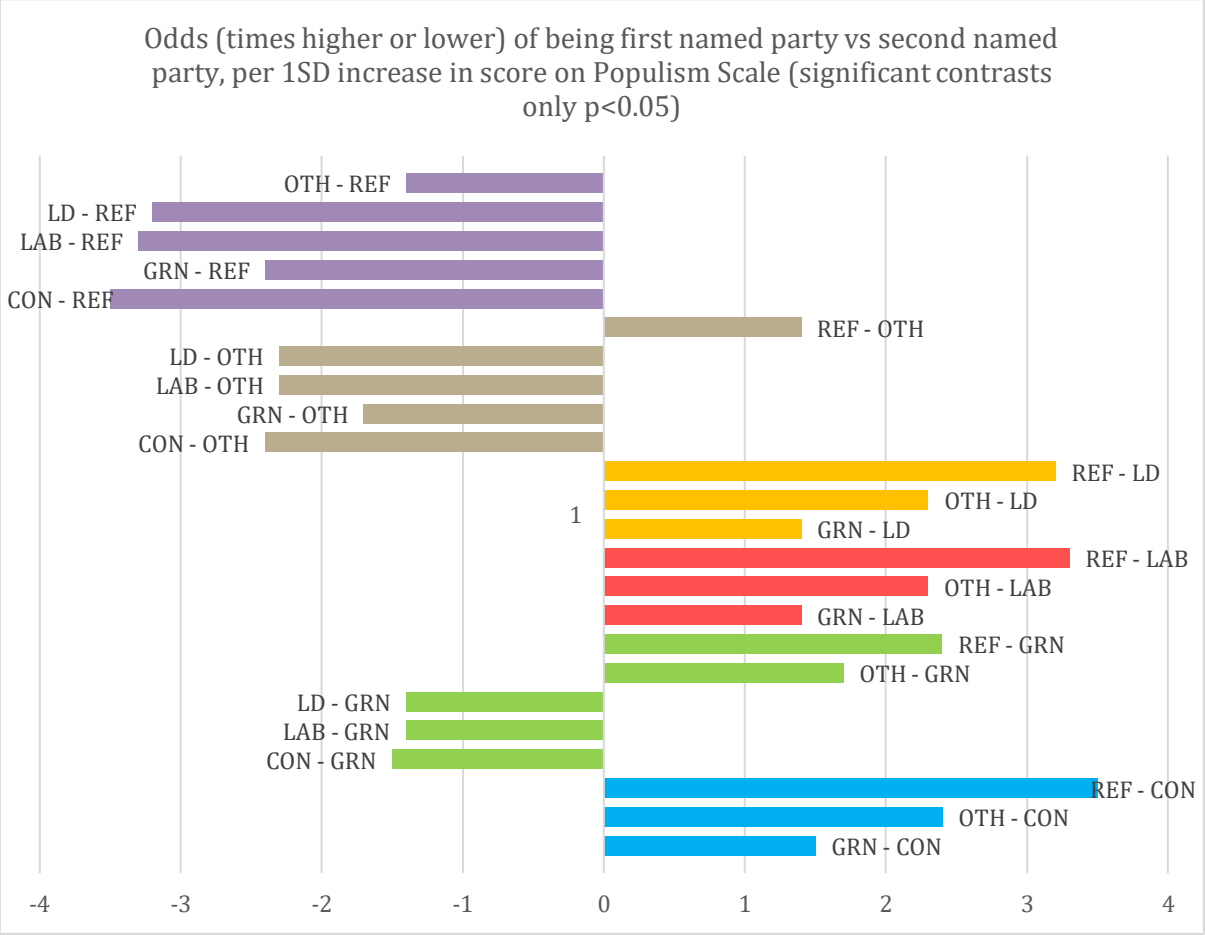


Figure 18: Significant Odds Ratios, Populism (Populism) as predictor of party alignment

7.3.3.3 English National Identity as a predictor of party alignment

Only one pair of parties (Conservative and Liberal Democrat) differ significantly on the English National Identity variable (Relative English National ID) once rurality,

populism, and left-right political placement are controlled for, with a small effect size; a 1SD increase in the relative Englishness score predicts odds of being Conservative rather than Liberal Democrat that are 1.6 times higher.

The estimated marginal means plot is again informative here in explaining the additional explanatory value of this variable in distinguishing Liberal Democrat from Conservatives (Figure 19, below).

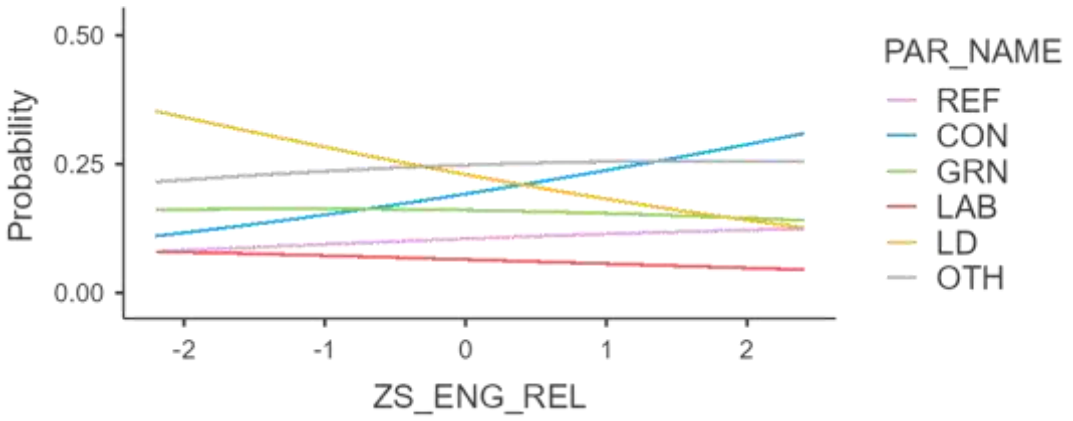


Figure 19: Probability Distribution - English National Identity (Relative English National ID) as a predictor of political party alignment

We have already seen (Section 7.3.1) that Relative English National ID is the strongest predictor of placement on the Left-Right scale. Since the Left-Right Alignment variable is also in the logistic regression model, this correlation likely "soaks up" variance that English nationalism alone would explain for some pairwise party comparisons, especially those like Labour-Conservative, where placement on the left right scale is a stronger predictor. This reduces the unique association of English nationalism in comparisons of Labour or Green Party to Conservative. However, the Liberal Democrat left-right mean is closer to the centre, and the plot above shows a distinct 'mirror' pattern for Liberal Democrat and Conservative; a sense of strong English identity (or lack thereof, in the case of Liberal Democrat) is

very clearly associated with these two party identities, more so than for others, once the other variables in the model are accounted for[38].

7.3.3.4 Left-Right self-placement as a predictor of party alignment

Self-placement on the Left-Right scale is the most powerful predictor in the logistic regression model, even accounting for controlling the other predictors, with many large or very large effect sizes in the pairwise comparisons. Figure 20, below, shows the difference in odds of party membership for each 1SD increase in the Left-Right Alignment scale (1.99 points on a 10-point scale). Note the much larger scale of the bar graph, with odds ratios in the magnitude of 50:1 and even 100:1, compared with around 2-3:1 for the previous predictors. Most notable is that Reform UK and Conservative aligned respondents place themselves so similarly on the Left-Right scale that this measure cannot reliably distinguish between them. This is in sharp contrast to their markedly different positions on the populism predictor; the results demonstrate that 'right-wing' does not automatically equal 'populist', despite the regular twinning of those terms in popular discourse.

[38] Given that the Liberal Democrats consistently maintained the most pro-EU stance both during and since the Brexit referendum, this sense of 'low Englishness' makes some intuitive sense, but is not explored here since the Liberal Democrat grouping is not a focal group for the study.

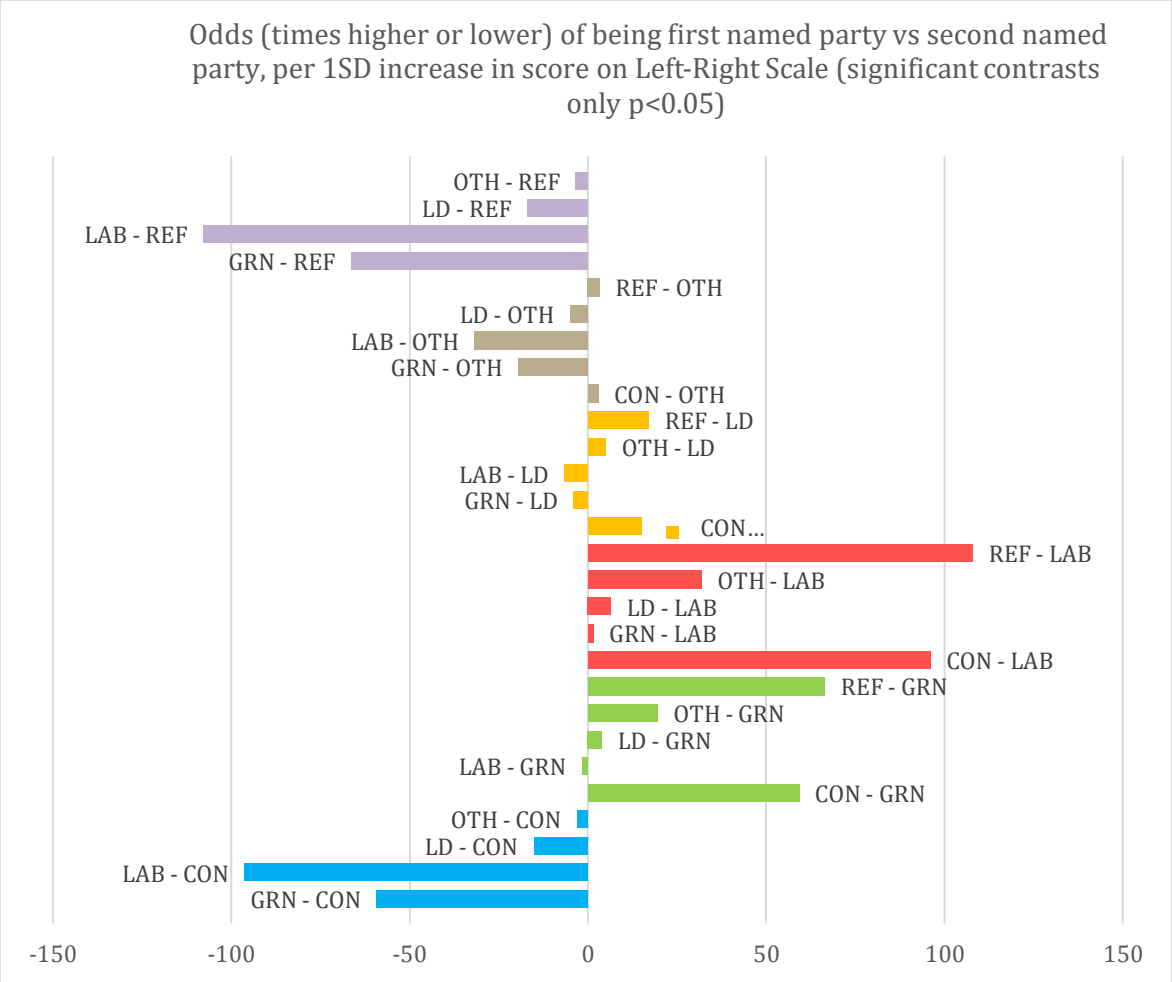


Figure 20: Significant Odds Ratios, Left-Right self-placement (Left-Right Alignment) as predictor of party alignment

Figure 21, below shows the probability distributions from the estimated marginal means. Unlike continuous but milder slopes for other predictors, the marginal means curves exhibit sharp transitions where party probabilities rise or fall rapidly particularly across the mid-point of the scale. It reveals self-placement on the Left-Right scale that tallies with common understandings of the parties in popular discourse. On the left, Labour has the steepest downward slope, with a slightly broader left-of-centre probability distribution for Green Party. Probability of either party membership drops sharply beyond the centre. Conservative, on the other hand, rises steeply from the centre, suggesting Left-Right scores clustered around the 6-7 range, flattening at the high end and signifying that, beyond a certain right-wing position, predicted probability of Conservative alignment does not increase markedly. The continuing upward slope for Reform UK indicates a consistent

increase in the probability of being aligned with this party at very high right-wing positions, reflecting their more concentrated and extreme right positioning, with less flattening. 'Other' occupies a centre-right position, with the Liberal Democrats occupying their traditionally understood centre-left role.

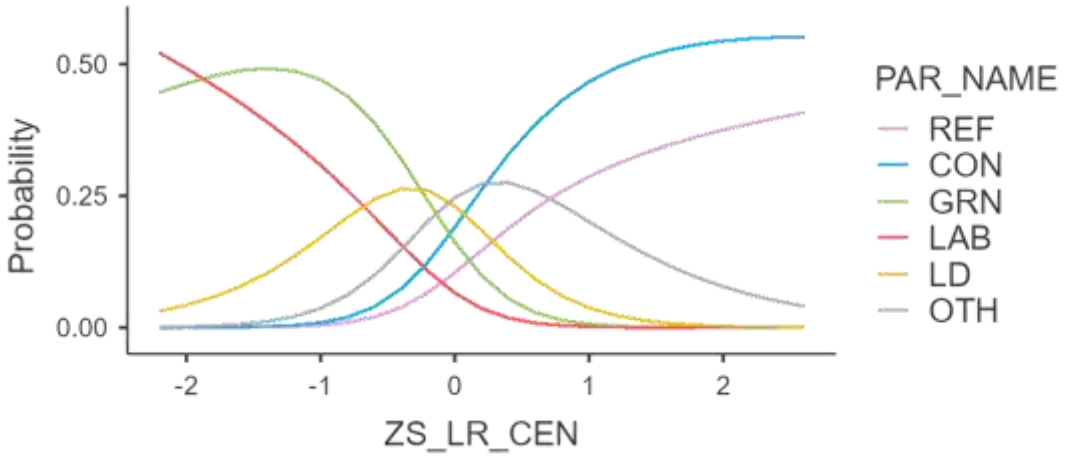


Figure 21: Probability Distribution – self placement on Left-Right scale (Left-Right Alignment) as a predictor of political party alignment

The regression models above imply that, contrary to popular narratives that conflate the political right with populism across the board, members of the Conservative group do not share this profile with either Reform UK or the more amorphous 'Other' grouping. The Conservative group is also characterised by higher rurality (from a 'within rural' sample), compared to the other parties of the right (and indeed all parties). The 'Other' group should not be dismissed as a motley collection of 'floating voters'; rather this grouping represents a meaningful political identity of its own, characterised by quite high levels of English national identity and high populism scores, though not markedly rural. However, although its members broadly consider themselves to be right of centre, this is only marginally so compared to Conservative and Reform UK. The final party of the right, Reform UK, is characterised by high populism, high Englishness, the highest self-perception of rightward placement, but low rurality scores that cannot distinguish members of this group from Labour supporters on that measure.

Finally, it is worth noting that populism is not confined to the political right; Green Party supporters *do* distinguish themselves on this scale, though it is evident that

their populist tendencies are not as strong as the other, highly populist groupings of Reform UK and 'Other'.

7.3.4 Linear Regression 3 – All variables as predictors of Resistance to Rural Climate Initiatives

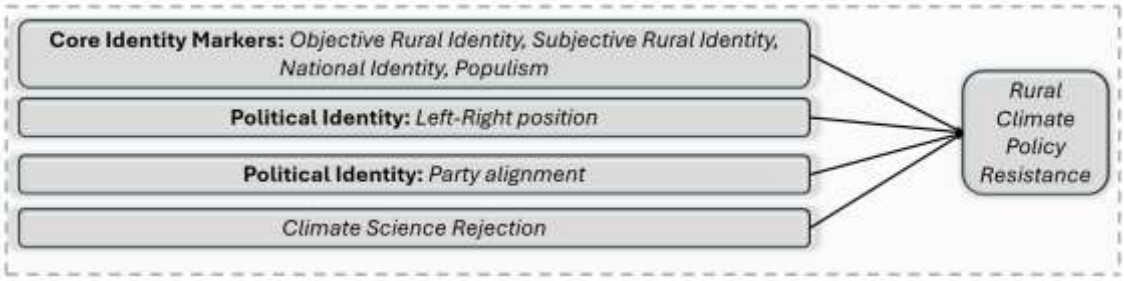


Figure 22: Schematic indicating relationships being tested in this section

A final linear regression model was constructed including all predictors to the final outcome (Figure 22). Adding predictors in hierarchical blocks results in statistically significant and practically meaningful additional explanatory value with each additional variable, culminating in a 6-predictor model with a combined R value of 0.736 (adjusted R2 0.54), and p=<0.001. Results are presented in Table 55, below.

				Overall Model Test			
Model	R	R^2	Adjusted R^2	F	df1	df2	p
1	0.179	0.0321	0.0308	23.4	1	704	< .001
2	0.330	0.1088	0.1063	42.9	2	703	< .001
3	0.471	0.2215	0.2181	66.6	3	702	< .001
4	0.652	0.4251	0.4218	129.6	4	701	< .001
5	0.721	0.5193	0.5159	151.3	5	700	< .001
6	0.736	0.5419	0.5353	82.2	10	695	< .001

Note. Models estimated using sample size of N=706

Model Comparisons

Comparison							
Model		Model	ΔR^2	F	df1	df2	p
1	-	2	0.0766	60.46	1	703	< .001
2	-	3	0.1127	101.58	1	702	< .001
3	-	4	0.2036	248.30	1	701	< .001
4	-	5	0.0943	137.27	1	700	< .001
5	-	6	0.0225	6.83	5	695	< .001

Model Specific Results Model 6

Omnibus ANOVA Test

	Sum of Squares	df	Mean Square	F	p
RUR_CEN	8.23	1	8.231	19.88	< .001
ENG_REL	5.51	1	5.515	13.32	< .001
POP	9.45	1	9.452	22.82	< .001
LR_CEN	21.77	1	21.766	52.56	< .001
CC_CAUSE_NCEN	26.33	1	26.326	63.57	< .001
PAR_NAME	14.15	5	2.829	6.83	< .001
Residuals	287.82	695	0.414		

Note. Type 3 sum of squares

Table 55: Hierarchical Linear Regression, six predictors

7.4 Introduction to the Path Analysis

Neither linear nor logistic regression can offer insight as to *why* these associations might exist. In the final part of this chapter, I therefore turn to Path Modelling, a restricted form of Structural Equation Modelling (SEM), to examine whether the relationships between some variables and the outcome are partially, or even largely, mediated through others.

7.4.1 Understanding the methods used: Introduction to Structural Equation Modelling

SEM is a powerful technique that allows multiple regression terms to be simultaneously estimated, and is accommodating of mixed variable types, meaning that parameter estimates can be calculated for binary, ordinal and continuous variables in the same model. (Fandiño-Losada et al., 2016; Curran and Bauer, 2023). Thus, where regression models measure how two things appear to move together, SEM goes deeper by proposing and testing cause-and-effect relationships. As soon as the concept of causality has been introduced, the researcher has imposed upon the regression equations a one-way relationship. "*Structural equations attain their causal interpretation prior to, and independently of, any statistical relationships among their constituents*" (Pearl, 2009; Tarka, 2018), meaning that the causal inference comes from theory, and the model is used to confirm this. By making explicit assumptions about all relationships in the model, including error relationships, a researcher makes claims about the causal structure of the system. When done well, this is invaluable for policy recommendations, not least because it can reveal mediated relationships; the influence of some variables on the final outcome is at least partially indirect, acting first on an intermediary variable, which then influences the outcome. (Pearl, 2012; Bollen and Pearl, 2013). Such relationships are not possible to model with linear or logistic regression.

The final distinction between regression models and all forms of SEM concerns measures of model fit. Simple Regression Models, can be viewed as a special, restricted form of SEM. They are always 'just-identified' or 'saturated' models. The model uses every possible path and relationship between the variables (significant

or otherwise) to estimate the effects of the predictors on the outcome. Saturated models cannot be subjected to tests of *causal* (structural) fit, not because they are inherently 'right', but because that maximised availability of coefficients and covariances is always sufficient for reproducing the data. (Hayduk and Glaser, 2000).

In SEM, researchers first hypothesise and specify the structure of causal relationships that they believe exists in the population. In doing so, they make theoretical causal assumptions, that suggest ways in which the coefficients of particular paths can be restricted to zero, or other fixed values. (Cole and Preacher, 2014; Curran and Bauer, 2023). It is this restriction of certain paths in the model that allows for the model to be 'unsaturated' or 'over-identified', which is never the case in a linear or logistic model. In an unsaturated model, "*there is more than one possible solution, and the task is to select the one that comes closest to explaining the observed data*" (Kelloway, 1998, pg 15). Since there are more parameters that *could* be estimated than actually *are* being estimated, additional degrees of freedom are created in the model, which allows for tests of model fit of whether the proposed causal structure is plausible, when compared with the data, and ultimately, for different models to be compared. (Schumaker, 2010; Bollen and Pearl, 2013; Curran and Bauer, 2023).

Variables in SEM are referred to as either 'exogenous' variables (for things that are not predicted by anything else in the model), and 'endogenous' variables, for things that are. Endogenous variables can act like traditional outcome variables (dependent in all relations), or as mediator variables (dependent in some but not in all relations). Endogenous variables can therefore predict, while at the same time themselves being predicted by other variables in the model (Israëls, 1987). Some variables are fully mediated, and have no direct path to the final outcome at all. This more obviously represents the sort of complex system found in the social sciences, offering analytical opportunities that are not possible in standard regression models. In general (although there are exceptions using more advanced techniques), SEM models assume a causal flow that runs only in one direction (i.e.

there are no feedback loops between variables). This principle is adopted in the research presented here.

7.4.2 Motivation for Path Model

The choice of Path Modelling, rather than full Structural Equation Modelling, is motivated by the focus on the *structural relationships* (hypothesised causal and mediated paths) between variables. Unlike a full SEM, a Path Model contains no latent variables (whereas a full SEM contains both latent and observed variables).[39]

I examine to what extent the effects of the core identity variables (rurality, nationalism and populism) are meaningfully transmitted through political identity, focusing principally on the idea that the Party Alignment variable (PAR_NAME) acts as a sort of 'prism', into which formative attitudinal influences flow with different strengths, and which then refracts some inputs into concrete attitudes about climate science, and ultimately, resistance to rural climate policy as measured by the RRCI scale.

Two variables within the model (the Populism predictor and final outcome variable 'RRCI_GF) are themselves factor scores from latent variables. I expressly use the factor scores rather than the full latent variables because simultaneously estimating the items on the RRCI_GF scale in particular, which is derived from 18 items, would heavily bias the estimation towards *maximising the measurement of the latent variable itself*, at the expense of estimating the structural relationships between it and the predictors, which are the main focus of this chapter. (Vandenburg and Grelle, 2009; Lance *et al.*, 2016; Lai, 2024) The robustness, stability and uni-dimensionality of that scale have been amply demonstrated in Chapter 6, justifying this choice. Similarly, the measure of Populism is taken from a well-used and established survey instrument used in multiple iterations of the British Election Survey.

[39] Latent variables are those that cannot be measured directly, and in a full SEM the estimation process simultaneously fits the measurement model of the latent variables (through Confirmatory Factor Analysis) as well as estimating the structural elements of the model (the proposed causal paths).

7.4.3 Model Fit in SEM and Path Models

Contrary to normal practice, where the researcher hopes to be able to reject the null hypothesis to show an effect, in SEM tests of 'global fit' a researcher is looking for a *non*-significant result, which is interpreted as support for the hypothesised model. Hayduk (2014) terms this the 'notable-null hypothesis', rather than a 'nil-null hypothesis'.

The non-significant result for model fit indicates that the *implied* variance-covariance matrix in the proposed model structure so closely mirrors the *actual* variance-covariance matrix of the sample dataset that the model can be accepted as truly representative of the sample (and, by extension, the population where the sample has been drawn in such a way that inference is possible).

A decades-long debate about the appropriate uses of the tests of fit for SEMs rumbles on. To the uninitiated, the literature covering these debates is near impossible to navigate, but reasonable insight can be gleaned via Hu and Bentler, 1999; Tomarken and Waller, 2003; Barrett, 2007; Markland, 2007; Millsap, 2007; Bollen and Davis, 2009; Ropovik, 2015; Lance et al., 2016; Marcoulides and Yuan, 2017; Xia and Yang, 2019; Peugh and Feldon, 2020; Ximénez et al., 2022; McNeish and Wolf, 2023; McNeish and Manapat, 2024.

The only true statistical test of model fit (Model Chi-Squared, [χ^2] Test) is often significant, purely as a result of trivial differences revealed by large samples. I look for a non-significant χ^2 test result in the first instance. Following Carmines and McIver, 1983, if the Model χ^2 is significant, I look for a χ^2/degrees of freedom ratio <3, which diagnoses a model with significant χ^2 that is nonetheless probably well-fitted.

A wider range of model fit indices are also available, which are not true statistical tests, but instead "*indicate the degree to which a model might be 'discrepant*" (Barrett, 2007). I refer, with caution, to the widely used cutoffs for the following measures:

a) Absolute measures of fit (RMSEA and SRMR) <0.08 (acceptable) <0.05 (excellent)
b) Relative measures of fit (TLI and CFI) ≥ 0.95
c) Model comparison test (AIC and BIC) no absolute scale, smaller result preferred, recognising that BIC penalises complexity more.

However, I note the persistent survival of these 'rules of thumb' despite decades of criticism that they should not be mindlessly applied. I treat them as indicators that a model may have acceptable fit, but engage in a thoughtful consideration of the relative fit of models, accounting for context and complexity, rather than as binary 'fit/no-fit' measures that would risk useful model refinement being abandoned before time. (Shi et al, 2019; Xia and Yang, 2019; van Laar and Braeken, 2021). I also look for model structures that provide adequate degrees of freedom for fit indices to be reliable, relative to the complexity of my models. Given the sample size available, I take df>10 as the level at which fit results can be relied upon (Kenny et al, 2015). A fuller explanation can be found in the Methods Annex.

7.4.4 Model Estimation Method

I estimate the Path Models using Maximum Likelihood estimation with robust Satorra–Bentler corrections to account for departures from multivariate normality; the dataset (N = 707) comprised a mix of continuous and ordinal measures, including one theoretically important continuous predictor that exhibited substantial positive skew. Although all continuous variables were mean-centred, assumptions of normality were not met, a common feature of Likert type and attitudinal data. Robust Satorra–Bentler corrections adjust model χ^2 values, standard errors, and fit indices for nonnormality, providing more accurate statistical inference.

In addition, I use bootstrapping to estimate the sampling distribution of the parameter estimates. Bootstrapping is a computationally intensive process that fits models repeatedly to multiple random draws from the original sample (with replacement). Tests of model fit are then based on the empirical distribution of these repeated samples, rather than the assumed hypothetical normal distribution

that ML estimation relies on for best performance. 1000 bootstrapped samples were drawn for each estimation, providing a rigorous basis for the significance testing. (Curran and Bauer, 2023). I use percentile bootstrapping, rather than the more commonly applied bias-corrected bootstrapping, following the advice of Fritz, *et al* (2012) and Tibbe and Montoya, (2022), that this approach minimises the likelihood of Type I Error.

7.4.5 Mediation Analysis

In regression analysis, it is widely understood that association does not imply causation. This fundamental caution extends to more complex statistical approaches, including SEM. Traditionally therefore, causation was not inferred from statistical models unless the data were derived from experimental design (Kim, 2016).

A *mediator variable* explains at least part of the underlying mechanism of the relationship between two other variables (Kim, 2016). Effectively, mediators 'transmit' the effect of a predictor on an outcome (MacKinnon et al., 2007). The total effect of a predictor on the final outcome can therefore be expressed as the decomposition of its direct effect, and any additional indirect effect that it has on the outcome via mediators. These indirect effects can act to both amplify or suppress the effect of one variable on another, reflecting the complexity of social processes, and this analytical ability is unique to SEM.

While traditionally applied only to experimental data, mediation analysis techniques have increasingly come to be used with observational data. While a SEM cannot be said to "prove" causation from associations alone, it can be used to test whether observed data are *consistent with* the causal structure hypothesised by the researcher. If the model fits well, then the specification is justified and the conclusions can be interpreted as *indicative of* causal relationships, on the assumption that no confounding variables not included in the model also play a part.

Once acceptable fit is achieved, I therefore interpret the path model results with the caveat that all the causal assumptions made "*remain only one study away from*

rejection" and only become more plausible when they "*have survived a variety of tests in different samples and under different circumstances"*. (Bollen and Pearl, 2013).

7.5 Model Specification and Fitting

7.5.1 Model Specification

An initial model was specified (detailed in Figure 23, below) drawing on the theoretically proposed relationships originally outlined in Figure 12, and subsequently informed by the findings of the linear and logistic regression modelling outlined in 7.3.1 to 7.3.4, above. The original categorical party alignment variable (PAR_NAME) was recoded here as a set of Effect Coded variables. These sit in the centre of the model, allowing party alignment to act as the 'prism' through which the strength of paths to the final outcomes is then interpretable.

Unlike binary dummy coding (coded 1,0, with results interpreted with reference to an intercept representing the mean of a selected reference group), effect coded variables are trichotomous (coded 1, 0, -1). The -1 coded group is sometimes referred to as a baseline group, but *does not* represent the intercept from which all other results are compared. Instead, it acts as a group whose mean is incorporated such that all parameter estimates sum to zero. This ensures that coefficients reflect deviations from the overall *mean of the means of all the groups* (the unweighted grand mean), rather than from a specific reference group[40]. (Alkharusi, 2013; te Grotenhuis et al., 2017). In the present study, this ensures the predictive effects of party choice on the outcome variables are neither weighted towards the largest group, nor subject to bias by selection of an arbitrary party to act as a baseline. Instead, they represent deviations from the 'political centre' or 'average voter' in the sample set, a more meaningful comparison.

The nature of effect coding, like all dummy coding, is that the effect coded variables act as a set. Thus, paths from or to the effect coded variables must run to all or none

[40] The -1 coded group's coefficient can be manually calculated as minus the sum of the other coefficients, if a full set of results is needed.

of them; insignificant paths cannot be pruned for parsimony, because there is statistical interdependency in the set. Mutual exclusivity also requires forcing pairwise covariances across the set.

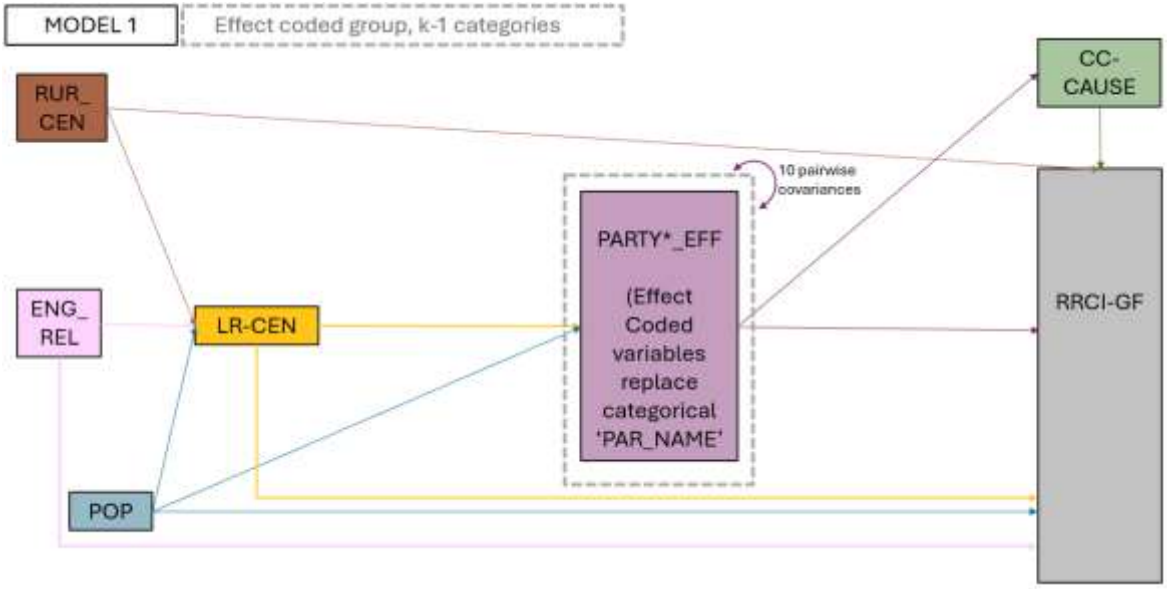


Figure 23: Model 1 (Initial Path Model specification)

7.5.2 Testing model fit, and re-specification

Table 56, below, presents the structure and fit measures for all iterations of the model re-specification.

Model 1, (Figure 23) although adequate in terms of the Approximate Fit Indices CFI, TLI, RMSEA and SRMR, nonetheless returned a significant χ^2 test of overall model fit, with a χ^2/df ratio of 5, suggesting the hypothesised structure was not a near-exact fit to the data.

Given the more nuanced modelling abilities of Path Models compared to simple regression, I next re-specified the model to reintroduce the 'RUR_URB' variable (Subjective Rural Identity). This *had* reached statistical significance in some of the earlier simple linear models, but had not seemed to offer substantial additional explanatory value, and had thus been dropped from consideration.

The re-inclusion of the RUR_URB variable in the model (Model 2) resulted in mixed, though generally favourable fit statistics. While the coefficients for this predictor to the outcome were of borderline significance (p=0.059) and the Likelihood Ratio Test (LRT) was not significant ($\Delta\chi^2$ = 9.3, Δdf = 7, p = 0.23, suggesting the added complexity was not statistically justified), several key fit indices nonetheless showed meaningful improvement. RMSEA improved from 0.069 (pClose = 0.039) to 0.058 (pClose = 0.186), moving from marginal to good fit and demonstrating clear evidence of close fit to the data. TLI also improved from 0.939 to 0.951, crossing the conventional threshold for good fit, while CFI and SRMR remained stable. I concluded that this variable most likely has a small but important role as a complement to the other measure of rurality, Objective Rural Identity. However, since the χ^2/df ratio remained >2 (at 3.86), I proceeded with further, theory driven refinements.

In Model 3, I introduced additional paths directly from Objective Rural Identity to the party effect coded variables, given that it had acted as a useful predictor that substantially differentiated Conservative from Labour and Reform UK groups in logistic regression.

The addition of the five new paths to the effect-coded variables in Model 3 resulted in a sizeable improvement in model fit that is unusual when adding substantial complexity. The LRT was highly significant ($\Delta\chi^2$ = 26.3, Δdf = 5, p < 0.001), strongly supporting the retention of the additional paths. Unexpectedly, despite adding five new parameters, the model achieved better fit with greater parsimony, as evidenced by the chi-square decreasing from 81.1 to 54.8, while degrees of freedom only decreased from 21 to 16. All practical fit indices showed consistent improvement: CFI increased from 0.983 to 0.989, TLI from 0.951 to 0.958, SRMR decreased from 0.025 to 0.020, and RMSEA improved from 0.058 to 0.053 (pClose = 0.345). AIC also decreased by 11 points, indicating improved predictive accuracy, though BIC (which is known to penalise complexity) increased by 11 points. Overall, this suggests that the paths represent important relationships and a more accurate representation of the underlying causal structure. However, since the χ^2/df remained >2 (at 3.42) I considered whether further, theory driven refinements could still be made.

In the earlier models, the effects of Populism on Rejection of Climate Science had been specified to run entirely through Party Alignment, but linear regression had suggested this may be too simplistic. In Model 4, I therefore added an additional predictive path from Populism to Rejection of Climate Science. The addition of this single direct path (in addition to the path via the effect-coded mediators) resulted in substantial model improvement. The LRT was highly significant ($\Delta\chi^2 = 24.6$, $\Delta df = 1$, $p < 0.001$), providing strong statistical justification for retaining this additional pathway. Model fit reached excellent levels across all indices: CFI = 0.995, TLI = 0.982, SRMR = 0.015, and RMSEA = 0.035 (pClose = 0.886). $\chi^2(15) = 30.2$, $p = 0.022$, with a favourable chi-square to degrees of freedom ratio of 2.01. Crucially, at this point the χ^2/df reached 2, and the improvement in the χ^2 p-value from <0.001 to 0.022 indicated a model that is approaching perfect reproduction of the observed covariance matrix. Both information criteria also improved (AIC = 9213, BIC = 9491), suggesting that the direct pathway captures a theoretically important relationship that had previously forced model misspecification. Model 4 (see Figure 24, below) was therefore retained for all subsequent analyses.

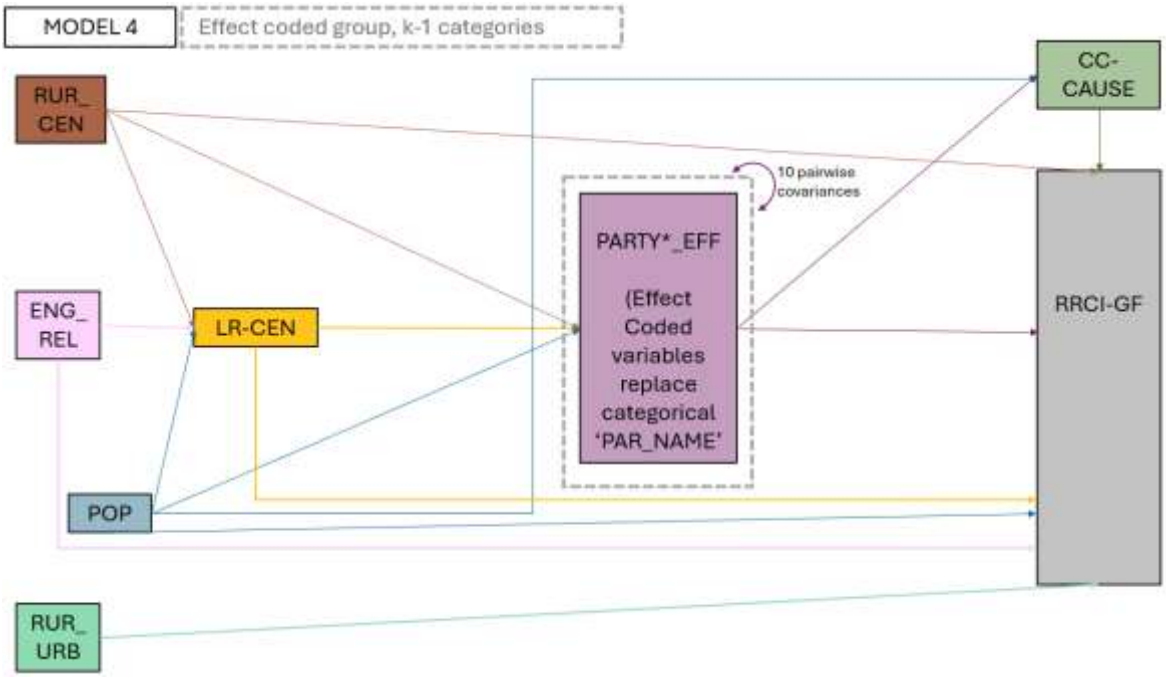


Figure 24: Model 4 (Final Path Model specification)

7.5.3 Model Fit Measures

All Rounds: n=707; ML estimation; bootstrapped SE (percentile, 1000 samples); non-centrality parameter (λ) of baseline model >1400

Specification - Path Model 1:

All *PAR*_EFF codes ~ Populism +Left-Right Alignment

Left-Right Alignment~ Populism + Objective Rural Identity + Relative English National ID

Rejection of Climate Science ~ All *PAR*_EFF codes

RRCI_GF ~ Populism + Objective Rural Identity +Relative English National ID + Left-Right Alignment+ Rejection of Climate Science + All *PAR*_EFF codes

All *PAR*_EFF codes ~~ pairwise

Free Parameters: 54

χ^2 (Satorra Bentler)	**df**	**χ^2/df**	**CFI**	**TLI**	**SRMR**	**RMSEA**	**RMSEA CI (lower)**	**RMSEA CI (upper)**	**AIC**	**BIC**
71.8 (p<0.001)	14	5.1	0.984	0.939	0.025	0.069 (pClose = 0.039)	0.051	0.087	9245	9491

Specification - Path Model 2: As per Model 1, with additional variable Subjective Rural Identity as predictor of RRCI								***Free Parameters: 55***		
χ^2 (Satorra Bentler)	**df**	**χ^2/df**	**CFI**	**TLI**	**SRMR**	**RMSEA**	**RMSEA CI (lower)**	**RMSEA CI (upper)**	**AIC**	**BIC**
81.1 (p<0.001)	21	3.9	0.983	0.951	0.025	0.058 (pClose = 0.186)	0.043	0.073	9243	9494
Specification - Path Model 3: As per Model 2, with variable Objective Rural Identity now predicting all party effect codes as well								***Free Parameters: 60***		
χ^2 (Satorra Bentler)	**df**	**χ^2/df**	**CFI**	**TLI**	**SRMR**	**RMSEA**	**RMSEA CI (lower)**	**RMSEA CI (upper)**	**AIC**	**BIC**
54.8 (p<0.001)	16	3.4	0.989	0.958	0.020	0.053 (pClose = 0.345)	0.037	0.071	9232	9505
Specification - Path Model 4: As per Model 3, with variable Populism now predicting Rejection of Climate Science as well								***Free Parameters: 61***		
χ^2 (Satorra Bentler)	**df**	**χ^2/df**	**CFI**	**TLI**	**SRMR**	**RMSEA**	**RMSEA CI (lower)**	**RMSEA CI (upper)**	**AIC**	**BIC**
30.2 p =0.022	15	2.0	0.995	0.982	0.015	0.035 (pClose = 0.886)	0.013	0.055	9213	9491

Table 56: Model Fit Measures

7.6 Path Model Results

7.6.1 Understanding complexity in interpreting effect-coded variables

Although effect coded variables bring benefits in interpreting onward paths to the final outcome (since they can be interpreted as deviations from the group means) this does introduce complications that reduce the ease with which the coefficients in the *front half* of the model can be interpreted. Where effect coded variables are *being predicted*, interpretation is similar to a traditional dummy-coded linear regression model; the party acting as the -1 coded group acts as the 'perspective' from which other party relationships with the predictors are viewed. Altering the -1 coded party group in the set affects the magnitude, significance and (in some cases) the sign of the coefficients leading from predictors to party in individual paths. This, in turn, requires cautious interpretation of direct coefficients, and is particularly evident in coefficients for parties that occupy a similar distribution on the predictor variables, as would be evident in a normal dummy coded approach with a specific reference group.

To ensure that (a) these fluctuations do not impact the overall 'story' told by the model, and (b) the results are not biased by presentation of only one baseline model, complete I carried out six iterations of the analysis (with each party acting as the -1 coded 'invisible' group in the effect coded scheme). Model Fit statistics were identical across all specifications (whichever party group acts as the -1 coded group), confirming mathematical equivalence, and close examination of the full indirect effects and total effects showed that overall variation in standardised coefficients in *full* paths vary by a maximum of 0.033.

7.6.2 Direct Paths - predicting party alignment

7.6.2.1 Populism (Populism) as a predictor of party alignment

Tables 57 a-f, below reveal that, despite the complexities of effect coding, the predictive strength of Populism is easily interpreted for the variables Conservative and Reform UK. Populism is always negatively and significantly associated with membership of the

Conservative group, regardless of the baseline party in the model, with effect sizes ranging from small (with Labour and Liberal Democrat contrasts) to large (with Reform UK contrast). This suggests that, controlling for other predictors on the model, members of the Conservative group have the lowest propensity towards populism.

By contrast, Populism is always positively associated with membership of the Reform UK group, regardless of the baseline party in the model, with effect sizes ranging from very small (and near significance) for the contrast with 'Other', to medium (when contrasted with Labour or Liberal Democrat), to a large effect size when contrasted with Conservative. This suggests that, controlling for other predictors on the model, the Reform UK group has the highest propensity towards populism (though only barely distinguishable from the 'Other' group on this measure).

The predictive strength of Populism on 'Other' reflects a similar but slightly attenuated version of the Populism to Reform UK pattern, suggesting that members of the 'Other' group have a propensity to higher populism scores when compared to all other groups except Reform UK.

For the remaining three groups, the pattern requires more caution. Generally, the predictive strength of Populism on Liberal Democrat suggests that members of this group have a lower propensity to populism than any other group apart from Conservative. However, the predictor cannot distinguish between Liberal Democrat and Labour in a way that is statistically significant.

For members of the Green Party group, the overall pattern suggests that Green Party group members occupy a populism middle-ground. Controlling for all other predictors in the model, members of this group have a lower propensity to populism than members of the 'Other' group (fractionally), and the Reform UK group (substantially), while having a higher propensity towards populism than Labour, Liberal Democrat (small effect size) or Conservative (medium effect size).

Finally, the Labour variable as predicted by Populism presents the most variable pattern. By contrast with Green Party, 'Other' and Reform UK group members, Labour members display a lower propensity to populism, but a higher propensity than

Conservative. As previously noted, Labour and Liberal Democrat are not distinguishable on this measure.

PARTY EFFECT CODES PREDICTED BY POP

Each small table shows the coefficient for the relationship between POP and that party code, in each different baseline model

Dep	Pred		
GRN_EFF	POP		
'Minus-one' coded party in model		β	p
	OTH	-0.073	0.043
	GRN		
	LAB	0.079	0.045
	LD	0.088	0.013
	CON	0.176	<.001
	REF	-0.141	<.001

Dep	Pred		
LAB_EFF	POP		
'Minus-one' coded party in model		β	p
	OTH	-0.160	<.001
	GRN	-0.079	0.040
	LAB		
	LD	0.007	0.837
	CON	0.109	<.001
	REF	-0.229	<.001

Dep	Pred		
LD_EFF	POP		
'Minus-one' coded party in model		β	p
	OTH	-0.172	<.001
	GRN	-0.088	0.016
	LAB	-0.007	0.843
	LD		
	CON	0.106	0.002
	REF	-0.244	<.001

Dep	Pred		
CON_EFF	POP		
'Minus-one' coded party in model		β	p
	OTH	-0.255	<.001
	GRN	-0.176	<.001
	LAB	-0.109	<.001
	LD	-0.106	0.001
	CON		
	REF	-0.316	<.001

Dep	Pred		
REF_EFF	POP		
'Minus-one' coded party in model		β	p
	OTH	0.072	0.059
	GRN	0.141	<.001
	LAB	0.229	<.001
	LD	0.244	<.001
	CON	0.316	<.001
	REF		

Dep	Pred		
OTH_EFF	POP		
'Minus-one' coded party in model		β	p
	OTH		
	GRN	0.073	0.048
	LAB	0.160	<.001
	LD	0.172	<.001
	CON	0.255	<.001
	REF	-0.072	0.069

Tables 57a-f: Direct Effect of Populism on party alignment per baseline model, negative coefficients in red, significant (p<0.05) in green

7.6.2.2 Objective Rural Identity (Objective Rural Identity) as a predictor of party alignment

Tables 58a-f, below, also demonstrate that the predictive strength of Objective Rural Identity is most easily interpreted for the variables Conservative and Labour. Objective Rural Identity is always positively and significantly associated with membership of the Conservative group, and always negatively associated with Labour, regardless of the baseline party in the model.

Similarly, the measure meaningfully distinguishes Labour members from all other groups apart from Reform UK, by their propensity to lower levels of rurality, confirming the simple regression results that Reform UK and Labour voters have similar levels of 'low objective rurality'.

As with the simple regression, the effect sizes of the coefficients of this predictor are small to very small. However, this is contextualised when one considers that the entire

sample is drawn from rural places, and thus the ability of this index to distinguish respondents is constrained. Finding practically and statistically meaningful differences, particularly in prediction of a concrete marker of identity like political party alignment (which has practical meaning in everyday policy contexts, and operates at the whole-population level) is likely to be important, and the contrast between Conservative (most rural) and Labour/Reform UK (least rural) is particularly notable.

PARTY EFFECT CODES PREDICTED BY RUR_CEN

Each small table shows the coefficient for the relationship between RUR_CEN and that party code, in each different baseline model

'Minus-one' coded party in model	Dep: GRN_EFF / Pred: RUR_CEN β	p
OTH	0.008	0.801
GRN		
LAB	0.073	0.018
LD	0.001	0.969
CON	-0.069	0.045
REF	0.059	0.033

'Minus-one' coded party in model	Dep: LAB_EFF / Pred: RUR_CEN β	p
OTH	-0.068	0.030
GRN	-0.073	0.012
LAB		
LD	-0.078	0.011
CON	-0.143	<.001
REF	-0.014	0.608

'Minus-one' coded party in model	Dep: LD_EFF / Pred: RUR_CEN β	p
OTH	0.007	0.839
GRN	-0.001	0.970
LAB	0.078	0.007
LD		
CON	-0.076	0.047
REF	0.063	0.043

'Minus-one' coded party in model	Dep: CON_EFF / Pred: RUR_CEN β	p
OTH	0.080	0.046
GRN	0.069	0.043
LAB	0.143	<.001
LD	0.076	0.052
CON		
REF	0.128	<.001

'Minus-one' coded party in model	Dep: REF_EFF / Pred: RUR_CEN β	p
OTH	-0.054	0.155
GRN	-0.059	0.039
LAB	0.014	0.623
LD	-0.063	0.041
CON	-0.128	0.002
REF		

'Minus-one' coded party in model	Dep: OTH_EFF / Pred: RUR_CEN β	p
OTH		
GRN	-0.008	0.816
LAB	0.068	0.037
LD	-0.007	0.842
CON	-0.080	0.055
REF	0.054	0.141

Tables 58a-f: Direct Effect of Objective Rural Identity on party alignment per baseline model, negative coefficients in red, significant (p<0.05) in green

7.6.2.3 Left-to-Right self-placement (Left-Right Alignment) as a predictor of party alignment

Finally, Tables 59a-f also confirm the broad outcome of the earlier logistic regression, in demonstrating that self-placement on the left-right scale is a powerful predictor of party alignment.

However, unlike the earlier logistic regression, a subtle difference emerges in the coefficients for Left-Right Alignment as a predictor of party in the path model; Conservative group members show the highest propensity to have high scores (to the right on the Left-Right Alignment scale), higher even than Reform UK, in all models.

This is most likely because the Left-Right Alignment variable itself plays an endogenous role in the path model, being predicted by Relative English National ID (the measure of English Nationalism), which does not directly predict party.

The Conservative group shows stronger direct effects of left-right placement on party choice, despite the Reform UK group having a slightly higher mean score on Left-Right Alignment (6.89 vs 6.74). Both groups also display similar scores and distributions on Relative English National ID (Conservative vs Reform UK means of 0.149 vs 0.161, and distributions 0.818, and 0.854). The path model therefore seems to reveal that the Reform UK group's right-wing positioning appears more tightly coupled to nationalist sentiment, with much of this relationship flowing through the mediated pathway Relative English National ID → Left-Right Alignment→ Party Alignment. In contrast, while Conservative voters may derive some of their right-leaning ideological positioning from nationalist sentiment, these are likely to be enhanced by other influences (broader economic conservatism, traditionalism etc), creating a stronger direct effect of left-right placement for Conservatives once the nationalism-mediated pathway is statistically controlled.

PARTY EFFECT CODES PREDICTED BY LR_CEN

Each small table shows the coefficient for the relationship between LR_CEN and that party code, in each different baseline model

Dep	Pred		
GRN_EFF	LR_CEN		
'Minus-one' coded party in model		β	p
	OTH	-0.347	<.001
	GRN		
	LAB	-0.025	0.577
	LD	-0.223	<.001
	CON	-0.540	<.001
	REF	-0.489	<.001

Dep	Pred		
LAB_EFF	LR_CEN		
'Minus-one' coded party in model		β	p
	OTH	-0.339	<.001
	GRN	0.025	0.559
	LAB		
	LD	-0.208	<.001
	CON	-0.543	<.001
	REF	-0.488	<.001

Dep	Pred		
LD_EFF	LR_CEN		
'Minus-one' coded party in model		β	p
	OTH	-0.142	<.001
	GRN	0.223	<.001
	LAB	0.208	<.001
	LD		
	CON	-0.370	<.001
	REF	-0.300	<.001

Dep	Pred		
CON_EFF	LR_CEN		
'Minus-one' coded party in model		β	p
	OTH	0.234	<.001
	GRN	0.540	<.001
	LAB	0.543	<.001
	LD	0.370	<.001
	CON		
	REF	0.089	0.021

Dep	Pred		
REF_EFF	LR_CEN		
'Minus-one' coded party in model		β	p
	OTH	0.155	<.001
	GRN	0.489	<.001
	LAB	0.488	<.001
	LD	0.300	<.001
	CON	-0.089	0.018
	REF		

Dep	Pred		
OTH_EFF	LR_CEN		
'Minus-one' coded party in model		β	p
	OTH		
	GRN	0.347	<.001
	LAB	0.339	<.001
	LD	0.142	<.001
	CON	-0.234	<.001
	REF	-0.155	<.001

Tables 59a-f: Direct Effect of Left-Right Alignment on party alignment per baseline model, negative coefficients in red, significant (p<0.05) in green

7.6.3 Indirect Paths (Mediated Relationships)

Table 60, below, presents the Total Indirect Effect, Direct Effect, and Total Effect for each predictor in the model, contextualised with effect size estimates (per Funder & Ozer), showing the proportion each predictor's effect that is mediated through other predictors in the model. Non-significant and borderline significance coefficients are highlighted red and yellow, respectively.

Predictor	ALL Party Effect Coded models																				
	TOTAL INDIRECT EFFECT							DIRECT EFFECT							TOTAL EFFECT							Proportion of total effect mediated
	Estimate	SE	Lower CI	Upper CI	β	p	Effect Size	Estimate	SE	Lower CI	Upper CI	β	p	Effect Size	*Estimate*	*SE*	*Lower CI*	*Upper CI*	*β*	*p*	*Effect Size*	
POP	0.193	0.024	0.147	0.241	0.205	<0.001	m	**0.131**	**0.029**	**0.079**	**0.190**	**0.139**	<0.001	s	*0.324*	*0.030*	*0.262*	*0.379*	*0.344*	*<0.001*	*l*	60%
RUR_CEN	0.016	0.005	0.006	0.026	0.06	0.002	vs	**0.028**	**0.007**	**0.014**	**0.042**	**0.108**	<0.001	s	*0.044*	*0.008*	*0.029*	*0.059*	*0.17*	*<0.001*	*s-m*	35%
ENG_REL	0.114	0.019	0.075	0.151	0.107	<0.001	s	**0.102**	**0.033**	**0.040**	**0.164**	**0.095**	**0.002**	vs-s	*0.217*	*0.035*	*0.155*	*0.288*	*0.202*	*<0.001*	*m*	53%
LR_CEN	0.087	0.016	0.054	0.119	0.184	<0.001	s-m	**0.138**	**0.021**	**0.093**	**0.180**	**0.291**	<0.001	m-l	*0.226*	*0.015*	*0.195*	*0.253*	*0.475*	*<0.001*	*vl*	39%
CC_CAUSE_NCEN	N/A	N/A	N/A	N/A	N/A	N/A	N/A	**0.489**	**0.059**	**0.367**	**0.609**	**0.275**	<0.001	m-l	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	0%
RUR_URB	N/A	N/A	N/A	N/A	N/A	N/A	N/A	**0.152**	**0.080**	**-0.016**	**0.311**	**0.050**	**0.059**	vs	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	0%
GRN_EFF	-0.146	0.020	-0.186	-0.108	-0.090	<.001	vs-s	**-0.272**	**0.065**	**-0.402**	**-0.152**	**-0.167**	<.001	s-m	*-0.417*	*0.067*	*-0.551*	*-0.291*	*-0.256*	*<0.001*	*m-l*	35%
LAB_EFF	-0.124	0.019	-0.160	-0.087	-0.073	<.001	vs-s	**-0.012**	**0.065**	**-0.146**	**0.107**	**-0.007**	**0.859**	vs	*-0.134*	*0.070*	*-0.265*	*0.002*	*-0.078*	*0.054*	*vs-s*	94%
LD_EFF	-0.126	0.019	-0.165	-0.089	-0.072	<.001	vs-s	**-0.153**	**0.060**	**-0.279**	**-0.037**	**-0.087**	**0.011**	vs-s	*-0.279*	*0.060*	*-0.403*	*-0.167*	*-0.158*	*<0.001*	*s-m*	46%
CON_EFF	0.002	0.017	-0.031	0.035	0.001	0.896	ne	**-0.049**	**0.063**	**-0.171**	**0.079**	**-0.031**	**0.441**	vs	*-0.050*	*0.064*	*-0.172*	*0.078*	*-0.032*	*0.433*	*vs*	0%
REF_EFF	0.291	0.039	0.220	0.367	0.173	<.001	s-m	**0.286**	**0.072**	**0.145**	**0.429**	**0.170**	<.001	s-m	*0.577*	*0.070*	*0.440*	*0.717*	*0.343*	*<0.001*	*l*	50%
OTH_EFF*	0.104	0.030	0.050	0.167	0.064	<.001	vs-s	**0.199**	**0.063**	**0.072**	**0.319**	**0.123**	**0.001**	s	*0.303*	*0.070*	*0.153*	*0.437*	*0.186*	*<0.001*	*s-m*	34%

All results reported from model OTH coded -1, except *.

*** coefficients for OTH taken from GRN baseline model to obtain SE, CI and pValues. (Raw estimate & β confirmed as consistent with coding scheme of 1- ∑ all other coefficients in the OTH -1 coded model).**

Raw and standardised estimates in non-party paths identical across models, with minor fluctuations in CI and SE values.

Estimates for paths including party-effect codes vary slightly due to shifting baseline effect in front half of model. Max variance in Total Effect of standardised estimate =0.033.

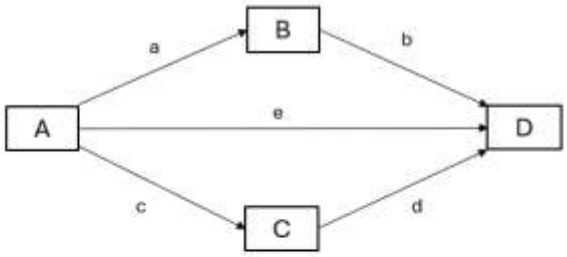
Total Effect = sum of 'total indirect' effect and 'direct effect' coefficients.

Effect Size: ne= no effect, vs=very small, s=small, m=medium, l=large, vl=very large (Funder & Ozer)

Bootstrapped standardised estimates

Table 60: Direct Effect, Total Indirect Effect and Total Effect of predictors on outcome 'Resistance to Rural Climate Initiatives'

A Specific Indirect Effect is the effect of a given predictor on Resistance to Rural Climate Initiatives, (RRCI_GF), *as mediated by* other relationships in the model. The Total Indirect Effect for any predictor is the sum of all its Specific Indirect Effects leading to the outcome. As per standard practice, these are summed regardless of whether individual indirect paths reach statistical significance. (Curran and Bauer, 2023). Since a Specific Indirect Effect is the product (not the sum) of two effects, it is not unusual for these effects to be smaller than those in simple regression, and they are interpreted in light of this (Kenny, 2025). The relationship between Specific Indirect Effects, Total Indirect Effects and Total Effects is illustrated in Figure 25, below.



TOTAL EFFECT: Sum of the values on **all possible paths** from predictor to outcome
TOTAL INDIRECT EFFECT: Sum of **all possible indirect** paths from predictor to outcome
TOTAL SPECIFIC EFFECT: Product of any **single indirect** path leading from predictor to outcome

e	direct effect of A on D
a x b	Specific Indirect Effect (A on D, via B)
c x d	Specific Indirect Effect (A on D, via C)
(a x b) + (c x d)	Total indirect Effect (sum of products)
(a x b) + (c x d) + e	TOTAL EFFECT of A on D

Figure 25: Indirect, Direct, and Total Effects illustration

7.6.4 Interpreting Indirect Effects in the model – Party Alignment

Table 60 gives the results for all predictors, extracted from the model with the 'Other' group coded as -1[41].

Taking the 'back half' of the model first, I consider the predictive effect of party alignment on Resistance to Rural Climate Initiatives. This is comprised of the direct

[41] Coefficients for 'Other' itself are taken from the Green Party-1 baseline model, in order to obtain SE, CI and pValues, however, the raw estimate & β are confirmed as consistent with the coding scheme of 1-∑ all other coefficients in the 'Other' -1 coded model.

predictive power of party alignment alone, as well as the mediating relationship between party and the rejection of climate science to the final outcome.

The Total Effects are all statistically significant at <0.001 for Green Party, Liberal Democrat, 'Other' and Reform UK, while Labour hovers near, but just above p<0.05 in all models.

Green Party and Liberal Democrat group membership predicts scores lower than the mean on the outcome variable, with very small indirect effects via Rejection of Climate Science variable. Additionally, membership of both groups directly predicts lower than mean scores on the outcome variable as a Direct Effect, the impact of which is greater for Green Party membership. In both cases, less than half of the total effect is mediated via their low scores on the rejection of climate science variable; thus acceptance of climate science contributes meaningfully to Green Party and Liberal Democrat group members' acceptance of rural climate policy, but does not account for the majority of it. Party affiliation accounts for a significant proportion, with a stronger effect of being a Green Party member than a Liberal Democrat.

Labour group membership predicts a negative, slightly below-the-mean position on the outcome, though at a very small effect size which is just outside significance at the p<0.05 in all models. Alignment with the Labour party therefore weakly predicts a lower resistance to rural climate policy. Notably though, this effect is almost entirely mediated through their low rejection of climate science; for Labour supporters, the path to acceptance of climate policy appears to operate almost exclusively through acceptance of climate science.

On the right-leaning side of the political spectrum, membership of both Reform UK and 'Other' groups *directly* predicts scores that are *above* the mean on the outcome variable, with medium effect size for Reform UK and small effect size for 'Other'. In terms of mediated relationships, 'Other' have a similar (but opposite sign) mediation pattern to Green Party and Liberal Democrat; around 35% of their increased resistance to rural climate policy is mediated via their *higher* than average scores on rejection of climate science, but the majority of their rejection of climate policy does not come via that route.

The Total Effect prediction for Reform UK is amplified to a large effect size, because their Rejection of Climate Science path is much stronger than all other parties, resulting in high RRCI_GF scores, and large total effect size that is a combination of both the direct and indirect paths being of similar magnitude.

Finally, membership of the Conservative group is a notable exception in predictive value on RRCI_GF; neither the Indirect nor Direct Effects are remotely significant. Coefficients are near zero for Direct Effects and very small for Indirect Effects. Alignment with the Conservative Party is not a meaningful predictor of Resistance to Rural Climate Initiatives, either directly or via rejection of climate science, when compared to the mean position for members of all groups.

7.6.5 Interpreting Indirect Effects in the model – Core Predictors

I turn now to the longer mediated paths in the model, those that flow from the core attitudinal predictors of Populism, Rurality, English Nationalism and Left-Right positioning. These each predict the RRCI_GF outcome variable directly, as well as through multiple indirect (mediated) paths. As is common in mediated relationships, these are not straightforward to interpret; the indirect paths from the predictors to the final outcome variable are formed from the products of the coefficients that make up that path, some of which are negative (having a suppressor effect on the RRCI_GF score), and some of which are positive (having an amplifying effect on the RRCI_GF score).

For all of the core predictors, the Total Indirect Effect is positive (predicting increased RRCI_GF score), and statistically significant. However, these observed positive totals reflect the *net* result of these competing processes, and in some cases (particularly Objective Rural Identity) this aggregate effect masks important variability in the constituent pathways via the party effect coded variables.

Populism has a medium, positive Total Indirect Effect (β 0.205, $p<0.001$) on RRCI_GF scores, and a small-to-medium Direct Effect (β 0.139, $P<0.001$), which, in combination give a statistically significant Total Effect on the outcome variable with a large effect size (β 0.344, $p<0.001$). Around 60% of the total effect is mediated, and, since Populism

predicts both Left-Right position, party choice, and rejection of climate science, it has the highest number of paths to the final outcome.

Objective Rural Identity has a very small, positive Total Indirect Effect (β 0.06, p=0.002) on RRCI_GF scores, and a small Direct Effect (β 0.108, P<0.001), which, in combination give a statistically significant Total Effect on the outcome variable with a small-to-medium effect size (β 0.170, p<0.001). Around 35% of the total effect is mediated, and should be contextualised with the knowledge that Objective Rural Identity is attempting to discern between participants from a survey distributed only in rural areas.

Relative English National ID has a small, positive Total Indirect Effect (β 0.107, p<0.001) on RRCI_GF scores, and a small Direct Effect (β 0.095, P=0.002), which, in combination give a statistically significant Total Effect on the outcome variable with a medium effect size (β 0.202, p<0.001). 53% of the total effect is mediated. Relative English National ID works entirely through Left-Right position and does not directly influence party choice.

Left-Right Alignment has a small-to-medium, positive Total Indirect Effect (β 0.184, p<0.001) on RRCI_GF scores, and a medium-to-large Direct Effect (β 0.291, P<0.001), which, in combination give a statistically significant Total Effect on the outcome variable with a very large effect size (β 0.475, p<0.001). Around 40% of the total effect is mediated.

7.6.6 Schematic Model Interpretation

Figure 26, below, provides a schematic of the amplifying and suppressing relationships in the model. For paths leading to the effect-coded party variables, thick dashed lines indicate those relationships where the sign and/or magnitude of the coefficients fluctuate depending on the -1 coded baseline (as can also be deduced from the Direct Effect tables, Tables 57a-Tables 59f). These serve principally to show how the parties relate to one another, and reveal why simple coding against a single party baseline cannot adequately capture the complexity of the party-specific paths.

However, there are several notable exceptions. The Conservative Party group shows distinctively stable paths in all models regardless of which other party is the baseline. They have the highest Objective Rurality and Left-Right Alignment position (always positive coefficients) and lowest Populism (always negative). It is also the only party where a full Indirect Path *never* reaches significance. Essentially, Conservative party alignment does not act as a predictor of increased resistance to rural climate policy by comparison to the mean position of all participants. The mean scores of the Conservative group respondents are likely related to the deeper identity markers of rurality, English national identity, and broad left-right self-identity, rather than Conservative party alignment.

The Reform UK group is a stark contrast, the only group where the Populism coefficient is always positive in every model (regardless of the baseline group), and the strongest coefficients of all parties on climate science rejection and direct resistance to rural climate policy.

Low rurality scores are always associated most strongly with the propensity to be in the Labour group, and the Labour group members are distinctive in being the only group whose relationship to the final outcome, (lower than mean) resistance to rural climate policy, is almost entirely mediated by their high level of climate science acceptance. The model does not predict lower than mean scores on the RRCI_GF variable for Labour group members directly, only via the climate science variable.

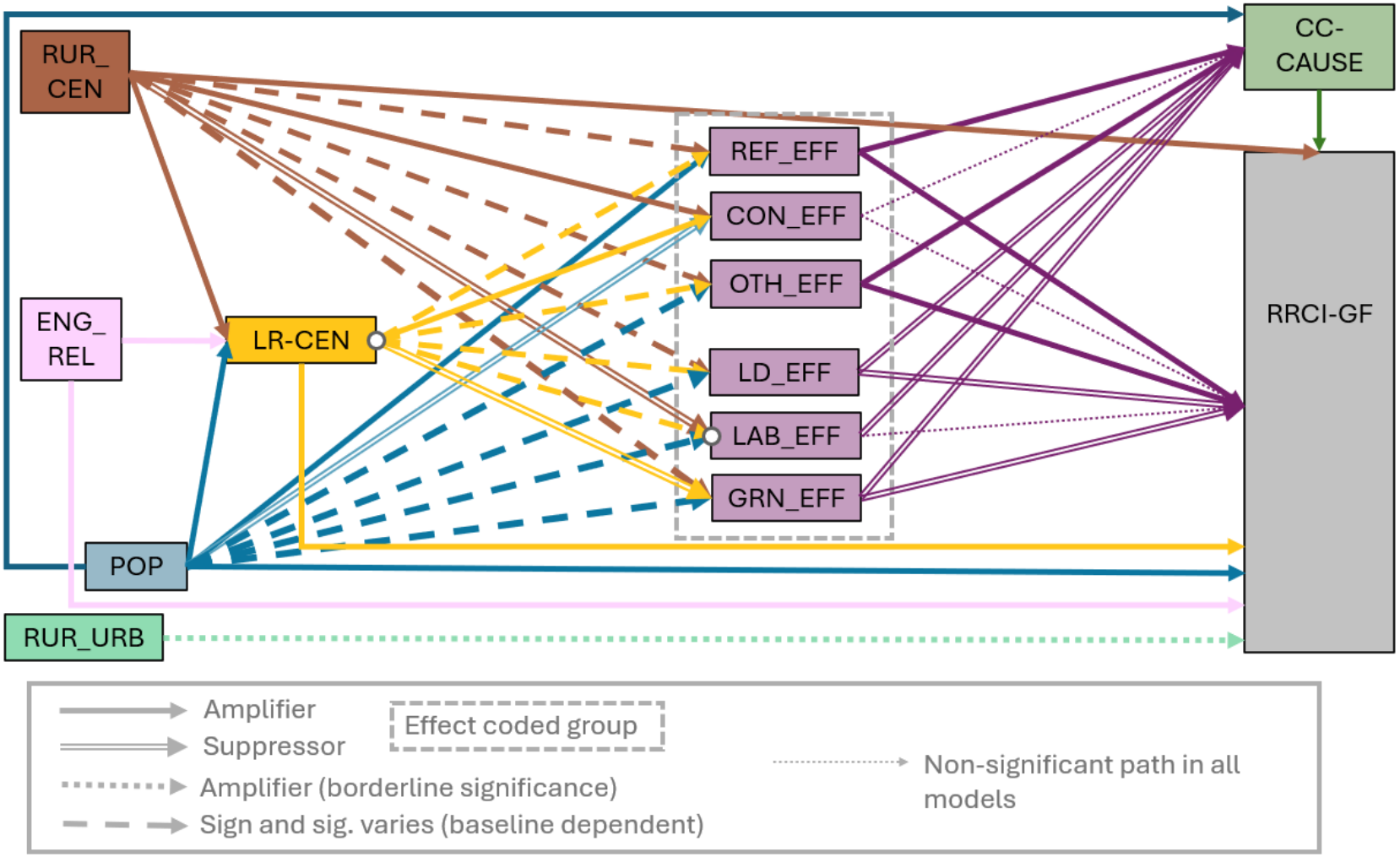


Figure 26: Schematic of amplifying, supressing, and non-significant paths

7.7 Discussion

The work in this chapter has demonstrated a statistically and practically meaningful predictive relationship between the core identity predictors, party alignment and rejection of climate science with the final outcome, Resistance to Rural Climate Initiatives. Through an iterative process of Path Model specification, fit-testing re-specification, the work establishes a plausible set of structural relationships between predictors and outcome.

7.7.1 Differences on the political right

The motivating question for the thesis as a whole, ('How can climate policy making be made more inclusive of the views and concerns of rural, right-leaning communities in England?') focuses on right-of-centre voters, and the structural relationships highlight very sharply that attitudinal divisions on the political right are wider than they are on the left.

The most striking finding, which runs counter to so much of the mainstream narrative of climate journalism in the UK, is that alignment with the Conservative party, in and of itself, does not offer much in the way of predictive ability of either climate science denial or resistance to rural climate initiatives. On both measures, the Conservative group in this sample represent a 'political middle ground'. There is a zero level of outright rejection of the concept of climate change in this group, and their mean level of belief (1.3 on the 1-3 ordinal scale) is imperceptibly different from the mean of the means of all party groups. Similarly, while this group's mean scores on the Resistance to Rural Climate Initiatives scale is slightly above the mean, it is (a) closer to it than any other party group and (b) not statistically different from that mean, once again presenting the Conservative-aligned participants in the sample as the nearest thing there is to the 'average voter'.

On the other hand, on deeper identity markers, the Conservative group are very much not average. They dominate the higher levels of rurality (on a measure that, in this sample, is attempting to distinguish between people who *all* live in rural

places), and display high levels of English national identity, partly explaining why they score highest of all on self-placement on the left-right scale, for which English nationalism was the strongest predictor. Conversely, this is also the group for which the Populism predictor suggests the lowest likelihood of membership, once other variables are controlled for.

There are substantial contrasts between the Conservative group members and those who aligned with Reform UK. For the latter, rejection of climate science is extremely high, so high in fact, that it has limited ability to also predict their rejection of rural climate policies. A not insignificant minority in this group (10%) are of the belief that the climate simply is not changing at all, which must surely run counter to their everyday experiences of climatic events in the UK over recent years, and suggests that rejection of climate science is perhaps a 'tenet of the faith' for this group. The clearest divide between the Reform UK and Conservative participants in this study is on Populism, increases in which overwhelmingly predict odds of being Reform vs Conservative, more so than any other pairwise comparator.

On other measures though, members of Conservative and Reform are strikingly similar – on English Nationalism and self-placement on the Left-Right scale, the two groups are indistinguishable. This is a very important finding, because it suggests that a strong sense of national identity or a strong sense of oneself as being right-wing, is not, in and of itself, a precursor to strongly rejecting either climate science or climate policy; Conservative and Reform UK voters are indistinguishable on these measures, but Reform UK voters have markedly higher scores on the Resistance to Rural Climate Initiatives scale. In fact, their scores are so much higher than the Conservative group scores that the distance between Conservative and Reform in one direction is almost exactly the same as the distance between Conservative and Green in the other.

The very fledgling nature of Reform UK at the time the survey was issued may mean that, were the survey to be re-issued today, many of the people who had placed themselves 'Other' on the survey might be more likely to select Reform UK instead, now they are more familiar with its policy offer. It is notable how similar the

distribution of data is for the 'Other' group when compared with Reform UK, and it is not improbable that some of those views may have crystallised and strengthened since the survey was distributed.

7.7.2 Core predictor influences

All of the core variables (English Nationalism, Rurality, Populism and Left-Right placement) are shown to have positive and statistically significant effects on the outcome variable scores (i.e. tending to increase resistance to rural climate policy). These are reasonably distal from the final outcome, and therefore although the Effect Size of the predictive relationships are, in the case of Objective Rural Identity and Relative English National ID for example, are quite small, the fact remains that both of these variables are still able to offer explanatory value, and even a small effect size is likely to be consequential where a trait can be measured at the population level. Indeed, participants in the Conservative group had the highest levels of Objective Rurality, and it is likely that it is that trait, possibly combined with a strong sense of English nationalism, that better predicts their RRCI score, rather than their Conservative group membership.

Populism has a medium indirect effect and a small direct effect, combining to create a large total effect overall. It clearly divides the non-mainstream political groupings (Reform UK, 'Other', Green Party) from the established parties (Labour, Liberal Democrat, Conservative). In addition, around 12% of its impact is mediated by the rejection of climate science variable, and it is involved in some quite substantial Specific Indirect Paths involving both Reform UK and the rejection of climate science. But populism is known to be a 'slippery' measure, being a thin ideology that requires a host. The Green Party aligned participants, though more populist than Labour, Liberal Democrats and Conservative, nonetheless show the lowest RRCI scores overall, illuminating how left-wing and right-wing populism operate differently in relation to climate science.

7.7.3 Limitations of the study

The data that underpin the modelling in this chapter were collected from surveys distributed only in rural areas. Though this was by design, it does mean that the conclusions cannot be extrapolated to urban populations.

This work is situated at a time of huge upheaval in the UK political scene. The rise of Reform UK has been meteoric over the last 2 years. On the one hand, to have included Reform UK on the survey as a named party at all was a prescient move, given that it had not long been established, was not yet incorporated as a bona fide political party, and had no elected representatives at either national or local level in the UK. The fact that the party was included on the survey and so many respondents indicated alignment with this fledgling movement, in all probability has been the means of revealing patterns of Conservative attitudes that had long been obscured by the inclusion of previously politically homeless Reform UK voters, who had been squatting in the Conservative 'Big Tent' for a long time.

On the other hand, the similarly large cohort of 'Other' voters in the survey may well represent 'Reform-lite'. If a substantial proportion of this cohort were to move their allegiance from this more nebulous 'other' grouping to the Reform UK grouping, this could affect the integrity and fit of the models presented here. If such a move included a hardening of attitudes, it would effectively alter the 'Other' shape on the radar diagram in Figure 11 of this chapter so that it shrinks away from Reform, while at the same time enlarging the number of people aligning with Reform directly. Ultimately, this could have the effect of widening the 'statistical gap' between Reform supporters and everyone else, by shifting the mean of the group means.

7.7.4 Opportunities for future work

The most obvious next step is for further quantitative work using the same measurement instrument, but drawing on data from a larger, nationally representative sample that includes urban residents, to see if the patterns revealed here are specific to rural communities or not.

Supplementing this survey and modelling work with follow-up interviews would allow for researchers to really explore respondents' views on the acceptability of rural climate policy, and add further nuance; surveys and regression models can tell us *what* is happening, Path Models can tell us *how* it is happening, but only qualitative work can really tell us *why* it is happening. In light of the seismic changes ongoing in UK politics at the time of writing and the strongly stated proposals from Reform UK to largely repeal climate policies in the UK, it seems vital and timely that researchers should sit down with an open mind and engage in really deep explorations of why this position is so attractive to so many UK citizens at this time.

8 Discussion and Conclusions

8.1 Introduction

I began this PhD with the broad aim of addressing the question "How can climate policy making in the UK be made more inclusive of the views and concerns of rural, politically right-leaning communities in England?" Through a review of the literature, that broad aim was operationalised through three research questions, each of which is addressed in at least one of the empirical chapters of the thesis.

1. Does political identity lead to differential rates of participation in Climate Assemblies and differences in attitudes towards the legitimacy of these policy-making forums? (Chapters 4 and 5).
2. How can resistance to rural climate policy initiatives be reliably measured? (Chapter 6).
3. What are the pathways by which political identity, populism, and rural identity shape resistance to rural climate policy in England? (Chapter 7).

The thematic split of the thesis is between the work in Chapters 4 and 5, which focused on *how climate policy is made* (answering RQ1), and the work in Chapters 6 and 7, which address the implications of *what climate policy commits rural areas to* (responding to RQ2 and RQ3). This final chapter draws those two halves together, providing a discussion of the empirical results and conclusions and their practical and theoretical implications.

Responding to the results, in the first half of the thesis, Section 8.4 of this Chapter focuses on what the evidence says about political identity as a predictor of attitudes to climate assemblies, while Sections 8.5 to 8.6 go beyond the empirical work to provide theoretically informed conclusions and recommendations on how practice could be altered in the use of Deliberative Mini Publics for climate policy making.

Turning then to the second half of the thesis, Sections 8.7 and 8.8 consider what the results tell us about patterns of resistance to rural climate policy (and the potential causal pathways that lead to them), while Sections 8.9 and 8.10 again go beyond those direct empirical findings to consider the relationship of those findings to the wider literature, and what this might mean for the delivery of climate policy in rural areas.

8.2 Summary of contributions

This thesis makes four contributions to the academic literature on deliberative democracy for climate policymaking and the measurement of political attitudes towards climate policy in rural areas. The first two emerge from the work in Chapters 4 and 5, and the second two from the work in Chapters 6 and 7.

On the question of how climate policy is made, this thesis provides the first empirical evidence (from multiple processes) that Conservative-aligned citizens systematically under-volunteer for climate DMPs. It also demonstrates that although Reform UK-aligned citizens state that they *would* participate in a Climate Assembly, they are almost entirely motivated by a defensiveness born of climate scepticism; they do not display a high level of support for the idea of a deliberative process for policymaking, in and of itself. These findings challenge assumptions of political neutrality embedded in standard DMP recruitment practice (where political alignment is not directly used as a selection variable), and introduces the concept of 'specious descriptive representativeness' as a meaningful risk category for deliberative climate governance, to describe a mini-public that matches socio-demographic targets while being ideologically unbalanced. Informed by these findings, the Sortition Foundation now regularly recommends use of political identity as a recommended sortition variable in climate assembly recruitment.

On the question of what climate policy commits rural areas to, this thesis contributes a new, robust psychometrically validated measurement instrument (the 18-item Resistance to Rural Climate Initiatives (RRCI) scale). It also contributes the first path model analysis of the causal routes by which political identity, populism, English nationalism, and rural identity combine to generate resistance to rural

climate policy in England. The path model findings reposition Conservatism as a statistical centre-ground on climate resistance in rural England, driven primarily by protective rurality and English national identity rather than populism, whilst demonstrating that Reform UK resistance operates through a substantially different and more ideologically oppositional causal structure. The results challenge the use of 'the political right' as a homogenous category in the climate attitudes literature, particularly in relation to the UK, where Reform UK is a recently emergent party.

Taken together, these contributions span deliberative democracy theory, political psychology, psychometrics, and structural equation modelling and validate the deliberately interdisciplinary design of a thesis that sought to produce findings credible to audiences who are persuaded by numbers rather than narratives.

8.3 Limitations

As noted in the empirical results chapters, there are limitations of the study that principally relate to the sampling strategy and limited time-scale of the project, which precluded any additional rounds of scale validation with additional populations.

1. **Sample selection and generalisability**. The thesis relies on a rural-only, England-only sampling strategy, which means that the results should not be extrapolated to be representative of urban populations. Political identity effects may manifest differently in more diverse geographic or demographic settings.

2. **Cross-sectional design and the Reform UK timing issue**. The work in this thesis captures a single point in time, which came during a period of unusually rapid political change in the UK, particularly on the right, although also at a time when the Green Party's 'left-populism' has gained increased support. The 'Other' party grouping in the path model data, collected before Reform UK's increased public profile, may partially contain a substantial portion of voters that would now more clearly state an alignment with

Reform UK itself. Replication with more recent data and confirmed party alignments would be needed to validate the causal claims of Chapter 7.

3. **Scale validation priorities for future work**. The RRCI scale is shown to be robust and stable within the rural English context in which it was developed, but further validation work would be needed, particularly in urban and suburban populations, other UK nations, and potentially other national contexts, to be sure of its robustness. It is, however, good practice for scales to be re-subjected to Factor Analysis with each use in any case, to ensure that demographic differences in samples do not affect the Factor Structure. Moving beyond this, the scale could be refined and re-tested with the addition of items on energy transmission infrastructure, which is increasingly part of the anti-net-zero narrative in UK politics.

4. **Exploratory nature of the work**. Due to time limitations, the strength of the results in Chapter 5 and Chapter 7 would be best enhanced through replication studies with new independent samples and pre-registered hypotheses.

8.4 *How climate policy is made:* What this thesis tells us about political identity and the use of Climate Assemblies

The research presented in the first half of the thesis finds that political ideology is a robust predictor of support for, intention and motivation to participate in, and views on who and what should be included in a climate DMP.

The section began with a small-scale case study, reviewing the political makeup and views of the participants in the Herefordshire Citizens Climate Assembly (HCCA), finding that they were unlikely to have been politically representative of the voter population of Herefordshire, with too few Conservative voters in attendance. In addition, of those that took part, the 'appropriate scope' of climate assemblies was viewed differently by those on the political left versus those on the right.

Through subsequent collaboration with a DMP recruitment body, questions on political party alignment were included as a selection variable when recruiting for three further 'real-world' climate-themed Deliberative Mini Publics. In each case, the proportion of Conservative-aligned volunteers was lower than the target (in the region of one third to one half of the target), and this systematic under-volunteering from Conservatives is mirrored by a systematic over-volunteering by Green party and Labour party respondents in all three cases.

Finally, a large-n survey on hypothetical intentions to participate in climate DMPs confirmed those emerging findings, demonstrating a higher propensity overall for left-leaning citizens to support the concept of climate DMPs, to volunteer for them, and to do so with a 'climate concerned' motivation. This survey, occurring at a time of substantial political change on the right in UK politics, also revealed a distinctive pattern on the right; Conservatives are considerably more 'climate concerned' than Reform UK voters, but substantially less likely than supporters of *any* other party volunteer for Climate DMPs. This raises the possibility that Conservative reluctance to participate is at least in part a function of underlying concerns with the process itself, and not specifically a rejection of the climate topic. By contrast, though Reform UK voters' intention to participate is not significantly lower than would be expected by chance alone, their motivation is substantively different than for supporters of all other parties. Of Reform UK voters who would take part, almost 90% would do so to represent the point of view that climate change is an exaggerated threat.

I now move beyond the direct findings of the first two results chapters into a more general discussion of what the implications of the findings might be for the use of DMPs for making climate policy.

8.5 Why might political identity affect support for Deliberative Mini Publics on climate?

8.5.1 Climate DMPs as a challenge to Conservative principles

Core Conservative beliefs on democracy and representation were presented in the Literature Review, and I briefly revisit these to consider why they present plausible reasons for Conservative under-volunteering for Climate DMPs.

First, in general, Conservatism is rooted in the idea that social systems develop organically, representing the aggregated wisdom of the past. Conservatism's core concern (all the way back to Burke), is that even well-meaning attempts to overhaul social systems often fail to grasp their true complexity, leading to complications that risk either worsening the situation, or introducing entirely new problems (Lammers and Baldwin, 2018). It follows that the introduction of new ways of policy-making that seem to circumvent existing systems would be viewed as suspect when seen from this normative perspective.

Second, and probably more fundamental, is the Conservative belief in the primacy of representative democracy: constituents elect representatives, and it is for representatives to undertake policy-making in the best interests of their constituents. Indeed, during the UK Conservative Party conference of October 2023, the then UK energy Minister (Lord Callanan) publicly dismissed the role of Citizens Assemblies, stating that "*People take the trouble to get themselves elected, it's their right to take decisions, and I'm intrinsically suspicious of Citizens' Assemblies and the idea behind them*". This view was echoed later in a separate session of the conference by Conservative MP Katherine Fletcher, who told delegates that "*the ultimate Citizens' Assembly is 1,000 years old and is tacked onto Westminster Hall. If people want a vote, get elected*" (Carpenter, 2023).

However, Conservative emphasis on representative democracy does not flow solely from straightforward deference to preserving traditional 'ways of doing'. It is also founded on the conception that elected representatives are needed *specifically because* 'the people' are not equally endowed with the ability to rationally deliberate

on complex issues. When policy deliberation does occur, Conservative philosophy leans toward the idea that such deliberation should be carried out by capable representatives, mediated by tradition and authority, and without succumbing to 'popular passions' (Bourke, 2015 p.195).

Taken together, it feels unsurprising that Conservatives will likely view these new forums for policymaking with greater suspicion than supporters of other political parties.

8.5.2 Climate DMPs and epistemic trust

Of the small sample used for the HCCA (reported in Chapter 4) the results showed that Conservatives were under-represented and that participants that were broadly right-leaning were more likely to want to widen the scope of any similar assembly held in the future. Larger samples used for the analysis in Chapter 5, again showed Conservative under-volunteering, and a distinctly different motivation for volunteering from Reform UK supporters.

I theorise that those on the political right might view the organisers of climate assemblies as having pre-determined what will be treated as settled premise versus what remains open for deliberation (their 'epistemological framing'). There are those citizens (primarily on the political left) who will broadly accept information put forward by climate scientists and summarised by bodies such as the IPCC. This acceptance of 'settled science' is really an exercise in epistemic trust (of institutions); it does not stem from engagement with primary evidence, *per se*, since very, very few of them will have had the opportunity or skills to engage with climate modelling in a pure sense. For participants with high levels of epistemic trust, the idea of lengthy debates on indisputable things will largely feel like a waste of everyone's time. Climate science, rather than being part of the debate, merely forms the starting point from which (solution-focused) dialogue then begins.

For some right-leaning participants (particularly those that may predominantly consume media that regularly presents climate science as mired in controversy), however, their starting point is further back. They may think it only right that the

science itself is included in the deliberative process, and they may wish to engage in what they see as reasoned dialogue about 'unsettled' science, about uncertainty in predictions, or their doubts about the scale of the problem itself, *before* entering the realms of solutions.

To illustrate this dynamic, consider that the HCCA began with a 15-minute session on climate science and a 12-minute session on impacts. These are likely to have been viewed as useful primers or reminders for a participant pre-disposed to take this scene-setting information on board uncritically. But they may have been challengingly light for someone of a more sceptical pre-disposition. This is particularly pertinent when linked to the likely outcomes of such an assembly; developing policy recommendations that some worry will curtail industrial development and restrict traditional farming practices is not a rational step for someone who does not subscribe to the idea that ecological collapse is imminent, or (taking a Conservative position) that such radical action to address a problem could itself threaten the economy or social order, unleashing more immediate problems (Stanley *et al.*, 2024).

Climate Change is one of the most politically salient issues of our time, and political group loyalty is expressed and remade through cleavage to particular viewpoints. Although my data does not provide any conclusions on this issue, I posit that unquestioningly accepting climate science is easier for those on the left because it is ideologically *assonant*; it bolsters rather than undermines their other dearly-held political goals such as anti-capitalism, borderless societies, and ecologism. Conservatives, on the other hand, or those who hold nationalist or populist views, must look for ways to reconcile the science with alternative values. Though the foundational scientific concepts of climate change are value-free (such as the basic physical process by which greenhouse gases can trap heat within the atmosphere), if the scientific information is perceived as 'bound up' in public and academic discourse with left-leaning normative imperatives about how society should respond, climate science becomes 'epistemologically contaminated'. Examples of such normative imperatives include degrowth and post-colonial reparations, alongside acceptance of higher regulatory oversight, particularly from adherence to

international standards, and other limits on sovereignty, found in such works as D'Alessandro *et al.*, 2020; Chapman and Ahmed, 2021; Shi, 2021; Hickel *et al.*, 2022; Fanning and Hickel, 2023; Murombedzi and Chikozho, 2023; Stilz, 2025.

This elision of 'what is happening?' with 'what is to be done about it'? creates *ideological dissonance* for those on the political right (defined by Nisbet et al, (2015) as a form of cognitive discomfort that arises when people are exposed to information that clashes with a strongly held personal belief). When confronted with such dissonance on any given topic, evidence shows that people from *all* parts of the political spectrum – i.e. humans generally *as* humans, not party political agents – will engage in motivated reasoning and bias. With regard to the topic of climate change, several reaction pathways present themselves.

One route for those on the political right would be to seek out more ideologically comfortable market-driven solutions and 'technofixes', and to want to know that they are 'up for discussion'. Since there is a substantial body of peer-reviewed literature on topics such as solar geo-engineering or large-scale carbon capture and storage, it can seem suspicious to some groups if these are excluded from the scope of deliberative processes, or dismissed with only a brief overview. Having space to raise and discuss questions of international diplomacy is also pertinent, particularly since (even in a local climate assembly) the global and interconnected nature of the problem is clearly a central issue. While participants with a liberal-globalist outlook might comfortably accept moral imperatives that presuppose that the UK will now take a leading role in carbon reduction (related to the UK's historic carbon emissions and colonial activities), for others it is the UK's *current* and *relative* emissions that are more relevant. It is not morally objectionable to wonder why the UK would risk economic pain while the US President exhorts his countrymen to 'drill, baby, drill'.

Where ontological claims on climate physics (what is happening) seem inextricably entangled with a particular normative agenda (what ought to be done), a more extreme response pathway is to seek and promote 'alternative facts' on climate physics. Rekker (2025) demonstrates that people (of all political persuasions) will

tend to contest 'ideology-incongruent' research topics, and further complexity arises from the fact that not all peer-reviewed evidence is considered to have the same value by all citizens. Epistemic trust is itself linked to value congruence; for example, evidence from the US suggests that overall, Conservatives tend to trust 'production' science (science that leads to new technologies and economic growth) more than they trust 'impact science', which highlights negative social or environmental impacts from economic production (McCright *et al.*, 2013). And there is (admittedly only embryonic) evidence that there may be legitimate, scientific grounds for this distinction between bodies of 'scientific' knowledge. For instance, a recent meta study of 561 peer-reviewed articles on 'degrowth' found that almost 90% of the studies reviewed were opinion rather than analysis (Savin and van den Bergh, 2024), a finding that lends some credence to concerns about being asked to 'follow the science', and the perceived hegemony of left-wing normativity in the wider field of climate policy making.

The final type of response would of course be simply to avoid participation in a forum for discussion altogether. Where this occurs, as it seems it may have done in the HCCA, it throws into doubt the legitimacy of the any deliberative process that makes claims to descriptive representativeness, if it can be argued that the particular demographic that has excused itself from the process is likely to have held substantively different views than the group that did attend.

8.5.3 Political identity: a necessary selection variable for DMPs on climate change?

Dijk *et al* (2023) demonstrate that political identity outweighs other identities as a driver of polarisation, being a more salient characteristic than, for example, religion, language or ethnicity. Furthermore, Schkade et al (2007) show that when people who already broadly share an ideological world view are allowed to deliberate on an ideologically polarised issue *in the absence of people who disagree with them*, they become *more* polarised in their views. Schkade *et al* have shown how 'ideological amplification' occurs in such settings in relation to discussions on immigration,

same sex marriage, and climate policy, with left-leaning and right-leaning groups separately diverging into increasingly polarised policy positions when left to deliberate in isolation. I argue that it is therefore crucial that *political/ideological* representativeness is recruited for, not simply because it is an additional characteristic to add to age, ethnicity and so on, but because it is likely to be *more* important than them; in the absence of political heterogeneity, climate assemblies will tend to create amplified versions of the shared group norms of the participants.

If there is a risk of ideological capture and ideological amplification within deliberative climate processes (where my findings suggest that it is more likely that left-of-centre individuals will volunteer, and where normatively restricted framings and underrepresentation by right-leaning citizens could serve to reinforce left-leaning normative positions), then solving this imbalance is more nuanced than merely ensuring that a small number participants have been selected for holding the view that climate change is not real. Indeed, only around 5% of the UK population hold this view (DESNZ, 2024). Rather, it is also about ensuring representation of the full range of views on the most appropriate policy responses.

8.6 Wider significance: Implications for future practice in Climate mini-publics

8.6.1 Recruitment adjustments for climate DMPs

Reflecting on the above, in this section I consider changes that could help to overcome politically-driven disaffection with, or distrust of, climate DMPs. Working within the deliberative democracy paradigm, two relatively simple adjustments to recruitment practice for DMPs could easily be introduced.

Firstly, to mitigate against lower volunteering to the pool in the first place from one political/ideological grouping, organisers should reflect on unwitting use of normative framings in the literature used to advertise Climate Assemblies, for example, phrasing and contextual positioning for the assembly that intrinsically speaks of a left-liberal/globalist world view and thus feeds or challenges the

unconscious biases of potential participants. With reference to Conservative ideology in particular, clear indications from the outset about how the outcomes of a given DMP will flow back into established decision-making structures, including endorsement from Conservative representatives, could help here. This does, of course, pre-suppose that the outcomes of a citizens assembly *are* being used to feed back into existing structures, and indeed, some DMP proponents would argue for a more radical approach; that the whole point of DMPs is to bypass moribund political processes, effectively remaking the political system. Without entering into any detailed exegesis of literature on whether DMPs should in theory do this, it seems adequate to point out that in practice, in the UK at least, they do not. To date, DMPs in the UK have been used in *inform* policy, rather than *compel* it, and ensuring this is prominently communicated from the outset might assuage Conservative concerns and increase volunteering from this group.

Secondly, ensuring that a political identity question is used as standard when recruiting for climate assemblies other DMPs on politically partisan issues would allow for correction at the pool stage, if the response rates to the invitations seem to be skewed on political lines. Indeed, as a result of this study, practice change on this has already begun, allowing for recruitment corrections on at least three deliberative climate processes in the UK.

8.6.2 Discursive, rather than descriptive, representation?

Alternatively, given the current strong focus of DMP practitioners on descriptive representation, a more radical approach would entail a clean break with this idea, and a pivot towards 'discursive representation'. This would transparently reject essentialist reproductions of group identities in an assembly, in favour of purposely selecting specific *discourses* to be considered, moving from a 'politics of presence' to a 'politics of ideas' (Dryzek and Niemeyer, 2008). In the context of the highly partisan differences revealed in this study, and more widely evident in UK political discourse with the rise of Reform UK, reframing content and process design around discourses, not demographics, could be a useful tool to regain epistemic trust from

a substantial segment of society. This proposal feeds, to some degree, the proposals for increased agonism in climate mini-publics, developed in the next section.

8.6.3 Minimising societal *antagonism* through deliberative *agonism*

8.6.3.1 The rise of antagonistic climate politics

Climate policy making in England is at a critical juncture: while the past 6-7 years have seen a dramatic rise in the deployment of Deliberative Mini Publics as a mechanism for making climate policy, an even more recent and dramatic development is the rise of Reform UK, a party that has grown from nothing to front-runner to win the next General Election in only 4 years. Via populist political logic, the party has aggregated a broad collection of social and economic policy issues into a holistic 'people vs the elites' appeal, and prominent among these aggregated grievances is their contention that the UK Government's Net Zero targets will impoverish 'ordinary people'.

Populism runs on powerful negative emotions like anger, resentment and fear, by reducing politics to a simple two-sided battle of good against evil, where facts and rational arguments are subservient to emotional impact (Ungureanu and Popartan, 2020). Reform UK has risen so quickly because times are manifestly hard for many people in England, not least because of the cost-of-living crisis that began in 2021 and saw 10 months of double-digit inflation, from which many households have not recovered (ONS, 2023; Citizens Advice, 2025). Reform UK has not *created* resentment from nowhere, it has fed on genuine grievances, acknowledged them, and offered itself as the solution with (among other things) the plausible-sounding efficiency savings that would come from scrapping what, to many voters, is the bafflingly impenetrable technocratic formulation that is 'Net Zero'. It has also, far more than any other party, gained votes from those who were previously non-voters (Green and Miori, 2025), an indicator that its appeal lies with those who already felt disaffected and abandoned by the political system.

This study, and others (e.g. Smith, 2024) show that Reform UK voters are now a very distinctive group as far as climate change is concerned. Despite the availability of increasingly comprehensive empirical data on the causes and likely impacts of climate change, Reform UK's supporters are far less likely than other voters to believe in man-made climate change. These views simply cannot be dismissed as fringe when multiple current polls suggest that, were a General Election to be held tomorrow, Reform UK would win more seats than any other party (Electoral Calculus, 2025; English and Difford, 2025; IPSOS, 2025).

The intensity of moral condemnation in climate discourse, where scepticism about climate change has been framed by senior public figures in morally judgemental terms that conflate it with holocaust or genocide denial (Harpin, 2019; Tollerton, 2025), increasingly allows proponents of a particular approach to climate action to 'confiscate' the space for debate. Paxton discusses how this reduces political engagement from certain groups, because *"when we claim dominant ideals to be 'objective', then it renders them uncontestable by others*" (Paxton, 2020 p.64). By this, she means that when one side frames its position in terms of universal values like "humanity," "justice," "democracy," they make it practically impossible for opponents to disagree without seeming inhumane, unjust, or undemocratic. In doing so, they create of their opponents enemies whose views can be entirely dismissed, rather than 'legitimate adversaries' to be openly debated. In this, Paxton is echoing the work of Chantal Mouffe, discussed in the Literature Review. A long-time critic of the fundamental Habermasian ideals of *rationalistic* and *individualistic* dialogue that underpin deliberative democracy (which she argues serve only to suppress the reality of the *collective* political identities of participants, Mouffe, (1999, p. 754 -756)), she instead supports the concept of 'agonistic pluralism', where citizens are encouraged to engage with others "*with whose ideas we are going to struggle, but whose right to defend those ideas we will not put into question"*.

8.6.3.2 Designing agonistic climate assemblies

In practical terms, I believe this more pragmatic and realistic understanding of human behaviour could be coupled with a strategy that encourages many *more* Citizens Assemblies (echoing the call of (Willis, 2020 p.4) that "*more democracy, not less, is needed to tackle the climate crisis*"). This new generation of agonistically-designed assemblies would be focused on process, rather than outcome, providing widespread opportunities for citizens to acknowledge, rather than suppress, their partiality, while collectively working for ways to reconcile those with better climate outcomes (Paxton, 2020. p.167).

Such content and process adjustment is considerably more complex and not without trade-offs, especially as it may necessitate even more targeted recruitment and longer processes, all of which adds cost. But given that Reform UK's website was until quite recently hosting information that outright denied the existence of anthropogenic climate change (Ward and Sethi, 2024), it is likely that Reform UK voters will only feel that their concerns are fully addressed if process design includes longer assemblies, and it is clear that 'people like them' were able to bring their views to the table. These would allow for genuine engagement with this resurgent scepticism of the climate science itself, direct engagement with points of view around national responsibility and sovereignty, and more flexibility for participants, within reason, to call for additional speakers who themselves represent different normative points of view.

This proposed turn away from DMPs based largely on Habermasian deliberative theory is not to suggest that the groundwork that has been laid by the 'deliberative turn' in English climate politics was for naught, only that embracing *agonistic* designs (designed around the idea of 'legitimate adversaries', with different moral values) could now be more fruitful, and hopefully less likely to exacerbate the increasingly *antagonistic* discourse on Net Zero that has come to dominate English climate politics.

As a form of democratic innovation, Deliberative Mini Publics have offered a new proposition for strengthening democracy, by attempting to introduce a more nuanced understanding of complex policy issues into public debate, with an aim of better informing the aggregated preferences that are subsequently expressed through voting in a party-political system. But the results presented in Chapters 4 and 5 support the position that political ideology is ineliminable from all forms of public discourse. Given that the UK's Net Zero policy agenda is now clearly established as a key site of public antagonism, for climate DMPs to perform this role well in an increasingly politically polarised nation, it is increasingly important that efforts are made to ensure that political identity is actively centred in the process.

But political identity also shapes something more fundamental: what rural communities believe climate policy itself ought to do to the places they live in, and what it threatens about the landscapes, traditions and identities they value. It is to those questions of resistance to change and the pathways that connect identity to that resistance, that the second half of this Discussion Chapter now turns.

8.7 *What climate policy commits rural areas to:* What this thesis tells us about political identity and resistance to rural change from climate policy

The research presented in the second half of the thesis finds that resistance to rural climate initiatives is a multidimensional construct with a strong hierarchical structure, that pathways to this resistance vary substantially by political identity, and that the differences on the political right are wider than those on the left with regard to this issue.

The section began by developing and validating an 18-item measurement instrument to assess Resistance to Rural Climate Initiatives (RRCI), finding (through exploratory and confirmatory factor analysis) that resistance to landscape change in rural areas takes the form of a nuanced bifactor structure. The structure

comprises a dominant General Factor onto which all items load, representing broad resistance to rural change. This resistance is anchored in items that represent threats to national identity, traditions and attachment to place, alongside two Specific Factors that capture resistance to particular climate policy interventions: land management changes (such as rewilding and afforestation), and installation of energy infrastructure.

Through subsequent Path Model analysis, routes to this resistance were investigated, revealing that the core identity markers of Populism, English Nationalism, and Objective Rurality operate (through political party alignment as a crucial 'refractive lens') to generate plausible differential causal pathways to climate policy resistance. These pathways vary substantially between parties. Conservative voters represent a statistical middle ground, distinguished primarily by high levels of rurality and English nationalism, yet showing no meaningful direct or mediated relationship with heightened resistance beyond these deeper identity markers. In stark contrast, Reform UK voters, while also highly nationalist, are less 'objectively rural'[42], and are also characterised by exceptionally high Populism levels and strong rejection of climate science. They also have the highest levels of resistance to rural climate policy of any party grouping. Labour voters, conversely, showed the lowest resistance, with this relationship almost entirely mediated through their very high levels of acceptance of climate science, rather than through direct effects of party alignment itself.

Finally, not to be overlooked are the participants who chose 'Other' as the party group they most aligned with. This group share a high English nationalism profile with both the Conservative and Reform UK participants in the sample, along with higher populism scores than all groups other than Reform UK. Participants in this group selected none of the five main parties in the list, which could be cautiously interpreted as a higher level of overall dissatisfaction with the current political offer. However, the timing of the survey was before Reform UK's steep rise in public

[42] As measured by their score on the Rural Index detailed in Appendix 8.1 rather than their own self-perception as 'a country person'.

consciousness, and before their election successes. Given the similarities in profile otherwise between the 'Other' and Reform UK participants on the Populism measure, it is possible that a sizeable proportion of this group would now indicate support for that party, and since this group also have the second highest mean score on the RRCI scale, much of what pertains to the discussion of Reform UK participants that follows is likely to also be relevant to many in the 'Other' group.

8.7.1 Interpreting the results

As noted in the results chapters, the data that underpins much of the analysis in this thesis is drawn from a rural sample. This has essentially controlled for *spatial* rurality in the sample, and since only around 17% of England's population lives in rural areas (Barton *et al*, 2024), it can also be seen as controlling for the 'tyranny of the majority', whereby the aggregated views of voters at the national level are always going to be skewed towards the views of urban participants, purely due to weight of numbers. This means that the results presented here should not be extrapolated to urban populations; further research would be needed to establish if the same attitudinal breakdown emerges in an urban sample.

As noted in Chapter 3 (Methodology), the survey was not randomly sampled, and therefore I make no statistically inferential claim that the exact prevalence of attitudes revealed here would be replicated in any other rural English sample. However, the systematic approach to recruitment of survey respondents across rural England (principally through delivery of 22,000 leaflets in randomly selected rural areas, yielding a large sample of n=723) has produced statistically robust patterns that broadly align with theories of political identity. The results are unlikely to be sampling artefacts and are therefore instructive for thinking about why the Conservative/Reform difference in particular is so striking.

Since the motivating question for the thesis was 'How can climate policy-making be made more inclusive of the views and concerns of rural, politically right-leaning communities in England', the discussion that follows focuses only on the results that pertain to those groups that fall to the right of centre on the Left-Right scale in my sample (Conservative, Reform UK, and 'Other'). I now go beyond the results

presented to consider how and why the right-leaning participants in the sample differentially relate to their rurality, particularly symbolically through a nationalist/populist lens, by drawing on some of the theoretical and empirical background provided in the Literature Review.

8.8 Discussion – drivers of resistance to rural climate policy

Considering the results at a dichotomous level, it is immediately clear that the three parties of the political left (Green, Labour and Liberal Democrat) all have group mean scores below zero on the mean-centred RRCI outcome scale, and their mean scores are more clustered together than those of the groups on the political right. With a spread of 0.27 on the 5.25-point factor scale, this indicates that left-leaning participants have a reasonably strongly-shared perspective on the appropriateness and acceptability of rural change as a result of climate policy.

By contrast, the differences on the political right are more pronounced. The Conservative mean score of 0.19 is slightly above the zero midpoint of the factor scale, but not *statistically* significantly higher than the mean of the means for all participants. It differs substantially from the group mean for Reform UK supporters, which is 0.99. With the 'Other' group at a mean of 0.47, this gives a spread of factor scores for the right-leaning parties of 0.79, much broader than on the left. This suggests that although there may be a shared *low-level* of resistance that is allied with right-leaning political ideals, some other factors act to considerably amplify this for the Reform group in particular.

8.8.1 Right-leaning self-identification as a predictor of resistance to rural climate initiatives

As discussed in the Literature Review (Section 2.5.4), climate policy has become an increasingly polarised issue in UK politics, particularly since the 2008 financial crisis. While environmental concern grew across the political spectrum in the 1990s and 2000s, the Conservative Party more than any other has experienced sustained periods of internal tension between calls for climate action and appeals to core beliefs about free markets and economic liberties, with backbench pressure leading

to periodic retreats from green commitments (Carter, 2006; Carter and Clements, 2015). More recently, the radical right has successfully exploited climate policy as a wedge issue, successfully framing it as an unaffordable expense for both businesses and households (Dickson and Hobolt, 2025).

In this context (which Dickson and Hobolt show has been particularly strong driver of political partisanship since 2021), it is unsurprising that the participants in this study who placed themselves further to the right on the Left-Right scale would show heightened levels of resistance to climate policy in general, which itself could manifest in RRCI mean scores higher than those for the left-leaning participants overall.

However, since the Reform UK and Conservative voters in the sample show such a wide difference on the RRCI scale, but were indistinguishable on left-right placement, perceiving oneself as 'being right leaning' cannot by itself provide a satisfactory explanation for the wide spread of scores on resistance to rural change from climate policy.

8.8.2 English nationalism's role in predicting resistance to rural climate initiatives on the political right

Recall that the measure of English Nationalism used in the study was a 'Moreno' scale, measuring the *relative* strength of Englishness compared with other UK identities. This approach was motivated by the work of Henderson *et al.*, (2017), who found that 'English-rather-than-British' types of self-perception were a powerful predictor of Brexit voting in 2016. Critiques of climate change policy are often motivated by the same issues that powered anti-EU sentiment, relating to remote, decision-making on highly complex policy issues that are perceived as having been 'imposed' by unelected elites (Lockwood, 2018).

On this measure, the Conservative participants in the study had the highest scores of all, but were closely followed by Reform UK and then 'Other' (and once again, the left-leaning participants clustered below the centre of this scale). Given the ordinal nature of the scale, this means that overall, the left-leaning participants feel their

sense of Englishness less than they do another UK constituent nationality (such as Britishness), while the mean scores of the right-leaning participants indicate the opposite.

The Literature Review considered in some detail how landscape, place attachment and sense of national identity are connected (Section 2.8.3), and the RRCI scale (documented in Chapter 7) has at its heart a series of items that specifically relate to the role of landscape in directly constituting an individual's sense of national identity. For those who feel their national identity more strongly, it is therefore unsurprising that they would have higher scores overall on the RRCI scale.

However, Englishness, when allied with Reform UK alignment, seems to work more strongly as a predictor than when it is allied with Conservatism, and I reflect below on why that might be.

8.8.2.1 National identity – flexible or fearful?

The Englishness measure only captures the relative strength of Englishness, and not the *character* of that sentiment, i.e. how does someone *feel* their Englishness? The dividing line may be that one type of English identity largely draws on civic pride, whereas another is more fear-based, perceiving England as 'under siege'. Climate policies (and those who propose them), rather than climate change itself, may therefore be felt as yet another front in that siege. It is possible that the relationship between different right-leaning political identifications (Conservative or Reform) and resistance to rural climate policy is filtered through a 'confident' vs a 'fearful' conception of Englishness (categorisations that align with the findings of More in Common, (2025b, 2025a)).

Furthermore, as detailed in the Literature Review (Section 2.5.3.2) traditional Conservatism's foundational principles, which include concepts like the intergenerational contract, gradual evidence-based change, and 'oikophilia' (or love of home), can accommodate substantial rural change where it aligns with local stewardship and community-level decision-making (Oakeshott, 1962; Scruton, 2017). This potentially explains lower resistance among Conservative voters

(depending on the circumstances under which such policies are implemented), because genuinely locally-rooted climate initiatives can be reconciled with traditional notions of land-based business and positive environmental stewardship.

By contrast, Reform UK represents a populist movement without a coherent ideology, uniting voters primarily through threat-based activation of emotions, and a shared conviction that mainstream parties have failed them, which has been a remarkably successful strategy even though many supporters hold conflicting positions on policy priorities (Deo, 2025). Reform UK's framing of climate policy largely avoids mention of the predicted medium-term and long-term severe impacts of climate change *itself* on treasured localities (and indeed, on the nation). Instead, their message casts climate *policies,* and by extension, the people who promote them, as the primary proximate threat to valued places, and as an unfair imposition on hard-working people. In this, their work is made easier by some climate activists. Binding the need for climate action to wider radical political change with strong globalist, social justice messages, and insisting that the two cannot be separated (Tyfield, (Manuscript submitted for publication) Lancaster Environment Centre, Lancaster University), seems most antagonistic to Reform UK voters: surveys suggest 72% of Reform UK voters believe that people who campaign on climate change are *'out of touch with most of the country'*, compared to just 37% of the public as a whole (Climate Barometer, 2024a, 2024b).

8.8.3 Rurality's role in predicting resistance to rural climate initiatives on the political right

Conservatives in the sample had the highest rurality score (from an 'all-rural' sample), out of any party group. The higher mean score for the Conservative group came from their higher propensity to score points *right across* the index. The highest-scoring participants (simultaneously employed in rural jobs such as farming and rural land agency, members of rural associations like the NFU and local agricultural societies, and participants in rural hunting sports) were far more likely to be Conservative than another party.

Returning to the theories of Conservatism and 'place-stewardship' outlined in Section 2.5.3.2 of the Literature Review, it seems conceivable that Conservatives are more likely to have control or influence over land management, or at least move in social and professional circles with people that do. They can therefore imagine types of rural climate action as consistent with diversified agricultural business models. This can more readily align with landscapes as living tradition, moulded by both preservation and adaptation to new opportunities. They may still attract censure for 'delaying climate action', since it is reasonably likely that what they perceive as an acceptable pace of landscape change may never seem fast enough for those who advocate that the science cannot wait for this sort of 'Oakeshottian' approach (returning to the activist tension noted by Tyfield, above). It is also conceivable that traditional Conservative notions of distributism[43] (as opposed to capitalism or socialism) potentially underpin their lower resistance to rural climate initiatives. A 'Little England' vision of locally owned, land-based business *could* be more easily reconciled to changing agricultural practices, renewable energy installations, and reforestation projects that respond to wider change, but where decision making is rooted in evolving business opportunity at the local level, rather than 'imposed from above'.

By contrast, Reform UK supporters had among the lowest rurality scores. Recall that this sample is drawn from rural places, but that the vast majority of participants are 'spatially rural', i.e. living in a rural area, only. Unlike the highest-scoring participants (mostly Conservative with multifaceted rural identities), I posit that 'spatially rural' Reform UK voters will have fewer levers of control over if, how and when their places change, making them more likely to respond with defences rooted in an emotionally deep, but experientially shallow, nostalgia for place. In this I also draw on the work of Chou et al. (2022). They report that simply 'feeling' connected to a locality (rather than 'being embedded' in it) predicts a higher likelihood of voting for radical-right parties. 'Feeling connected' (*"this paradoxical state of pining*

[43] Distributism, often attributed to GK and Cecil Chesterton, with Hillaire Belloc. advocates for widespread enterprise, encouragement of small businesses, family farming, and locally rooted companies with democratic management in their communities.

for an idealised community while simultaneously being isolated from one's actual community" p.136) is a psychological state that can be easily manipulated. This also links to the work of Bolet (2021), whose highly specific but very revealing work examines the decline in village pubs in England. Bolet understands pubs as local 'socio-cultural spaces' that are often the only option for socially embedding in rural communities for those not engaged in rural employment and sport, thus their decline leads to an increase in support for radical right parties. This difference between 'being rural' and 'feeling rural' is potentially one of the key drivers of both resistance to landscape change, and receptiveness to Populist messages when treasured landscapes seem threatened. This brings us to the final variable through which paths to resistance were traced: Populism.

8.8.4 Populism as the clear dividing line on the political right

The most striking difference between the right leaning participants in the study are their markedly different Populism profiles. Here, the Conservative group's mean score dropped below the overall mean (below even that of the Green supporters), making the difference between Conservative and Reform on this measure the starkest of all.

As noted in the Literature Review, Populism as a concept has long proven difficult to define, with different scholars describing it variously as an ideology that specifically sets the 'pure people' against 'corrupt elites' (Mudde, 2004), or as a political style of performative communication (Moffitt, 2016), as well as ranging from narrow definitions of specific populisms, such as "*a rural movement seeking to realise traditional values in a changing society*" (Canovan, 1981), to the widest definition of all, which defines Populism as constitutive of all politics, through the making and re-making of 'us' and 'them' (Laclau, 2005).

It is the definition of Populism as a 'performative strategy' that provides the most convincing interpretation for making sense of the results revealed in the present study. Populists are "*fully personalistic and therefore, following the leader's whims, more pragmatic and opportunistic*", which sets them apart from other ideologically dogmatic extremists, even when they share some core messages (Weyland, 2017

p.50). Thus, to secure votes and cement power, Populist leaders expertly weave sometimes disconnected chains of grievances together, often aligned with conflicting ideologies. But they do not fabricate them from thin air. They make simplistic connections between issues, often assigning outcomes to the wrong causes or actors but, more often than not, they draw on sharp and gritty realities; degraded environments and public realm, stagnant or falling living standards, services in decline and threats to valued places or identities. Rural change caused by climate policies therefore becomes a grievance that populist politicians can exploit, and in doing so, create a defensive, fear-based appeal.

8.9 A Pragmatic Interpretation of Resistance to Rural Climate Policy

The crucial question for this thesis then becomes, why is it that Conservative and Reform UK voters, who share similar levels of Englishness and right-wing identification, diverge so sharply on climate policy resistance?

We have seen that Conservatives in our sample have reasonably muted resistance (higher than left-leaning survey respondents, but not hugely higher than the mean of the means). Reform voters have much higher resistance scores, associated with very high populism and rejection of 'climate science' itself. It may be possible to make sense of these differences by drawing on Pragmatist Philosophy's ideas about the temporality of 'truth'. By this I return to the idea briefly covered in Chapter 3 (on Methodology), that people use experiences of the past to evaluate knowledge claims in terms of their potential consequences in the future, rather than merely considering the empirical content of the claim *in the moment*.

The Concluding Discussion for Part 1 of this thesis has already referred to "*the acceptance of settled science as 'an exercise in epistemic trust' (of institutions); it does not stem from engagement with primary evidence, per se*" (Section 6.2.2). In addition, Table 2 of the Literature Review laid out the 'sequential hierarchy' of claims that are made under the umbrella term 'Climate Science' – they include those things that we know *have happened*, and things that we are highly confident *have caused that to happen.* But other 'truth claims' in the Climate Science basket include *things that*

have not yet happened, along with a significant number of normative claims about '*what ought to happen now'*. I contend that the difference between Conservative and Reform voters (which we could possibly extend to the difference between *almost everybody else* and Reform voters) is that their judgements regarding the '*will happen*' and '*ought to happen*' claims reflect strikingly divergent experiences (common across these groups, and so readily crystallising into settled within-group narratives) of how similar claims have played out in the past.

Unpacking that a little, I turn first to William James, who, in his foundational lectures on Pragmatism, articulated that "*Truth lives, in fact, for the most part on a credit system. Our thoughts and beliefs 'pass,' so long as nothing challenges them, just as bank-notes pass so long as nobody refuses them"* (James, 1907, Lecture VI). Pragmatism thus consists of using our experience of the past – i.e. our *own* personal and/or collective experience – to extrapolate forward to (and so reach a judgement regarding) the (as yet unknown) future (Gillespie *et al,* 2024).

So, what does past climate policy – and especially when viewed through the lens of someone situated in rural England without much control over their own lives – tell us about future climate policy? We may note at least three key elements here that collectively shape the judgement of the rural Reform UK supporter: the political economy of climate policy in the UK; degree of socio-political empowerment; and cultural-political identity, specifically regarding climate issues, as this has evolved in recent years.

8.9.1 How is UK climate policy delivery constrained?

Stanley *et al.* (2025) comprehensively demonstrate that the UK's political economy creates a uniquely constrained position in addressing climate change that makes meaningful local control over, or benefits from, decarbonisation structurally impossible. Path-dependent commitments to "sound money" made in the 1980s, and adhered to by all parties since, have entrenched a political culture that insists on balanced budgets, low taxation, and minimal state intervention. The 1980s also saw the UK privatising energy production, allowing profits to flow to (increasingly

foreign) private owners, at the same time as using North Sea oil revenues to largely fund de-industrialisation and welfare costs.

The authors show how the financial crash of 2008 then effectively trapped all subsequent UK governments into 'weak de-risking' approaches to infrastructure development, because without the vast spending power of the US or the pooled spending power of the EU, the UK lacks sufficient funds for direct investment. To deliver climate policy, governments must therefore attract private companies to fund green projects by offering subsidies and guarantees.

This objective strategic position for the UK regarding the political economic 'fundamentals' of climate policy sets up an exceptionally unpromising foundation for formulation of a climate policy capable of offering empowerment and inclusion to already disenchanted rural voters[44]. Indeed, it leans strongly in the other direction, offering rich pickings for critique from that perspective. After decades in which 'PFI' (private-finance initiative) and PPP (public-private partnership) projects have dominated major infrastructure projects, and often with scandalous results, people quickly intuit that projects framed as 'for the public good' are creating guaranteed revenue streams for large, often foreign corporations. (Leake, 2025). Populist figureheads can then tap into the ensuing resentment, blaming the idea of climate policy *itself* (thus creating the space for 'motivated reasoning' rejection of climate science) rather than highlighting that the source of much resentment should lie with this UK-specific mode of implementation. Unfortunately, incumbent governments (whether Conservative or Labour) have not been able to offer a meaningful riposte because of the very fiscal straightjacket that the authors describe.

Crucially, this long period of fiscal constraint has coincided with slow and steady increase in public support for genuinely publicly owned utilities. In a 2017 study, Elliot and Kanagasooriam found that more than three-quarters of the British public

[44] And indeed disenchanted urban voters; however, since the focus of this thesis is rural voters and the Literature Review has shown how climate policy views rural areas as places of opportunity for 'big-lever' policies such as renewable energy, while simultaneously underfunding other climate solutions, it is arguable that the imposition is felt more keenly there.

favoured re-nationalisation of gas, electricity, water and railways, a proportion that held across all age groups. More recently, Smith (2024) finds very similar national proportions, but with illuminating party-by-party breakdowns; where 52% of Conservatives would like to see energy companies re-nationalised, this figure rises to 75% of Reform UK voters. This difference thus needs explanation in terms of a further factor.

8.9.2 Has history been viewed differently by Conservative and Reform UK voters?

This difference may partially reflect the 'spatially rural only' versus 'embedded rurality' distinction identified earlier, which would seem to align to some extent with degree of socio-political empowerment in those rural areas. In the aggregate, Conservative voters (more deeply embedded in rural institutions and economies) potentially have mechanisms to adapt to (and benefit from) climate policy. The history of climate policy implementation may have told Conservative voters a story with at least a few positive messages, such as domestic scale renewable subsidies to improve the homes that they own and live in, grants for EVs and chargers, or diversification and income generation projects on the farms that they run.

Reform voters, spatially present but less embedded and/or having less control, benefit less in this way. They are perhaps more likely to experience disruption without compensation. For them, climate policy history tells a different story, where the green revolution promises of the past 2-3 decades have delivered little in the way of meaningful benefit to their local economies, their services, or their bank balances. This same history has told them that their communities will not be prioritised for funding to live low-carbon lives themselves (Allen and Hinchcliff, 2020; Burbidge, 2023). Adding insult to injury, since large scale renewable energy generation has been concentrated in rural places, they see that rural communities have borne the brunt in a literal and physical sense too. (CPRE, 2025). It should hardly be surprising, then, that they would take a pragmatically dim view of claims about *what ought to happen now* against the evidence of *what has happened in the past*.

8.9.3 Climate activism and political polarisation

Finally, laying on top of these dynamics is a cultural-political ratchet of grievance that has further radicalised political identities, expanding the differences between Conservative and Reform voters. Recent developments (especially since 2019, with the explosion of climate activism that precipitated the rush of DMPs examined in Part 1 of this thesis) have also taught all voters on the political right that the mainstream demands of climate activists have become ever more entangled with normative frameworks that they simply do not share, and which are unable or unwilling to meet them where they are. Indeed, on this basis, they extrapolate that more climate policy means *more* radical, and *more* culturally alien demands that they would reject.

Tyfield, (Manuscript submitted for publication - Lancaster Environment Centre, Lancaster University) discusses the paradox by which a (rightly) concerned caucus of climate activists, having adopted increasingly confrontational tactics, while simultaneously tying necessary climate action exclusively to hard-left political and economic visions, are dismayed to find that they are losing traction. While Tyfield is clear that the hard-right climate denialists and Populist leaders gleefully benefit from, and stoke, the resultant discord, he is also clear that a workable climate justice strategy must focus on building a genuine "climate majority" (Barasi, 2017), by getting support for ambitious climate action from a majority of people as they currently are, with their current interests and political views.

In the absence of such explicit overtures by 'centre-ground' parties and the climate activism movement, rural voters already drawn to Reform UK for the first two reasons above are being attracted (and/or pushed) ever further toward the party and its associated extreme anti-climate positions, out of defiance toward political elites who view them with contempt, and activists who, failing to recognise their universalist principles as *normative* rather than *objective*, view them as either morally deficient or in need of consciousness-raising.

8.10 Wider significance: Implications for rural climate policy

8.10.1 Breaking the impasse: Radical Localism and Civic Nationalism

Having analysed the attitudes of rural voters to the current situation, this section offers some speculative suggestions for approaches which may be better supported. In the case of rural communities, for the 'climate majority' to be marshalled will require a form of radical localism that cannot be imposed through explicitly left-leaning, activist framings and the lexicons of 'community mobilisation', 'collective action' and 'consciousness-raising'. These are broadly alien to rural cultures and cannot (or will not) adapt themselves to the psychological reality that those on the political right (who dominate rural populations) tend towards smaller scale, hierarchical, closed order systems and tendencies to anthro-centric, rather than eco-centric world views (Graham *et al.*, 2013; Haidt, 2013; Waytz *et al.*, 2019; Duda et al, 2024). Nor are they likely to abandon strongly held national sentiment, for the same deep-rooted reasons. As such, "…*[t]he choice then is between stupid, short-sighted versions of nationalism and intelligent, far-sighted ones*" (Lieven, 2020). There is a danger that unless the views and lives of these groups are better acknowledged, this cohort will be pushed further into the path of Populist opportunists.

Radical localism, where genuine decision-making power and delivery funding for climate policy is devolved to the lowest level (contingent on a recognition that rural areas feel under-threat from climate policy in a way that urban areas do not), is an approach that would better align with rural areas' natural tendencies to self-organising autonomy (in the Burkean, rather than the Marxist tradition). It would require a casting-off of the normative straightjacket that demands an eco-centric world view as the only appropriate frame for action, and frames anthro-centric perspectives as inherently problematic manifestations of 'delay', (Dablander *et al.*, 2025), rather than accepting that some actors have legitimate alternative theories of change. Recent research suggests that this anthro-centric world view is indeed characteristic of smaller-scale societies (Samways, 2025) often resulting in qualitatively different types of environmental action; those with anthro-centric values tend toward practical, hands-on conservation behaviours such as tree

planting, restoration projects, and wildlife monitoring. Crucially, they do this at rates exceeding their eco-centric counterparts, who favour advocacy-based, petition-signing, awareness-raising action (Sockhill et al., 2022).

A 'radical localism' approach would reflect the psychological pragmatism of rural communities, and recognise that what they are seeking is not to be *organised* by *activists,* but *empowered by systems that they already recognise* and which they can work to change organically, not through revolution. Such an approach need hardly mention climate change at all. It would instead focus on maximising local control over decision-making on all types of infrastructure, with incentives for activities that clearly serve the *national* interest, linked to comprehensive, and crucially, *proportionate* compensatory mechanisms for communities and households where the infrastructure or changes are based. Analogous to the 'infrastructure wish lists' that local authorities already use in negotiating planning decisions, rural communities could be supported to develop strategic infrastructure and service plans that define what they need to thrive, which could become policy-relevant documents themselves. A relatively light-touch structure guiding development of these plans could ensure that they are 'climate-compliant'. Comprehensive, good quality public and active travel, walkable communities that maximise active lifestyles and reinvigorate outdoor childhood play, landowners supported to provide tree planting and provide nature conservation space, renewable energy generation that provides locally beneficial tariffs and meaningfully incentivises building additional capacity for export to other areas, a focus on building and retrofitting homes and businesses that are cheap to run and healthy to live and work in, and actions that ensure robust flood and heatwave defences: these are all 'climate action'. In this conception, though, they are pragmatically framed, locally controlled and, crucially, clearly delivered as part of existing systems and structures.

Combining this with support for a revived and positive civic nationalism for England within Britain, may be the only workable way to break both the social impasse and the Populist narrative that *climate policy itself* (and by extension, those who stridently campaign for it) is a threat to communities, places, and identities. But it would require the political centre to decentralise power to a much greater extent,

which (as evidenced by Palese, 2022) has historically proven difficult. Even were this delegation of power be forthcoming, the result would be the classically messy, piecemeal, anti-intellectual, practical approach to muddling through a problem (discussed Section 2.7.3 of the Literature Review) that Aughey, (2007) flags as the very hallmark of Englishness, and that Nairn (1977) bemoans as the core reason that the English have never had a revolution. And that might be a bigger barrier, because it would fall foul of those who believe that climate action, without a revolution, isn't really climate action at all.

Appendix: Chapter 3

APPENDIX 3.1: Full survey underpinning analysis presented in results chapters 5, 6 and 7.

No.	Question content	Var_name	Type_Main	Possible Values
1	How old are you? (you can type X if you prefer not to say)	AGE	Ratio	18-90
2	How would you describe your ethnic origin?	ETHNICITY	Categorical	• White = 1 • Black/African/Caribbean = 2 • Asian (Indian, Bangladeshi, Pakistani, any other Asian) = 3 • Mixed two or more ethnic groups = 4 • Other (Arab and any others) = 5 • Prefer not to say = 6
3	Are you male or female?	SEX	Categorical	• Male = 1 • Female = 2 • Prefer not to say = 0
4	Which English local authority area do you live in?	LANATIONAL	Categorical	UK local authority reference list

5	How would you describe the place where you currently live?	LIVE_NOW	Ordinal	A dense urban area in a major city = 1 A dense urban area in a large town or small city = 2 The suburbs of a major city = 3 The suburbs of a large town or small city = 4 A market town in a largely rural area = 5 A village in a largely rural area = 6 A hamlet or isolated rural house = 7
6	How would you describe the type of place where you spent THE MAJORITY of your childhood.	LIVE_CHILDHOOD	Ordinal	A dense urban area in a major city = 1 A dense urban area in a large town or small city = 2 The suburbs of a major city = 3 The suburbs of a large town or small city = 4 A market town in a largely rural area = 5 A village in a largely rural area = 6 A hamlet or isolated rural house = 7
7	Have you, or any members of your household, ever worked in the following professions: agriculture, forestry, gamekeeping, or rural land agency?	RURAL_JOB	Categorical	Yes= 1 No = 2
8	Regardless of where you live now, the kind of work you do, or where you grew up, which of these two phrases do you think most accurately reflects the kind of person you are?	RUR_URB	Categorical	Country person = 1 Urban/suburban person = 2

9	Are you a member of any of the following groups? (TICK ALL THAT APPLY)	RURAL_ASSOC	Categorical	National Farmers Union = 1 British Association for Shooting & Conservation (BASC) = 2 A local agricultural society = 3 A local hunt = 4 A local game-bird shoot = 5 The Countryside Alliance = 6 CPRE (The Countryside Charity, previously Campaign to Protect Rural England) = 7 Not a member of any groups = 0
10	If you heard someone talking about "real England," what type of place do you think they mean?	REAL_ENGLAND	Ordinal	A dense urban area in a major city = 1 A dense urban area in a large town or small city = 2 The suburbs of a major city = 3 The suburbs of a large town or small city = 4 A market town in a largely rural area = 5 A village in a largely rural area = 6 A hamlet or isolated rural house = 7
11	Below is a 'strength scale' about some different national identities in the UK. Zero means that you don't feel this sense of national identity at all, and 7 means you have a very strong sense of this national identity. Where would you place yourself on these scales? - Britishness	NAT_ID_BRIT	Interval	0-7

12	Below is a 'strength scale' about some different national identities in the UK. Zero means that you don't feel this sense of national identity at all, and 7 means you have a very strong sense of this national identity. Where would you place yourself on these scales? - Scottishness	NAT_ID_SCOT	Interval	0-7
13	Below is a 'strength scale' about some different national identities in the UK. Zero means that you don't feel this sense of national identity at all, and 7 means you have a very strong sense of this national identity. Where would you place yourself on these scales? - Englishness	NAT_ID_ENG	Interval	0-7
14	Below is a 'strength scale' about some different national identities in the UK. Zero means that you don't feel this sense of national identity at all, and 7 means you have a very strong sense of this national identity. Where would you place yourself on these scales? - Welshness	NAT_ID_WELSH	Interval	0-7
15	Below is a 'strength scale' about some different national identities in the UK. Zero means that you don't feel this sense of national identity at all, and 7 means you have a very strong sense of this national identity. Where would you place yourself on these scales? - Irishness	NAT_ID_IRISH	Interval	0-7

16	Generally speaking, which political party do you think best represents your views?	PARTY_ALIGN	Categorical	Green Party = 1 Labour Party = 2 Liberal Democrats = 3 Conservative = 4 Reform UK = 5 UKIP = 6 BNP = 7 Other = 0
17	In politics people sometimes talk of left and right. Where would you place yourself on this scale?	L-R_SCALE	Interval	1-10 (no neutral midpoint) and Don't know
18	On the subject of climate change, do you think..	CC_CAUSE	Categorical	The world's climate is changing , largely due to human activity = 1 The world's climate is changing, largely due to natural causes = 2 The world's climate is not changing = 3
19	How much do you agree or disagree with the following statements? - The people, not politicians, should make our most important policy decisions	POP_PEOPLE_IMP	Ordinal	1-5 likert Strongly Disagree to Strongly Agree
20	How much do you agree or disagree with the following statements? - I would rather be represented by a citizen than a specialised politician	POP_REPRESENT_ME	Ordinal	1-5 likert Strongly Disagree to Strongly Agree

21	How much do you agree or disagree with the following statements? - The politicians in the UK Parliament need to follow the will of the people	POP_WILL_PPL	Ordinal	1-5 likert Strongly Disagree to Strongly Agree
22	How much do you agree or disagree with the following statements? - What people call 'compromise' in politics is really just 'selling out' on one's principles.	POP_COMPROMISE	Ordinal	1-5 likert Strongly Disagree to Strongly Agree
23	How much do you agree or disagree with the following statements? - Elected officials talk too much and take too little action	POP_TALK_MUCH	Ordinal	1-5 likert Strongly Disagree to Strongly Agree
24	LS1-1: It doesn't matter to me what the English countryside looks like, as long as I know that changes we make are directly tackling climate change.	LS1-1_CHANGES_OK_4_CC	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
25	LS1-2: The English countryside is no place for industrial scale renewable energy installations like wind turbines or solar farms.	LS1-2_NO_RE_IN_RURAL	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
26	LS1-3: England's countryside would be changed for the better if there were far fewer sheep and cows in the fields.	LS1-3_BETTER_NO_LIVESTOCK	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .

27	LS1-4: Farmers should be supported to turn some of their drained fields back into natural wetlands.	LS1-4_NEW_WETLANDS	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
28	LS1-5: Rural areas in England should produce as much renewable energy as they can and export any spare energy to our towns and cities.	LS1-5_RURAL_EXPORT_RE	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
29	LS2-1: It is not the role of rural areas in England to provide renewable energy for towns and cities	LS2-1_RURAL_NOEXPORT_RE	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
30	LS2-2: I would find it upsetting if large areas of English farmland were 're-wilded' by returning them to nature.	LS2-2_UPSET_REWILD	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
31	LS2-3: If we are to successfully tackle climate change, England's countryside management strategy must be led by scientists, not farmers.	LS2-3_RURAL_SCIENTIST_MGMNT	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
32	LS2-4: It will damage the beauty of the English countryside if fields of grazing sheep are replaced with fields of crops instead.	LS2_4_DAMAGE_IF_CROP_no_SHEEP	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
33	LS2-5: Reducing the amount of meat in our diets would be a good thing for this country, because it would allow us to re-wild and re-forest large areas of England's countryside	LS2-5_NOMEAT_REWILD_IS_GOOD	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
34	LS2-6: I don't mind taxpayers' money being used to help farmers do all they can to tackle climate change, even if it means the English landscape will look very different	LS2-6_TAXPAY_FARMCHANGE_ FOR_CC_GOOD	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .

35	LS2-7: It saddens me to think of the English countryside changing	LS2-7_SAD_LANDSC_CHNG	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
36	LS3-1:It will negatively affect the English landscape if people reduce the amount of beef and dairy products that they eat.	LS3-1_LESS_MEAT_LANDSC_DAMG	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
37	LS3-2: The farmers and landowners who manage England's countryside now are best-placed to decide how we use rural areas to tackle climate change in the future	LS3-2_RURAL_FARMER_MGMNT	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
38	LS3-3: The real heart of English identity is found in our rural landscapes and places, not in our cities and towns.	LS3-3_ENG_ID_IN_RURAL	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
39	LS3-4: Preserving traditional ways of managing the countryside is vital, even if it means doing less than we otherwise could to tackle climate change	LS3-4_TRAD_MGMT_BEATS_CC	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
40	LS3-5: I am happy with the fact that, as our diets change to tackle climate change, so will the English landscape	LS3-5_DIET_CHNG_LS_OK	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
41	LS3-6: If the English landscape were radically different, it would change who we are as a nation	LS3-6_LANSDC_IS_NAT.ID	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
42	LS4-1:The English countryside is beautiful to me largely because it has been shaped by many generations of my country-people	LS4-1_LANDSC_BEAUTY_PAST_PPL	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .

43	LS4-2: The English countryside would be improved by large areas of new forestry and woodlands.	LS4-2_NEW_FORESTS_GOOD	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
44	LS4-3: Renewable energy should never be built on farmland where food could be grown instead	LS4-3_NO_RE_ON_FOOD_LAND	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
45	LS4-4: We should encourage the planting of fast-growing trees in England's countryside to tackle climate change, even if they are non-native species	LS4-4_NON_NATIVE_TREE_OK	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
46	LS4-5: In England, we should focus our efforts to tackle climate change in towns and cities, and leave the countryside alone	LS4-5_DO_CC_POLICY_IN_TOWN	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
47	LS4-6: I would rather that English rural landscapes are preserved as they are now	LS4-6_PREFER_LANDSC_NOW	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
48	LS4-7: I see no reason why farmers shouldn't generate renewable energy on their land, so long as they can still produce food around it.	LS4-7_RE_MIX_FOOD_OK	Ordinal	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .
49	Using the scale below, please indicate whether you think this would be a good way or a bad way of informing climate policy decisions in your local area.**(*see vignette below)** - Do you think this would be a good way or a bad way of making decisions in your local area.	DMP_GOOD.BAD	Interval	11pt scale with two ends marked. Respondents saw 'Completely disagree (0)' 1,2,3,4,5,6,7,8,9, 'Completely Agree(10)' .

50	And which of the following statements about a Citizens Assembly on climate policy comes closest to your views? (1) I would volunteer to take part so that I could represent the point of view that climate change is a serious environmental threat. (2) I would volunteer to take part so that I could represent the point of view that the threat of climate change is greatly over-exaggerated. (3) I would not volunteer to take part in a process like this	DMP_VOL_&_WHY	Interval	I would volunteer to take part so that I could represent the point of view that climate change is a serious environmental threat = 1 I would volunteer to take part so that I could represent the point of view that the threat of climate change is greatly over=-exaggerated = 2 I would not volunteer to take part in a process like this = 3
51	RANK_AGE- most important (1) to least important (6), which characteristics should be taken into account when picking a group of people to take part in a climate assembly?- People of different ages	DMP_RANK_AGE	Interval	1-6 (participants drag options into rank order, therefore data download for each participant gives each variable the number of their choice, where 1 = most important and 6 = least important
52	RANK_ETHNIC- most important (1) to least important (6), which characteristics should be taken into account when picking a group of people to take part in a climate assembly?-People from different ethnic groups	DMP_RANK_ETHNIC	Interval	1-6 (participants drag options into rank order, therefore data download for each participant gives each variable the number of their choice, where 1 = most important and 6 = least important
53	RANK_INCOME- most important (1) to least important (6), which characteristics should be taken into account when picking a group of people to take part in a climate assembly?-People with different levels of income	DMP_RANK_INCOME	Interval	1-6 (participants drag options into rank order, therefore data download for each participant gives each variable the number of their choice, where 1 = most important and 6 = least important

54	RANK_EDU_LEV - most important (1) to least important (6), which characteristics should be taken into account when picking a group of people to take part in a climate assembly?- People with different levels of education	DMP_RANK_EDU_LEV	Interval	1-6 (participants drag options into rank order, therefore data download for each participant gives each variable the number of their choice, where 1 = most important and 6 = least important
55	RANK_JOB_TYPE- most important (1) to least important (6), which characteristics should be taken into account when picking a group of people to take part in a climate assembly?-People with different types of jobs	DMP_RANK_JOB_TYPE	Interval	1-6 (participants drag options into rank order, therefore data download for each participant gives each variable the number of their choice, where 1 = most important and 6 = least important
56	RANK_POL_PARTY- most important (1) to least important (6), which characteristics should be taken into account when picking a group of people to take part in a climate assembly?-People who support different political parties	DMP_RANK_POL_PARTY	Interval	1-6 (participants drag options into rank order, therefore data download for each participant gives each variable the number of their choice, where 1 = most important and 6 = least important

*Q49 Vignette given describing a Climate Assembly "Imagine that residents in your area were given the opportunity to influence political decisions on Climate Change at the local level by participating in a 'Citizens Assembly'. The Assembly will be organised by an independent organisation. It will be composed of 100 randomly selected citizens from your area, ensuring a mix of different socio-economic backgrounds. These citizens will come together for a series of weekend and evening meetings, where they will hear from a range of expert speakers. They will be paid for their time, and supported with transport if they need it. The citizen group will discuss how Climate Change should be tackled locally, and will develop a list of recommendations for local policy makers. The recommendations are advisory, which means the local government can choose whether to take account of them when making local decisions."

Random presentation of 25, 50 or 100 people, random presentation of 'Local politicians' or 'an independent organisation' to control for these factors

Appendices: Chapter 4

APPENDIX 4.1: Election Results 2010, 2015, 2107, 2019

Percentage vote share, Herefordshire North and Herefordshire South Parliamentary Constituencies

North Herefordshire Constituency						
Election Year	Conser-vative	UKIP*	Liberal Democrat	Labour	Green	Independent
2010	51.80	5.7	31.0	7.1	3.2	1.2
2015	55.60	14.0	12.0	11.4	7.0	-
2017	62.00	-	11.7	18.9	5.5	1.8
2019	63.00	-	14.3	13.3	9.3	-

Hereford & South Herefordshire Seat							
Election Year	Conser-vative	UKIP*	BNP**	Liberal Democrat	Labour	Green	Independent
2010	46.20	3.4	2.0	41.1	7.2	-	-
2015	52.60	16.8	-	10.6	12.8	7.2	-
2017	53.50	2.3	-	7.0	23.8	2.4	11.0
2019	61.20	-	-	12.5	21.6	4.8	-

* UKIP = United Kingdom Independence Party

** BNP = British National Party

APPENDIX 4.2: Survey questionnaire – HCCA participants

How old were you on your last birthday?

What best describes your ethnic origin?

- White
- Black/African/Caribbean
- Asian (Indian, Pakistani, Bangladeshi, Chinese, any other Asian background)
- Mixed two or more ethnic groups
- Other (Arab or any others)
- Prefer not to say

Are you male or female?

- Male
- Female
- Prefer not to say

Generally speaking, do you think of yourself as most aligned with a particular party?

- Labour
- Conservative
- Green
- Liberal Democrat
- UK Independence Party (UKIP)
- British National Party (BNP)
- Other

If you answered 'Other' to the previous question, please feel free to enter the name of a different political party you feel most aligned to here:_____

Q4.7 In politics people sometimes talk of left and right. Where would you place yourself on this scale?

	1 (LEFT)	2	3	4	5	6	7	8	9	10 (RIGHT)
Where would you place yourself on this scale?										

How much do you agree or disagree with the following statements? [Hidden text: Scale name ACTIVE_OPEN_MIND]

5pt bipolar Likert Scale from Strongly Disagree to Strongly Agree

- Allowing oneself to be convinced by an opposing argument is a sign of good character
- People should take into consideration evidence that goes against their beliefs
- People should revise their beliefs in response to new information or evidence
- Changing your mind is a sign of weakness (RS)
- Intuition is the best guide in making decisions (RS)
- It is important to persevere in your beliefs even when evidence is brought to bear against them (RS)
- One should disregard evidence that conflicts with one's established beliefs (RS)

How much do you agree or disagree with the following statements? [Hidden text: Scale name NEW ECOLOGICAL PARADIGM – Dunlap et al]

5pt bipolar Likert Scale from Strongly Disagree to Strongly Agree

- We are approaching the limit of the number of people the earth can support

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- Humans have the right to modify the natural environment to suit their needs (RS)
- When humans interfere with nature, it often has disastrous consequences
- Human ingenuity will ensure that we do NOT make the earth un-liveable (RS)
- Humans are severely abusing the environment
- The earth has plenty of natural resources if we just learn how to develop them (RS)
- Plants and animals have as much right as humans to exist
- The balance of nature is strong enough to cope with the impacts of modern industrial nations (RS)
- Despite our special abilities, humans are still subject to the laws of nature
- The so called 'ecological crisis' facing humanity has been greatly exaggerated (RS)
- The earth is like a spaceship with very limited room and resources
- Humans were meant to rule over the rest of nature (RS)
- The balance of nature is very delicate and easily upset
- Humans will eventually learn enough about how nature works to be able to control it (RS)
- If things continue on their present course, we will soon experience a major ecological catastrophe (15)

On the subject of climate change, do you think..

- The world's climate is changing, largely due to human activity
- The world's climate is changing, largely due to natural causes
- The world's climate is not changing

Now thinking back about your experience of how the Climate Assembly was run, how much would you agree or disagree with the following statements? [Hidden text: Scale name LEGITIMACY]

5pt bipolar Likert Scale from Strongly Disagree to Strongly Agree

- The resources provided to us were neutral, with fair and balanced viewpoints provided
- The information provided was too narrow in scope (RS)
- As a group of citizens, I felt we were a good representation of Herefordshire society as a whole
- The information given by the expert speakers was unbiased
- There was enough time to discuss all the issues we wanted to cover
- I felt that we could ask for more information when we needed it.
- If we asked for more information, it was provided
- I felt I was given a fair number of opportunities to speak
- I felt all the other participants were given a fair number of opportunities to speak
- All members were heard equally

Which statement comes closest to your views?

- it was important for me to take part in the Herefordshire Climate Assembly to represent the point of view that climate change is a serious environmental threat
- it was important for me to take part in the Herefordshire Climate Assembly to represent the point of view that the threat of climate change is greatly over-exaggerated

And again thinking about how you felt while taking part in the Assembly, how much do you agree or disagree with the following statements? [Hidden text: Scale name INCLUSION]

5pt bipolar Likert Scale from Strongly Disagree to Strongly Agree

- Fellow participants respected what I had to say, even when they didn't agree with me
- I did not get to properly discuss the things that were important to me (RS)
- I had a lot in common with other participants in the Climate Assembly
- I was treated fairly and without discrimination by the facilitators
- My views were often not in line with the views of the majority of other participants (RS)
- I felt that my views were heard
- The facilitators tried to stop some people from giving their opinions (RS)
- I felt pressured to agree with the ideas or arguments of others (RS)
- My contributions, by and large, made it into the recommendations
- On the whole, I was comfortable with the final recommendations we came up with

How much do you agree with the following statements: "Any future Citizens Assembly on Climate Change should always have external speakers who represent the view that... [Hidden text: Scale name SCOPE]

5pt bipolar Likert Scale from Strongly Disagree to Strongly Agree

- Climate Change is a hoax
- Climate Change is a problem that can best be solved through the application of science and technology
- Policies that aim to tackle Climate Change should not be so strict that they discourage industrial development
- Policies that aim to tackle Climate Change should not radically alter established ways of farming and managing the countryside in England
- The Climate has always changed and humanity can learn to adapt to the changes that scientists now predict

APPENDIX 4.3: Probability distribution tables

Binomial probability tables for assessment of minimum number of Conservative voters in a sample of 40 residents, given known proportions of Conservative voters in the wider population.

Tables cut to 95% confidence level, to show probability of 'more than but not equal to' a given number of Conservatives at the stated value of (p) [estimated proportion in the population].

Binomial Probability distribution

n (number of trials) 40

p (probability of success) 0.439 LOWER BOUND

Possible values of x	Prob-exact	Prob-More than but not equal to
1	0.0%	100.0%
2	0.0%	100.0%
3	0.0%	100.0%
4	0.0%	100.0%
5	0.0%	100.0%
6	0.0%	100.0%
7	0.0%	100.0%
8	0.1%	99.9%
9	0.3%	99.6%
10	0.7%	98.9%
11	1.4%	97.5%
12	2.7%	94.8%

Binomial Probability distribution

n (number of trials) 40

p (probability of success) 0.516

MID RANGE ESTIMATE.

Possible values of x	Prob-exact	Prob-More than but not equal to
1	0.0%	100.0%
2	0.0%	100.0%
3	0.0%	100.0%
4	0.0%	100.0%
5	0.0%	100.0%
6	0.0%	100.0%
7	0.0%	100.0%
8	0.0%	100.0%
9	0.0%	100.0%
10	0.0%	99.9%
11	0.1%	99.8%
12	0.3%	99.5%
13	0.7%	98.8%
14	1.4%	97.4%
15	2.6%	94.8%

Binomial Probability distribution

n (number of trials) 40

p (probability of success) 0.621 UPPER BOUND

Possible values of x	Prob-exact	Prob-More than but not equal to
1	0.0%	100.0%
2	0.0%	100.0%
3	0.0%	100.0%
4	0.0%	100.0%
5	0.0%	100.0%
6	0.0%	100.0%
7	0.0%	100.0%
8	0.0%	100.0%
9	0.0%	100.0%
10	0.0%	100.0%
11	0.0%	100.0%
12	0.0%	100.0%
13	0.0%	100.0%
14	0.0%	100.0%
15	0.1%	99.9%
16	0.2%	99.6%
17	0.5%	99.1%
18	1.1%	97.9%
19	2.2%	95.7%
20	3.7%	92.0%

B: Hypergeometric probability table for assessment of number of Conservatives in any group of 40 residents given a known proportion in a sub-sample of 26.

N: 40

n: 26

x: 6

K	alpha (false alarm probability)
6	100.0000000%
7	96.4717039%
8	85.9937337%
9	68.9670320%
10	49.1940882%
11	31.0688897%
12	17.3187391%
13	8.4793566%
14	3.6153578%
15	1.3236660%
16	0.4069893%
17	0.1014304%
18	0.0193039%
19	0.0025053%
20	0.0001670%

Appendix: Chapter 5

APPENDIX 5.1: Pairwise comparisons, preferred selection variable ranking

Difference in how supporters of each different political party ranked the potential selection characteristics for recruitment to a hypothetical DMP.

Kruskal-Wallis

	χ^2	df	p	ε^2
RANK_AGE	1.61	5	0.900	0.00242

Dwass-Steel-Critchlow-Fligner pairwise comparisons

Pairwise comparisons - RANK_AGE

		W	p
CON	GRN	−0.2835	1.000
CON	LAB	−0.0479	1.000
CON	LD	−1.0768	0.974
CON	Other	0.8866	0.989
CON	REF	0.3966	1.000
GRN	LAB	0.1365	1.000
GRN	LD	−0.8229	0.992
GRN	Other	1.1278	0.968
GRN	REF	0.5897	0.998
LAB	LD	−0.8759	0.990
LAB	Other	0.6848	0.997
LAB	REF	0.2750	1.000
LD	Other	1.6943	0.838
LD	REF	1.2393	0.952
Other	REF	−0.3545	1.000

Kruskal-Wallis

	χ^2	df	p	ε^2
RANK_ETH	106	5	< .001	0.158

Dwass-Steel-Critchlow-Fligner pairwise comparisons

Pairwise comparisons - RANK_ETH

		W	p
CON	GRN	−6.0593	< .001
CON	LAB	−5.6462	< .001
CON	LD	−5.3699	0.002
CON	Other	−0.9019	0.988
CON	REF	6.5647	< .001
GRN	LAB	−0.0781	1.000
GRN	LD	−0.0702	1.000
GRN	Other	4.7524	0.010
GRN	REF	12.3399	< .001
LAB	LD	0.0813	1.000
LAB	Other	4.5017	0.018
LAB	REF	11.5172	< .001
LD	Other	4.2853	0.030
LD	REF	11.1152	< .001
Other	REF	7.1560	< .001

Kruskal-Wallis

	χ^2	df	p	ε^2
RANK_INC	6.59	5	0.253	0.00988

Dwass-Steel-Critchlow-Fligner pairwise comparisons

Pairwise comparisons - RANK_INC

		W	p
CON	GRN	−2.9910	0.280
CON	LAB	−1.8199	0.793
CON	LD	0.0436	1.000
CON	Other	−1.6133	0.865
CON	REF	0.0000	1.000
GRN	LAB	0.8902	0.989
GRN	LD	2.3375	0.564
GRN	Other	1.0340	0.978
GRN	REF	2.6480	0.419
LAB	LD	1.4841	0.901
LAB	Other	0.1099	1.000
LAB	REF	1.5494	0.884
LD	Other	−1.4324	0.914
LD	REF	−0.1271	1.000
Other	REF	1.3523	0.932

Kruskal-Wallis

	χ^2	df	p	ε^2
RANK_EDU	23.3	5	< .001	0.0349

Dwass-Steel-Critchlow-Fligner pairwise comparisons

Pairwise comparisons - RANK_EDU

		W	p
CON	GRN	3.083	0.247
CON	LAB	2.960	0.291
CON	LD	1.988	0.724
CON	Other	−0.810	0.993
CON	REF	−2.755	0.373
GRN	LAB	0.311	1.000
GRN	LD	−1.036	0.978
GRN	Other	−3.367	0.163
GRN	REF	−5.541	0.001
LAB	LD	−1.094	0.972
LAB	Other	−3.274	0.188
LAB	REF	−5.174	0.003
LD	Other	−2.446	0.512
LD	REF	−4.477	0.019
Other	REF	−1.597	0.870

Kruskal-Wallis

	χ^2	df	p	ε^2
RANK_JOB	27.2	5	< .001	0.0408

Dwass-Steel-Critchlow-Fligner pairwise comparisons

Pairwise comparisons - RANK_JOB

		W	p
CON	GRN	4.284	0.030
CON	LAB	3.165	0.220
CON	LD	2.204	0.626
CON	Other	−0.185	1.000
CON	REF	−2.153	0.650
GRN	LAB	−0.986	0.982
GRN	LD	−1.748	0.819
GRN	Other	−4.146	0.040
GRN	REF	−6.265	< .001
LAB	LD	−0.831	0.992
LAB	Other	−3.174	0.218
LAB	REF	−5.217	0.003
LD	Other	−2.268	0.596
LD	REF	−4.127	0.041
Other	REF	−1.725	0.828

Kruskal-Wallis

	χ^2	df	p	ε^2
RANK_POL	7.96	5	0.159	0.0119

Dwass-Steel-Critchlow-Fligner pairwise comparisons

Pairwise comparisons - RANK_POL

		W	p
CON	GRN	1.5169	0.892
CON	LAB	0.1509	1.000
CON	LD	1.5955	0.870
CON	Other	1.9923	0.722
CON	REF	−1.6532	0.852
GRN	LAB	−1.0248	0.979
GRN	LD	−0.0414	1.000
GRN	Other	0.5532	0.999
GRN	REF	−2.7805	0.362
LAB	LD	1.2116	0.957
LAB	Other	1.8420	0.784
LAB	REF	−1.5468	0.884
LD	Other	0.2577	1.000
LD	REF	−2.9990	0.277
Other	REF	−3.4722	0.138

Appendices: Chapter 6

APPENDIX 6.1: Descriptive statistics, Pilot Survey (n=95)

CODE	Question wording	N	Mean	Median	Std. Dev	Min	Max	Skew	Std. error skew	Kurtosis	Std. error kurtosis
1_ChangeNotMatterIfTackleCC	It doesn't matter to me what the English countryside looks like, as long as I know that changes we make are directly tackling climate change	95	5.49	6	2.9	1	11	0.192	0.247	-0.837	0.49
2_NoREinCountrysides	The English countryside is no place for industrial scale renewable energy installations like wind turbines or solar farms.	95	3.83	4	2.27	1	11	0.599	0.247	0.107	0.49
3_betterNoCows	The English countryside would be changed for the better if there were far fewer COWS in the fields	95	4.65	4	2.7	1	11	0.572	0.247	-0.0555	0.49
4_betterNoSheep	The English countryside would be changed for the better if there were far fewer SHEEP in the fields	95	5.06	5	2.63	1	11	0.441	0.247	-0.186	0.49
5_worseNoCows	One downside of people eating a more plant-based diet is that we will see fewer COWS in England's countryside	95	4.86	5	2.77	1	11	0.219	0.247	-0.637	0.49
6_worseNoSheep	One downside of people eating a more plant-based diet is that we will see fewer SHEEP in England's countryside	95	4.77	5	2.55	1	11	0.261	0.247	-0.306	0.49

CODE	Question wording	N	Mean	Median	Std. Dev	Min	Max	Skew	Std. error skew	Kurtosis	Std. error kurtosis
7_ruralExportRE	Rural areas in England should produce as much renewable energy as they can and export spare to urban areas	95	6.67	6	2.41	1	11	-0.129	0.247	0.114	0.49
8_ruralNoREforTowns	It is not the role of England's rural areas to provide renewable energy for towns and cities	95	5.03	5	2.8	1	11	0.453	0.247	-0.373	0.49
9_ruralScienceStrategy	If we are to successfully tackle climate change, England must have a countryside management strategy based on science, not tradition.	95	8.16	8	2.19	1	11	-0.548	0.247	0.176	0.49
10_ruralTraditionStrategy	The people who manage England's countryside now are best-placed to decide how we use rural areas to tackle climate change	95	5.25	5	2.41	1	11	0.361	0.247	0.0615	0.49
11_rewildingUpsetting	I would find it upsetting if large areas of English farmland were returned to a wild and un-managed state	95	4.48	4	2.88	1	11	0.575	0.247	-0.59	0.49
12_rewildingGood	Reducing the amount of meat in our diets would be a good thing for this country, because it would allow us to re-wild and re-forest large areas of England's countryside	95	7.36	8	2.95	1	11	-0.523	0.247	-0.541	0.49
13_REownedCommunity	Renewable energy systems like solar farms and wind turbines are only acceptable when they are directly owned by the communities where they are sited	95	5.13	6	2.57	1	11	0.053	0.247	-0.461	0.49
14_RE_Nationalised	The government should establish a national energy company that will build renewable energy in the English countryside for all of us	95	7.61	8	2.83	1	11	-0.624	0.247	-0.301	0.49
15_sadCityChange	It saddens me to think of English cities changing	95	3.83	3	2.47	1	11	0.618	0.247	-0.154	0.49
16_sadRuralChange	It saddens me to think of the English countryside changing	95	5.74	6	2.62	1	11	0.0476	0.247	-0.701	0.49

CODE	Question wording	N	Mean	Median	Std. Dev	Min	Max	Skew	Std. error skew	Kurtosis	Std. error kurtosis
17_IdentityInCities	The real heart of English identity is found in our cities and towns	95	3.76	4	2.06	1	11	0.415	0.247	0.203	0.49
18_IdentityInRural	Rural landscapes are more important to English identity than urban places	95	5.73	6	2.64	1	11	-0.0404	0.247	-0.42	0.49
19_TradMoreImportantthanCC	Preserving traditional rural English ways of life is vital, even if it means doing less than we otherwise could to tackle climate change	95	4.14	4	2.59	1	11	0.708	0.247	-0.0546	0.49
20_FundFarmersToTackleCC	I don't mind taxpayers' money being used to help farmers do all they can to tackle climate change, even if it means the English landscape will look very different	95	7.66	7	2.5	1	11	-0.559	0.247	0.187	0.49
21_CC_policyChangeCitiesForBetter	Tackling climate change offers a great opportunity to transform English towns and cities for the better	95	8.12	8	2.15	1	11	-0.752	0.247	0.831	0.49
22_CC_policyChangeRuralForBetter	Tackling climate change offers a great opportunity to transform England's countryside for the better	95	7.21	7	2.5	1	11	-0.414	0.247	-0.114	0.49
23_dietChangeLandscapeChangeGood	I am excited by the idea that, as our diets change to tackle climate change, so will the English landscape	95	5.84	6	2.69	1	11	-0.127	0.247	-0.552	0.49
24_newCropsGood	I find it encouraging to see new types of crops and plants growing in the English countryside	95	7.8	8	1.97	3	11	0.00409	0.247	-0.713	0.49
25_changeLandscape=changeNation	If the English landscape were radically different, it would change who we are as a nation	95	5.51	6	3.07	1	11	0.146	0.247	-1.17	0.49
26_ruralBeautyInWorkOfPast	The English countryside is beautiful to me largely because it has been shaped by many generations of my countrypeople	95	6.62	6	2.59	1	11	-0.4	0.247	-0.169	0.49

CODE	Question wording	N	Mean	Median	Std. Dev	Min	Max	Skew	Std. error skew	Kurtosis	Std. error kurtosis
27_ForestryImprovesCountryside	The English countryside would be improved by large areas of new FORESTRY	95	7.36	7	2.05	3	11	0.288	0.247	-0.618	0.49
28_WoodlandImprovesCountryside	The English countryside would be improved by large areas of new WOODLAND	95	8.56	9	1.85	3	11	-0.315	0.247	-0.333	0.49
29_WelcomeNonNativeTrees4CCS	We should encourage the planting of fast-growing trees in the English countryside to tackle climate change, even if they are non-native species	95	5.85	6	2.78	1	11	0.0646	0.247	-0.772	0.49
30_FocusCCPolicyCities	We should focus our efforts to tackle climate change in English towns and cities, and leave the countryside alone	95	4.25	4	2.58	1	11	0.685	0.247	0.159	0.49
31_PreserveRuralLandscapes	I would rather that English rural landscapes are preserved as they are now	95	5.42	6	2.73	1	11	0.124	0.247	-0.707	0.49
32_NoRE_OnFoodLand	Renewable energy should never be built on farmland where food could be grown instead	95	5.03	4	2.62	1	11	0.568	0.247	-0.0623	0.49
33_EncourageFarmersRE	I see no reason why farmers shouldn't generate renewable energy on their land, so long as they can still produce food around it.	95	8.82	9	2.09	1	11	-0.98	0.247	1.09	0.49
34_WindTurbinesInteresting	I think that wind turbines add interest to the English countryside	95	6.25	6	2.84	1	11	-0.094	0.247	-0.789	0.49
35_SolarFarmsWelcome	I think that solar farms in England's countryside are a welcome development	95	7.93	8	2.35	2	11	-0.495	0.247	-0.345	0.49

APPENDIX 6.2: Descriptive statistics, EFA cases, Full Survey (n=345)

Descriptives	N	Missing	Mean	Median	Std. Dev	Min	Max	Skew	Std. error skew	Kurtosis	Std. error kurtosis
LS1-1_CHANGES_OK_4_CC	345	0	3.77	3	3.12	1	11	0.851	0.131	-0.529	0.262
LS1-2_NO_RE_IN_RURAL	345	0	5.3	4	3.4	1	11	0.414	0.131	-1.08	0.262
LS1-3_BETTER_NO_LIVESTOCK	345	0	3.29	2	3.01	1	11	1.14	0.131	0.0902	0.262
LS1-4_NEW_WETLANDS	345	0	7.19	8	3.23	1	11	-0.504	0.131	-0.818	0.262
LS1-5_RURAL_EXPORT_RE	345	0	5.87	6	3.31	1	11	0.0297	0.131	-1.13	0.262
LS2-1_RURAL_NOEXPORT_RE	345	0	5.9	6	3.49	1	11	0.03	0.131	-1.31	0.262
LS2-2_UPSET_REWILD	345	0	4.93	4	3.5	1	11	0.445	0.131	-1.17	0.262
LS2-3_RURAL_SCIENTIST_MGMNT	345	0	4.97	5	3.35	1	11	0.315	0.131	-1.13	0.262
LS2_4_DAMAGE_IF_CROP_no_SHEEP	345	0	5.57	6	2.98	1	11	0.172	0.131	-0.827	0.262
LS2-5_NOMEAT_REWILD_IS_GOOD	345	0	5.33	5	3.76	1	11	0.236	0.131	-1.41	0.262
LS2-6_TAXPAY_FARMCHANGE_FOR_CC_GOOD	345	0	5.85	6	3.35	1	11	-0.0347	0.131	-1.21	0.262

Descriptives	N	Missing	Mean	Median	Std. Dev	Min	Max	Skew	Std. error skew	Kurtosis	Std. error kurtosis
LS3-1_LESS_MEAT_LANDSC_DAMG	345	0	5.36	5	3.42	1	11	0.267	0.131	-1.23	0.262
LS3-2_RURAL_FARMER_MGMNT	345	0	6.11	6	3.26	1	11	0.032	0.131	-1.21	0.262
LS3-3_ENG_ID_IN_RURAL	345	0	6.72	7	3.11	1	11	-0.282	0.131	-0.871	0.262
LS3-4_TRAD_MGMT_BEATS_CC	345	0	6.07	6	3.34	1	11	0.0112	0.131	-1.21	0.262
LS3-5_DIET_CHNG_LS_OK	345	0	5.52	6	3.4	1	11	0.0524	0.131	-1.28	0.262
LS3-6_LANSDC_IS_NAT.ID	345	0	6.12	6	3.49	1	11	-0.0761	0.131	-1.31	0.262
LS4-1_LANDSC_BEAUTY_PAST_PPL	345	0	7.66	8	3.02	1	11	-0.645	0.131	-0.629	0.262
LS4-2_NEW_FORESTS_GOOD	345	0	7.05	7	2.82	1	11	-0.419	0.131	-0.482	0.262
LS4-3_NO_RE_ON_FOOD_LAND	345	0	6.6	6	3.47	1	11	-0.102	0.131	-1.32	0.262
LS4-4_NON_NATIVE_TREE_OK	345	0	4.26	4	3.02	1	11	0.658	0.131	-0.621	0.262
LS4-5_DO_CC_POLICY_IN_TOWN	345	0	5.7	6	3.4	1	11	0.0907	0.131	-1.21	0.262

Descriptives	N	Missing	Mean	Median	Std. Dev	Min	Max	Skew	Std. error skew	Kurtosis	Std. error kurtosis
LS4-6_PREFER_LANDSC_NOW	345	0	6.43	6	3.03	1	11	-0.106	0.131	-0.963	0.262
LS4-7_RE_MIX_FOOD_OK	345	0	8.2	8	2.62	1	11	-0.948	0.131	0.406	0.262

APPENDIX 6.3: Descriptive statistics, CFA, Full Survey (n=378)

Item	N	Missing	Mean (with reverse scoring)	Mean (original)	Median (with reverse scoring)	Median (original)	Standard deviation	Minimum	Maximum	Skewness (note flipped sign for RV items)	Std. error skewness	Kurtosis	Std. error kurtosis
LS1.2_NO_RE_IN_RURAL	378	0	5.7	5.7	5	5	3.49	1	11	0.26	0.125	-1.28	0.25
LS1.3RV_BETTER_NO_LIVESTOCK	378	0	8.82	3.18	11	1	2.93	1	11	-1.2	0.125	0.273	0.25
LS1.4RV_NEW_WETLANDS	378	0	4.92	7.08	4	8	3.29	1	11	0.494	0.125	-0.924	0.25
LS1.5RV_RURAL_EXPORT_RE	378	0	6.25	5.75	6	6	3.25	1	11	0.0331	0.125	-1.09	0.25
LS2.1_RURAL_NOEXPORT_RE	378	0	6.31	6.31	6	6	3.45	1	11	-0.0202	0.125	-1.3	0.25
LS2.2_UPSET_REWILD	378	0	4.98	4.98	4	4	3.45	1	11	0.436	0.125	-1.11	0.25
LS2.3RV_RURAL_SCIENTIST_MGMNT	378	0	7.26	4.74	7	5	3.12	1	11	-0.244	0.125	-1.04	0.25
LS2.5RV_NOMEAT_REWILD_IS_GOOD	378	0	6.81	5.19	7	5	3.64	1	11	-0.194	0.125	-1.43	0.25
LS3.1_LESS_MEAT_LANDSC_DAMG	378	0	5.48	5.48	5	5	3.39	1	11	0.275	0.125	-1.15	0.25
LS3.3_ENG_ID_IN_RURAL	378	0	6.63	6.63	6	6	3.13	1	11	-0.23	0.125	-1.01	0.25
LS3.4_TRAD_MGMT_BEATS_CC	378	0	6.28	6.28	6	6	3.22	1	11	0.0678	0.125	-1.12	0.25
LS3.5RV_DIET_CHNG_LS_OK	378	0	6.51	5.49	6	6	3.36	1	11	-0.0744	0.125	-1.2	0.25
LS3.6_LANSDC_IS_NAT.ID	378	0	6.25	6.25	6	6	3.37	1	11	-0.0703	0.125	-1.27	0.25

Item	N	Missing	Mean (with reverse scoring)	Mean (original)	Median (with reverse scoring)	Median (original)	Standard deviation	Minimum	Maximum	Skewness (note flipped sign for RV items)	Std. error skewness	Kurtosis	Std. error kurtosis
LS4.1_LANDSC_BEAUTY_PAST_PPL	378	0	7.7	7.7	8	8	3.05	1	11	-0.714	0.125	-0.491	0.25
LS4.2RV_NEW_FORESTS_GOOD	378	0	4.85	7.15	5	7	2.68	1	11	0.405	0.125	-0.223	0.25
LS4.5_DO_CC_POLICY_IN_TOWN	378	0	5.86	5.86	6	6	3.38	1	11	0.00441	0.125	-1.19	0.25
LS4.6_PREFER_LANDSC_NOW	378	0	6.21	6.21	6	6	2.97	1	11	0.0534	0.125	-0.867	0.25
LS4.7RV_RE_MIX_FOOD_OK	378	0	4.08	7.92	4	8	2.89	1	11	0.85	0.125	-0.019	0.25

APPENDIX 6.4: Fit Measures used in Confirmatory Factor Analysis

Measure	Aim
Model χ^2	A *non*-significant χ^2 value, therefore a *failure to reject* the null hypothesis that the model structure and the sample data structure are the same. (i.e. the model fits the data).
χ^2/df ratio	Ideally less than 2 – accounts for fit per degree of freedom.
RMSEA	Broad guidelines suggest < 0.08 for acceptable fit, < 0.05[45] for close fit. Must interpret with confidence interval (CI) and associated p-value. Upper bound of CI should fall on or below 0.05. The p-value associated with the CI is 'pClose' – a test of close fit. It tests the null hypothesis that the *population* RMSEA is less than or equal to 0.05 (i.e., the model fits "closely" to the data). The alternative hypothesis is that the population RMSEA is greater than 0.05. Significant p-value allows us to *fail to reject* the null hypothesis that the model structure and the sample data structure are the same. (i.e. the model fits the data).
SRMR	<0.05 for good fit, <0.08 for acceptable fit. Biased upwards in very close fitting models, interpret in conjunction with RMSEA.
TLI	≥ 0.95 a traditional guideline, but should not be used as a target. Model refinement beyond this should be pursued where possible and appropriate. Baseline model must have large df for useful comparison.
CFI	≥ 0.95 but not used as a 'target', contextualised with metric space of model (defined via the noncentrality parameter (λ), calculated by subtracting the degrees of freedom of a model from its χ^2 value).
Modification Indices	Modification indices suggest ways the model could be improved - high values (generally >10) indicate that allowing certain items to correlate would significantly improve fit, possibly suggesting these items share something beyond the main factors. However, MIs can only suggest additions to a given structure. They cannot indicate where paths could be constrained to zero to improve fit.

[45] note <0.05 here is the target value of the RMSEA test (the substantive interpretation threshold), indicating an acceptable average amount of error per degree of freedom in the model for the model to be described as having a 'close fit'. It is *not* the same as the p-value (the statistical significance threshold, where >0.05 is generally considered the point at which we fail to reject the null hypothesis, and thus conclude that the model is a close fit to the data). The value '0.05' is coincidentally, and confusingly, the same 'magic number' for both.

APPENDIX 6.5: Model Structure and Fit Measures, 10 rounds Confirmatory Factor Analysis

The Confirmatory Factor Analysis process to develop the RRCI scale was completed over 10 rounds of model specification, modification, and re-specification. The tables below summarise the model specification and measures of fit for each round of testing and re-specification.

Model structure naming convention: Factor names shown underlined; '=~' means 'regressed on'; '~~' means 'covaries with').

Full Jamovi files, containing all Measurement Models, Covariance Matrices, Modification Indices tables etc for each round will be deposited at https://research.lancaster-university.uk/en/datasets/

All Rounds: n=378; robust standard errors; results mean adjusted scaled and shifted; non-centrality parameter (λ) of baseline model >1400, providing sufficiently broad metric space for fine-grained model differentiation using the CFI for each round (van Laar and Braeken, 2021).

CFA Round 1 - Single Factor Solution:

Single Factor~**LS3.1**_LESS_MEAT_LANDSC_DAMG+**LS2.5RV**_NOMEAT_REWILD_IS_GOOD+**LS4.2RV**_NEW_FORESTS_GOOD+**LS1.3RV**_BETTER_NO_LIVESTOCK+ **LS2.3RV**_RURAL_SCIENTIST_MGMNT+**LS1.4RV**_NEW_WETLANDS+**LS3.5RV**_DIET_CHNG_LS_OK+ **LS3.3**_ENG_ID_IN_RURAL+ **LS4.6**_PREFER_LANDSC_NOW +**LS4.1**_LANDSC_BEAUTY_PAST_PPL+**LS3.6**_LANSDC_IS_NAT.ID+**LS4.5**_DO_CC_POLICY_IN_TOWN+**LS3.4**_TRAD_MGMT_BEATS_CC+**LS2.1**_RURAL_NOEXPORT_RE+**LS1.2** _NO_RE_IN_RURAL+**LS1.5RV**_RURAL_EXPORT_RE+**LS4.7RV**_RE_MIX_FOOD_OK+**LS2.2**_UPSET_REWILD.

Free Parameters: 198, Iterations: 15

χ^2	df	χ^2/df	CFI	TLI	SRMR	RMSEA	RMSEA CI (lower)	RMSEA CI (upper)	Modification Indices
1128 (p<0.001)	135	8.36	0.911	0.899	0.072	0.140 (pClose<0.001)	0.132	0.147	22 MI >10. (Range 111 to 10.49). All suggest missing item to item correlations

CFA Round 2 – Three uncorrelated factors:

Resisting Land Use Change=~**LS2.5RV**_NOMEAT_REWILD_IS_GOOD+**LS1.4RV**_NEW_WETLANDS+**LS3.1**_LESS_MEAT_LANDSC_DAMG+**LS1.3RV**_BETTER_NO_LIVESTOCK+**LS2.3RV**_RURAL_SCIENTIST_MGMNT+**LS3.5RV**_DIET_CHNG_LS_OK+**LS4.2RV**_NEW_FORESTS_GOOD+**LS2.2**_UPSET_REWILD

Valuing Landscape Tradition and Identity=~**LS3.3**_ENG_ID_IN_RURAL+**LS4.6**_PREFER_LANDSC_NOW+**LS4.1**_LANDSC_BEAUTY_PAST_PPL+**LS3.6**_LANSDC_IS_NAT.ID+**LS4.5**_DO_CC_POLICY_IN_TOWN+**LS3.4**_TRAD_MGMT_BEATS_CC

Resisting Rural Renewables=~**LS2.1**_RURAL_NOEXPORT_RE+**LS1.2**_NO_RE_IN_RURAL+**LS1.5RV**_RURAL_EXPORT_RE+**LS4.7RV**_RE_MIX_FOOD_OK

Free Parameters:198, Iterations:14

χ^2	df	χ^2/df	CFI	TLI	SRMR	RMSEA	RMSEA CI (lower)	RMSEA CI (upper)	Modification Indices
7251 p<0.001	135	53.71	0.364	0.279	0.348	0.374 pClose <0.001	0.367	0.381	144 MI >10. (Range 11,154 to 11.33). All suggest both factors and items should correlate.

CFA Round 3 – Three correlated factors:

Resisting_Land_Use_Change=~**LS2.5RV**_NOMEAT_REWILD_IS_GOOD+**LS1.4RV**_NEW_WETLANDS+**LS3.1**_LESS_MEAT_LANDSC_DAMG+**LS1.3RV**_BETTER_NO_LIVESTOCK+**LS2.3RV**_RURAL_SCIENTIST_MGMNT+**LS3.5RV**_DIET_CHNG_LS_OK+**LS4.2RV**_NEW_FORESTS_GOOD+**LS2.2**_UPSET_REWILD

Valuing_Landscape_Tradition_and_Identity=~**LS3.3**_ENG_ID_IN_RURAL+**LS4.6**_PREFER_LANDSC_NOW+**LS4.1**_LANDSC_BEAUTY_PAST_PPL+**LS3.6**_LANSDC_IS_NAT.ID+**LS4.5**_DO_CC_POLICY_IN_TOWN+**LS3.4**_TRAD_MGMT_BEATS_CC

Resisting_Rural_Renewables=~**LS2.1**_RURAL_NOEXPORT_RE+**LS1.2**_NO_RE_IN_RURAL+**LS1.5RV**_RURAL_EXPORT_RE+**LS4.7RV**_RE_MIX_FOOD_OK

Resisting_Land_Use_Change ~~ Valuing_Landscape_Tradition_and_Identity

Resisting_Land_Use_Change ~~ Resisting_Rural_Renewables

Resisting_Rural_Renewables ~~ Valuing_Landscape_Tradition_and_Identity

Free Parameters: 201, Iterations: 27

χ^2	df	χ^2/df	CFI	TLI	SRMR	RMSEA	RMSEA CI (lower)	RMSEA CI (upper)	Modification Indices
388 p<0.001	132	2.94	0.977	0.973	0.040	0.072 pClose <0.001	0.064	0.080	Nine MIs >10. Range 27.56 to 10.77. Six of the nine would require theoretically illogical cross-loadings across factors

CFA Round 4 - Three correlated factors, one within-factor covariance on RLUC:

Resisting_Land_Use_Change=~**LS2.5RV**_NOMEAT_REWILD_IS_GOOD+**LS1.4RV**_NEW_WETLANDS+**LS3.1**_LESS_MEAT_LANDSC_DAMG+**LS1.3RV**_BETTER_NO_LIVESTOCK+**LS2.3RV**_RURAL_SCIENTIST_MGMNT+**LS3.5RV**_DIET_CHNG_LS_OK+**LS4.2RV**_NEW_FORESTS_GOOD+**LS2.2**_UPSET_REWILD

Valuing_Landscape_Tradition_and_Identity=~**LS3.3**_ENG_ID_IN_RURAL+**LS4.6**_PREFER_LANDSC_NOW+**LS4.1**_LANDSC_BEAUTY_PAST_PPL+**LS3.6**_LANSDC_IS_NAT.ID+**LS4.5**_DO_CC_POLICY_IN_TOWN+**LS3.4**_TRAD_MGMT_BEATS_CC

Resisting_Rural_Renewables=~**LS2.1**_RURAL_NOEXPORT_RE+**LS1.2**_NO_RE_IN_RURAL+**LS1.5RV**_RURAL_EXPORT_RE+**LS4.7RV**_RE_MIX_FOOD_OK

Resisting_Land_Use_Change ~~ Valuing_Landscape_Tradition_and_Identity

Resisting_Land_Use_Change ~~ Resisting_Rural_Renewables

Resisting_Rural_Renewables ~~ Valuing_Landscape_Tradition_and_Identity

LS4.2RV_NEW_FORESTS_GOOD ~~ LS2.2_UPSET_REWILD

Free Parameters: 202, Iterations to converge: 40

χ^2	df	χ^2/df	CFI	TLI	SRMR	RMSEA	RMSEA CI (lower)	RMSEA CI (upper)	Modification Indices
355 p<0.001	131	2.7	0.980	0.977	0.038	0.067 pClose <0.001	0.059	0.076	Seven MIs >10. Range 24.71 to 10.20. Five of the seven would require theoretically illogical cross-loadings across factors.

CFA Round 5 - Three correlated factors, two within-factor covariances on RLUC:

Resisting_Land_Use_Change=~**LS2.5RV**_NOMEAT_REWILD_IS_GOOD+**LS1.4RV**_NEW_WETLANDS+**LS3.1**_LESS_MEAT_LANDSC_DAMG+**LS1.3RV**_BETTER_NO_LIVESTOCK+**LS2.3RV**_RURAL_SCIENTIST_MGMNT+**LS3.5RV**_DIET_CHNG_LS_OK+**LS4.2RV**_NEW_FORESTS_GOOD+**LS2.2**_UPSET_REWILD

Valuing_Landscape_Tradition_and_Identity=~**LS3.3**_ENG_ID_IN_RURAL+**LS4.6**_PREFER_LANDSC_NOW+**LS4.1**_LANDSC_BEAUTY_PAST_PPL+**LS3.6**_LANSDC_IS_NAT.ID+**LS4.5**_DO_CC_POLICY_IN_TOWN+**LS3.4**_TRAD_MGMT_BEATS_CC

Resisting_Rural_Renewables=~**LS2.1**_RURAL_NOEXPORT_RE+**LS1.2**_NO_RE_IN_RURAL+**LS1.5RV**_RURAL_EXPORT_RE+**LS4.7RV**_RE_MIX_FOOD_OK

Resisting_Land_Use_Change ~~ Valuing_Landscape_Tradition_and_Identity

Resisting_Land_Use_Change ~~ Resisting_Rural_Renewables

Resisting_Rural_Renewables ~~ Valuing_Landscape_Tradition_and_Identity

LS4.2RV_NEW_FORESTS_GOOD ~~ LS2.2_UPSET_REWILD

LS4.2RV_NEW_FORESTS_GOOD ~~ LS1.4RV_NEW_WETLANDS

Free Parameters: 203, Iterations: 33

χ^2	df	χ^2/df	CFI	TLI	SRMR	RMSEA	RMSEA CI (lower)	RMSEA CI (upper)	Modification Indices
317 p<0.001	130	2.44	0.983	0.980	0.035	0.062 pClose =0.013	0.053	0.070	Seven MIs >10. Range 22.23 to 10.30. Six of the seven would require theoretically illogical cross-loadings across factors.

CFA Round 6 - Three correlated factors, three within-factor covariances on RLUC:

Resisting_Land_Use_Change=~**LS2.5RV**_NOMEAT_REWILD_IS_GOOD+**LS1.4RV**_NEW_WETLANDS+**LS3.1**_LESS_MEAT_LANDSC_DAMG+**LS1.3RV**_BETTER_NO_LIVESTOCK+**LS2.3RV**_RURAL_SCIENTIST_MGMNT+**LS3.5RV**_DIET_CHNG_LS_OK+**LS4.2RV**_NEW_FORESTS_GOOD+**LS2.2**_UPSET_REWILD

Valuing_Landscape_Tradition_and_Identity=~**LS3.3**_ENG_ID_IN_RURAL+**LS4.6**_PREFER_LANDSC_NOW+**LS4.1**_LANDSC_BEAUTY_PAST_PPL+**LS3.6**_LANSDC_IS_NAT.ID+**LS4.5**_DO_CC_POLICY_IN_TOWN+**LS3.4**_TRAD_MGMT_BEATS_CC

Resisting_Rural_Renewables=~**LS2.1**_RURAL_NOEXPORT_RE+**LS1.2**_NO_RE_IN_RURAL+**LS1.5RV**_RURAL_EXPORT_RE+**LS4.7RV**_RE_MIX_FOOD_OK

Resisting_Land_Use_Change ~~ Valuing_Landscape_Tradition_and_Identity

Resisting_Land_Use_Change ~~ Resisting_Rural_Renewables

Resisting_Rural_Renewables ~~ Valuing_Landscape_Tradition_and_Identity

LS4.2RV_NEW_FORESTS_GOOD ~~ LS2.2_UPSET_REWILD

LS4.2RV_NEW_FORESTS_GOOD ~~ LS1.4RV_NEW_WETLANDS

LS1.4RV_NEW_WETLANDS ~~ LS2.2_UPSET_REWILD

Free Parameters: 204, Iterations: 32

χ^2	df	χ^2/df	CFI	TLI	SRMR	RMSEA	RMSEA CI (lower)	RMSEA CI (upper)	Modification Indices
282 p<0.001	129	2.19	0.986	0.984	0.033	0.056 pClose =0.130	0.047	0.065	Four MIs >10. Range 17.72 to 13.44. All require theoretically illogical cross-loadings across factors.

CFA Round 7 - Bifactor Model (Specific Factor covariances and item covariances retained):

General_Factor=~**LS3.1**_LESS_MEAT_LANDSC_DAMG+**LS2.5RV**_NOMEAT_REWILD_IS_GOOD+**LS4.2RV**_NEW_FORESTS_GOOD+**LS1.3RV**_BETTER_NO_

LIVESTOCK+**LS2.3RV**_RURAL_SCIENTIST_MGMNT+**LS1.4RV**_NEW_WETLANDS+**LS3.5RV**_DIET_CHNG_LS_OK+**LS3.3**_ENG_ID_IN_RURAL+**LS4.6**_PREFER_LANDSC_NOW +**LS4.1**_LANDSC_BEAUTY_PAST_PPL+**LS3.6**_LANSDC_IS_NAT.ID+**LS4.5**_DO_CC_POLICY_IN_TOWN+**LS3.4**_TRAD_MGMT_BEATS_CC+**LS2.1**_RURAL_NOEXPORT_RE+**LS1.2** _NO_RE_IN_RURAL+**LS1.5RV**_RURAL_EXPORT_RE+**LS4.7RV**_RE_MIX_FOOD_OK+**LS2.2**_UPSET_REWILD.

Resisting_Land_Use_Change=~**LS2.5RV**_NOMEAT_REWILD_IS_GOOD+**LS1.4RV**_NEW_WETLANDS+**LS3.1**_LESS_MEAT_LANDSC_DAMG+**LS1.3RV**_BETTER_NO_LIVESTOC K+**LS2.3RV**_RURAL_SCIENTIST_MGMNT+**LS3.5RV**_DIET_CHNG_LS_OK+**LS4.2RV**_NEW_FORESTS_GOOD+**LS2.2**_UPSET_REWILD

Valuing_Landscape_Tradition_and_Identity=~**LS3.3**_ENG_ID_IN_RURAL+**LS4.6**_PREFER_LANDSC_NOW+**LS4.1**_LANDSC_BEAUTY_PAST_PPL+**LS3.6**_LANSDC_IS_NAT.ID+ **LS4.5**_DO_CC_POLICY_IN_TOWN+**LS3.4**_TRAD_MGMT_BEATS_CC

Resisting_Rural_Renewables=~**LS2.1**_RURAL_NOEXPORT_RE+**LS1.2**_NO_RE_IN_RURAL+**LS1.5RV**_RURAL_EXPORT_RE+**LS4.7RV**_RE_MIX_FOOD_OK

Resisting_Land_Use_Change ~~ Valuing_Landscape_Tradition_and_Identity

Resisting_Land_Use_Change ~~ Resisting_Rural_Renewables

Resisting_Rural_Renewables ~~ Valuing_Landscape_Tradition_and_Identity

LS4.2RV_NEW_FORESTS_GOOD ~~ LS2.2_UPSET_REWILD

LS4.2RV_NEW_FORESTS_GOOD ~~ LS1.4RV_NEW_WETLANDS

LS1.4RV_NEW_WETLANDS ~~ LS2.2_UPSET_REWILD

Free Parameters: 222, Iterations: 80

χ^2	df	χ^2/df	CFI	TLI	SRMR	RMSEA	RMSEA CI (lower)	RMSEA CI (upper)	Modification Indices
210.6 p<0.001	111	1.89	0.991	0.988	0.027	0.049 pClose =0.566	0.039	0.059	No MI >10 remaining.

CFA Round 8 - Bifactor Model (covariance RLUC~~VLTI removed):

General Factor=~**LS3.1**_LESS_MEAT_LANDSC_DAMG+**LS2.5RV**_NOMEAT_REWILD_IS_GOOD+**LS4.2RV**_NEW_FORESTS_GOOD+**LS1.3RV**_BETTER_NO_LIVESTOCK+**LS2.3RV**_RURAL_SCIENTIST_MGMNT+**LS1.4RV**_NEW_WETLANDS+**LS3.5RV**_DIET_CHNG_LS_OK+**LS3.3**_ENG_ID_IN_RURAL+**LS4.6**_PREFER_LANDSC_NOW+**LS4.1**_LANDSC_BEAUTY_PAST_PPL+**LS3.6**_LANSDC_IS_NAT.ID+**LS4.5**_DO_CC_POLICY_IN_TOWN+**LS3.4**_TRAD_MGMT_BEATS_CC+**LS2.1**_RURAL_NOEXPORT_RE+**LS1.2**_NO_RE_IN_RURAL+**LS1.5RV**_RURAL_EXPORT_RE+**LS4.7RV**_RE_MIX_FOOD_OK+**LS2.2**_UPSET_REWILD.

Resisting_Land_Use_Change=~**LS2.5RV**_NOMEAT_REWILD_IS_GOOD+**LS1.4RV**_NEW_WETLANDS+**LS3.1**_LESS_MEAT_LANDSC_DAMG+**LS1.3RV**_BETTER_NO_LIVESTOCK+**LS2.3RV**_RURAL_SCIENTIST_MGMNT+**LS3.5RV**_DIET_CHNG_LS_OK+**LS4.2RV**_NEW_FORESTS_GOOD+**LS2.2**_UPSET_REWILD

Valuing_Landscape_Tradition_and_Identity=~**LS3.3**_ENG_ID_IN_RURAL+**LS4.6**_PREFER_LANDSC_NOW+**LS4.1**_LANDSC_BEAUTY_PAST_PPL+**LS3.6**_LANSDC_IS_NAT.ID+**LS4.5**_DO_CC_POLICY_IN_TOWN+**LS3.4**_TRAD_MGMT_BEATS_CC

Resisting_Rural_Renewables=~**LS2.1**_RURAL_NOEXPORT_RE+**LS1.2**_NO_RE_IN_RURAL+**LS1.5RV**_RURAL_EXPORT_RE+**LS4.7RV**_RE_MIX_FOOD_OK

Resisting_Rural_Renewables ~~ Valuing_Landscape_Tradition_and_Identity

Resisting_Land_Use_Change ~~ Resisting_Rural_Renewables

LS4.2RV_NEW_FORESTS_GOOD ~~ LS2.2_UPSET_REWILD

LS4.2RV_NEW_FORESTS_GOOD ~~ LS1.4RV_NEW_WETLANDS

LS1.4RV_NEW_WETLANDS ~~ LS2.2_UPSET_REWILD

Free Parameters: 221, Iterations: 64

χ^2	df	χ^2/df	CFI	TLI	SRMR	RMSEA	RMSEA CI (lower)	RMSEA CI (upper)	Modification Indices
212.4 p=0.974	112	1.89	1.00*	1.00*	0.027	0.049 pClose =0.568	0.039	0.059	No MI >10 remaining

CFA round 9 - Bifactor Model (covariance RRR~~VLTI also removed):

General Factor=~**LS3.1**_LESS_MEAT_LANDSC_DAMG+**LS2.5RV**_NOMEAT_REWILD_IS_GOOD+**LS4.2RV**_NEW_FORESTS_GOOD+**LS1.3RV**_BETTER_NO_LIVESTOCK+**LS2.3RV**_RURAL_SCIENTIST_MGMNT+**LS1.4RV**_NEW_WETLANDS+**LS3.5RV**_DIET_CHNG_LS_OK+**LS3.3**_ENG_ID_IN_RURAL+**LS4.6**_PREFER_LANDSC_NOW+**LS4.1**_LANDSC_BEAUTY_PAST_PPL+**LS3.6**_LANSDC_IS_NAT.ID+**LS4.5**_DO_CC_POLICY_IN_TOWN+**LS3.4**_TRAD_MGMT_BEATS_CC+**LS2.1**_RURAL_NOEXPORT_RE+**LS1.2**_NO_RE_IN_RURAL+**LS1.5RV**_RURAL_EXPORT_RE+**LS4.7RV**_RE_MIX_FOOD_OK+**LS2.2**_UPSET_REWILD.

Resisting_Land_Use_Change=~**LS2.5RV**_NOMEAT_REWILD_IS_GOOD+**LS1.4RV**_NEW_WETLANDS+**LS3.1**_LESS_MEAT_LANDSC_DAMG+**LS1.3RV**_BETTER_NO_LIVESTOCK+**LS2.3RV**_RURAL_SCIENTIST_MGMNT+**LS3.5RV**_DIET_CHNG_LS_OK+**LS4.2RV**_NEW_FORESTS_GOOD+**LS2.2**_UPSET_REWILD

Valuing_Landscape_Tradition_and_Identity=~**LS3.3**_ENG_ID_IN_RURAL+**LS4.6**_PREFER_LANDSC_NOW+**LS4.1**_LANDSC_BEAUTY_PAST_PPL+**LS3.6**_LANSDC_IS_NAT.ID+**LS4.5**_DO_CC_POLICY_IN_TOWN+**LS3.4**_TRAD_MGMT_BEATS_CC

Resisting_Rural_Renewables=~**LS2.1**_RURAL_NOEXPORT_RE+**LS1.2**_NO_RE_IN_RURAL+**LS1.5RV**_RURAL_EXPORT_RE+**LS4.7RV**_RE_MIX_FOOD_OK

Resisting_Land_Use_Change ~~ Resisting_Rural_Renewables

LS4.2RV_NEW_FORESTS_GOOD ~~ LS2.2_UPSET_REWILD

LS4.2RV_NEW_FORESTS_GOOD ~~ LS1.4RV_NEW_WETLANDS

LS1.4RV_NEW_WETLANDS ~~ LS2.2_UPSET_REWILD

Free Parameters: 220, Iterations: 64

χ^2	df	χ^2/df	CFI	TLI	SRMR	RMSEA	RMSEA CI (lower)	RMSEA CI (upper)	Modification Indices
207.3 p=0.976	113	1.83	1.00	1.001	0.027	0.047 pClose =0.675	0.037	0.057	No MI >10 remaining.

CFA Round 10 Bifactor Model (VLTI Specific Factor removed altogether)

General Factor=~**LS3.1**_LESS_MEAT_LANDSC_DAMG+**LS2.5RV**_NOMEAT_REWILD_IS_GOOD+**LS4.2RV**_NEW_FORESTS_GOOD+**LS1.3RV**_BETTER_NO_LIVESTOCK+**LS2.3RV**_RURAL_SCIENTIST_MGMNT+**LS1.4RV**_NEW_WETLANDS+**LS3.5RV**_DIET_CHNG_LS_OK+**LS3.3**_ENG_ID_IN_RURAL+**LS4.6**_PREFER_LANDSC_NOW+**LS4.1**_LANDSC_BEAUTY_PAST_PPL+**LS3.6**_LANSDC_IS_NAT.ID+**LS4.5**_DO_CC_POLICY_IN_TOWN+**LS3.4**_TRAD_MGMT_BEATS_CC+**LS2.1**_RURAL_NOEXPORT_RE+**LS1.2**_NO_RE_IN_RURAL+**LS1.5RV**_RURAL_EXPORT_RE+**LS4.7RV**_RE_MIX_FOOD_OK+**LS2.2**_UPSET_REWILD.

Resisting_Land_Use_Change=~**LS2.5RV**_NOMEAT_REWILD_IS_GOOD+**LS1.4RV**_NEW_WETLANDS+**LS3.1**_LESS_MEAT_LANDSC_DAMG+**LS1.3RV**_BETTER_NO_LIVESTOCK+**LS2.3RV**_RURAL_SCIENTIST_MGMNT+**LS3.5RV**_DIET_CHNG_LS_OK+**LS4.2RV**_NEW_FORESTS_GOOD+**LS2.2**_UPSET_REWILD

Resisting_Rural_Renewables=~**LS2.1**_RURAL_NOEXPORT_RE+**LS1.2**_NO_RE_IN_RURAL+**LS1.5RV**_RURAL_EXPORT_RE+**LS4.7RV**_RE_MIX_FOOD_OK

Resisting_Land_Use_Change ~~ Resisting_Rural_Renewables

LS4.2RV_NEW_FORESTS_GOOD ~~ LS2.2_UPSET_REWILD

LS4.2RV_NEW_FORESTS_GOOD ~~ LS1.4RV_NEW_WETLANDS

LS1.4RV_NEW_WETLANDS ~~ LS2.2_UPSET_REWILD

Free Parameters: 214, Iterations: 50

χ^2	df	χ^2/df	CFI	TLI	SRMR	RMSEA	RMSEA CI (lower)	RMSEA CI (upper)	Modification Indices
233 p=0.888	119	1.95	1.00	1.001	0.029	0.050 p=0.461	0.041	0.060	No MI >10 remaining.

Appendices: Chapter 7

APPENDIX 7.1: Construction of the Rural Index

Detail of the items and weightings used in the construction of the Rural Index, used to measure 'Objective Rurality', for analysis in Chapter 7 (as opposed to 'Subjective Rurality' which is based on a participant's own self-perception as a town or country person).

The Rural Index is a composite index score made from responses to two ordinal and four binary items, with weightings derived through both empirical work and theory[46].

The six items that make up this composite index are made up of information about the type of place that respondents spent their childhood and now live as an adults (these are essentially spatial geography measures, and are the two ordinal items included in the index). Four binary items then measure whether respondents live in a 'rurally employed household', whether they are a member of rural trade bodies, rural shooting associations, and rural hunting-with-hounds associations. Possible Rural Index scores range from 0 to 18. My sample has scores from 0 to 16. It is mean-centred for use in the final models to aid with interpretability.

The six constituent parts of the composite index are detailed below.

[46] While I set out to develop an index that could be used in a range of other studies, a key aim of this study was to develop a measure that could discriminate *within* a rural sample, rather than *between* rural and urban samples, since my research sample is drawn only from rural places.

1. Childhood residence – Survey data were originally collected on a 7-point ordinal scale, where:
    - 1= Centre of large city,
    - 2= Centre of small city or large town,
    - 3= suburb of major city,
    - 4 – suburb of small city or large town,
    - 5 = Market town in a largely rural area,
    - 6= Village in a rural area,
    - 7 = Hamlet or isolated rural dwelling.

For the index these are grouped such that:

- 1,2,3,4 on original scale = NOT RURAL (weighted 0)
- 5 on original scale = RURAL TOWN (weighted 1)
- 6 on original scale RURAL VILLAGE (weighted 2)
- 7 on original scale = RURAL ISOLATION (weighted 5)

The weightings were applied after a series of binomial logistic regression analyses (with alpha corrections) to determine whether there were any threshold effects. This demonstrated a strong nonlinear relationship where childhood residence at the most rural category had a disproportionately strong effect on future rural jobs, trade association memberships and leisure pursuits.

2. Current residence – this is measured on the same original scale as the childhood residence item, and for the index is again weighted most strongly to RURAL ISOLATION, since logistic regressions showed that membership of the most isolated rural areas is a stronger indicator of having a rural job. The weighting is 4, rather than 5 as for the childhood residence, because the relationship is somewhat weaker.

For the index these are therefore grouped such that:

- 1,2,3,4 on original scale = NOT RURAL (weighted 0)
- 5 on original scale = RURAL TOWN (weighted 1)
- 6 on original scale RURAL VILLAGE (weighted 2)
- 7 on original scale = RURAL ISOLATION (weighted 4)

3. Rural_job –a binary measure of whether a person lives in a household where they or somebody else has what would be described as a rural job (farming, forestry, gamekeeping or land-agency). Approximately 30% of the respondents answered yes to this question. This question is weighted 3, since rurally employed households are a more embedded part of the rural economy.
4. Rural_trade –a binary variable showing whether a respondent is a member of the National Farmers Union or a local Agricultural Society – scores 3
5. Rural_Shoot –a binary variable showing whether a person is a member of a game shooting society. Scores 3
6. Rural_hunt –a binary variable showing whether a person is a member of a hunting with hounds society. Scores 3. (Note that I have purposely not combined the two rural sports as they are quite distinct in how they are viewed in UK society).

APPENDIX 7.2: Descriptive statistics by Party Alignment, variables used in Regression and Path Model construction

	Party Alignment	Objective Rural ID	Relative English National ID	Populism	Left-Right Alignment	Subjective Rural ID	Rejection of Climate Science	RRCI_GF
Mean	Conservative	5.97	0.161	-0.295	6.74	0.910	1.31	0.193
	Green Party	4.26	-0.269	-0.0915	3.48	0.940	1.02	-0.692
	Labour	3.26	-0.402	-0.412	3.10	0.807	1.03	-0.570
	Lib Dem.	4.63	-0.362	-0.323	4.59	0.895	1.05	-0.425
	'Other'	4.91	0.0280	0.403	5.84	0.901	1.55	0.471
	Reform UK	4.68	0.149	0.750	6.89	0.891	1.96	0.986
Standard deviation	Conservative	4.67	0.818	0.856	1.34	0.287	0.466	0.776
	Green Party	2.95	0.922	0.993	1.39	0.239	0.149	0.742

	Party Alignment	Objective Rural ID	Relative English National ID	Populism	Left-Right Alignment	Subjective Rural ID	Rejection of Climate Science	RRCI_GF
	Labour	2.24	0.787	0.977	1.14	0.396	0.164	0.670
	Lib Dem.	3.15	0.801	0.826	1.14	0.309	0.224	0.635
	'Other'	3.59	0.895	0.965	1.34	0.300	0.614	0.866
	Reform UK	3.36	0.854	0.807	1.24	0.313	0.494	0.662
Variance	Conservative	21.8	0.669	0.733	1.80	0.0822	0.217	0.602
	Green Party	8.73	0.849	0.986	1.92	0.0570	0.0222	0.550
	Labour	5.03	0.620	0.954	1.31	0.157	0.0270	0.449
	Lib Dem.	9.89	0.642	0.683	1.30	0.0952	0.0504	0.403
	'Other'	12.9	0.801	0.932	1.79	0.0901	0.377	0.751
	Reform UK	11.3	0.730	0.651	1.53	0.0981	0.244	0.439

	Party Alignment	Objective Rural ID	Relative English National ID	Populism	Left-Right Alignment	Subjective Rural ID	Rejection of Climate Science	RRCI_GF
Range	Conservative	21	4	4.48	9.00	1	1	3.63
	Green Party	15	4	4.99	7.00	1	1	3.98
	Labour	12	3	4.72	5.00	1	1	3.02
	Lib Dem.	18	3	4.22	5.00	1	1	4.21
	'Other'	18	4	4.04	7.00	1	2	4.26
	Reform UK	15	4	3.74	6.00	1	2	3.13

APPENDIX 7.3: Linear Regression Results

Objective Rural Identity, Populism, and Relative English National ID as predictors of Left-Right Political Alignment

Model Fit Measures

				Overall Model Test			
Model	R	R^2	Adjusted R^2	F	df1	df2	p
1	0.176	0.0309	0.0295	22.4	1	705	< .001
2	0.304	0.0926	0.0900	35.9	2	704	< .001
3	0.342	0.1170	0.1133	31.1	3	703	< .001

Note. Models estimated using sample size of N=707

Model Comparisons

Comparison							
Model		Model	ΔR^2	F	df1	df2	p
1	-	2	0.0617	47.9	1	704	< .001
2	-	3	0.0244	19.5	1	703	< .001

Model 1 – Objective Rural Identity

Omnibus ANOVA Test

	Sum of Squares	df	Mean Square	F	p
RUR_CEN	85.6	1	85.55	22.4	< .001
Residuals	2686.7	705	3.81		

Note. Type 3 sum of squares

[7]

Model Coefficients - LR_CEN

			95% Confidence Interval					95% Confidence Interval	
Predictor	Estimate	SE	Lower	Upper	t	p	Stand. Estimate	Lower	Upper
Intercept	0.0119	0.0734	−0.1323	0.156	0.162	0.872			
RUR_CEN	0.0967	0.0204	0.0566	0.137	4.738	< .001	0.176	0.103	0.248

Model 2 – Objective Rural Identity and Relative English National Identity

Omnibus ANOVA Test

	Sum of Squares	df	Mean Square	F	p
RUR_CEN	77.5	1	77.45	21.7	< .001
ENG_REL	171.1	1	171.10	47.9	< .001
Residuals	2515.6	704	3.57		

Note. Type 3 sum of squares

[7]

Model Coefficients - LR_CEN

			95% Confidence Interval					95% Confidence Interval	
Predictor	Estimate	SE	Lower	Upper	t	p	Stand. Estimate	Lower	Upper
Intercept	0.0649	0.0715	−0.0754	0.205	0.908	0.364			
RUR_CEN	0.0920	0.0198	0.0532	0.131	4.656	< .001	0.167	0.0967	0.238
ENG_REL	0.5608	0.0810	0.4017	0.720	6.920	< .001	0.249	0.1781	0.319

Model 3 - Objective Rural Identity, Relative English National Identity and Populism

Omnibus ANOVA Test

	Sum of Squares	df	Mean Square	F	p
RUR_CEN	76.7	1	76.71	22.0	< .001
ENG_REL	137.0	1	137.00	39.3	< .001
POP	67.8	1	67.77	19.5	< .001
Residuals	2447.8	703	3.48		

Note. Type 3 sum of squares

[7]

Model Coefficients - LR_CEN

			95% Confidence Interval					95% Confidence Interval	
Predictor	Estimate	SE	Lower	Upper	t	p	Stand. Estimate	Lower	Upper
Intercept	0.0619	0.0706	−0.0767	0.200	0.877	0.381			
RUR_CEN	0.0916	0.0195	0.0533	0.130	4.694	< .001	0.166	0.0968	0.236
ENG_REL	0.5075	0.0809	0.3487	0.666	6.273	< .001	0.225	0.1545	0.295
POP	0.3137	0.0711	0.1741	0.453	4.412	< .001	0.158	0.0878	0.229

APPENDIX 7.4: Linear Regression Results

Party Alignment and Rejection of Climate Science as predictors of Resistance to Rural Climate Initiatives (RRCI).

Model Fit Measures

			Overall Model Test			
Model	R	R^2	F	df1	df2	p
1	0.636	0.404	97.3	5	717	< .001
2	0.681	0.464	103.2	6	716	< .001
3	0.691	0.478	59.1	11	711	< .001

Note. Models estimated using sample size of N=723

Model Comparisons

Comparison							
Model		Model	ΔR^2	F	df1	df2	p
1	-	2	0.0595	79.44	1	716	< .001
2	-	3	0.0139	3.79	5	711	0.002

MODEL 1 – Party Alignment

Omnibus ANOVA Test

	Sum of Squares	df	Mean Square	F	p
PAR_NAME	262	5	52.468	97.3	< .001
Residuals	387	717	0.539		

Note. Type 3 sum of squares

Model 2 - Party Alignment and Rejection of Climate Science

Omnibus ANOVA Test

	Sum of Squares	df	Mean Square	F	p
PAR_NAME	80.0	5	16.008	32.9	< .001
CC_CAUSE_NCEN	38.6	1	38.618	79.4	< .001
Residuals	348.0	716	0.486		

Note. Type 3 sum of squares

Model 3 - Party Alignment, Rejection of Climate Science and Interaction term

Omnibus ANOVA Test

	Sum of Squares	df	Mean Square	F	p
PAR_NAME	50.14	5	10.029	21.03	< .001
CC_CAUSE_NCEN	11.68	1	11.676	24.49	< .001
CC_CAUSE_NCEN ✻ PAR_NAME	9.04	5	1.808	3.79	0.002
Residuals	339.01	711	0.477		

Note. Type 3 sum of squares

Model 3 Coefficient tables – Baseline CONSERVATIVE

Model Coefficients - RRCI_GF

			95% Confidence Interval					95% Confidence Interval	
Predictor	Estimate	SE	Lower	Upper	t	p	Stand. Estimate	Lower	Upper
Intercept *	0.2032	0.0553	0.0946	0.312	3.6726	< .001			
PAR_NAME:									
GRN – CON	−0.7051	0.1405	−0.9809	−0.429	−5.0202	< .001	−0.7437	−1.0346	−0.4529
LAB – CON	−0.5378	0.1425	−0.8176	−0.258	−3.7735	< .001	−0.5672	−0.8623	−0.2721
LD – CON	−0.3579	0.1230	−0.5993	−0.116	−2.9105	0.004	−0.3775	−0.6321	−0.1228
OTH – CON	0.0847	0.0891	−0.0902	0.260	0.9507	0.342	0.0894	−0.0952	0.2739
REF – CON	0.7021	0.1165	0.4734	0.931	6.0278	< .001	0.7406	0.4994	0.9818
CC_CAUSE_NCEN	0.5797	0.1171	0.3497	0.810	4.9486	< .001	0.3225	0.1946	0.4505
CC_CAUSE_NCEN ✻ PAR_NAME:									
CC_CAUSE_NCEN ✻ (GRN – CON)	0.0365	0.3885	−0.7263	0.799	0.0939	0.925	0.0203	−0.4041	0.4447
CC_CAUSE_NCEN ✻ (LAB – CON)	0.2448	0.4144	−0.5687	1.058	0.5908	0.555	0.1362	−0.3164	0.5888
CC_CAUSE_NCEN ✻ (LD – CON)	0.4043	0.3277	−0.2391	1.048	1.2338	0.218	0.2250	−0.1330	0.5829
CC_CAUSE_NCEN ✻ (OTH – CON)	0.2168	0.1576	−0.0927	0.526	1.3753	0.169	0.1206	−0.0516	0.2928
CC_CAUSE_NCEN ✻ (REF – CON)	−0.4525	0.1730	−0.7922	−0.113	−2.6149	0.009	−0.2518	−0.4408	−0.0627

* Represents reference level

Model 3 Coefficient tables – Baseline GREEN

Model Coefficients - RRCI_GF

			95% Confidence Interval					95% Confidence Interval	
Predictor	Estimate	SE	Lower	Upper	t	p	Stand. Estimate	Lower	Upper
Intercept *	−0.5020	0.129	−0.7554	−0.248	−3.8880	< .001			
PAR_NAME:									
CON – GRN	0.7051	0.140	0.4294	0.981	5.0202	< .001	0.7437	0.4529	1.035
LAB – GRN	0.1673	0.184	−0.1942	0.529	0.9086	0.364	0.1765	−0.2049	0.558
LD – GRN	0.3472	0.169	0.0144	0.680	2.0485	0.041	0.3662	0.0152	0.717
OTH – GRN	0.7899	0.147	0.5016	1.078	5.3805	< .001	0.8331	0.5291	1.137
REF – GRN	1.4073	0.165	1.0836	1.731	8.5366	< .001	1.4843	1.1429	1.826
CC_CAUSE_NCEN	0.6162	0.370	−0.1111	1.344	1.6634	0.097	0.3429	−0.0618	0.748
CC_CAUSE_NCEN ✻ PAR_NAME:									
CC_CAUSE_NCEN ✻ (CON – GRN)	−0.0365	0.389	−0.7993	0.726	−0.0939	0.925	−0.0203	−0.4447	0.404
CC_CAUSE_NCEN ✻ (LAB – GRN)	0.2083	0.543	−0.8584	1.275	0.3834	0.702	0.1159	−0.4776	0.709
CC_CAUSE_NCEN ✻ (LD – GRN)	0.3678	0.481	−0.5756	1.311	0.7654	0.444	0.2046	−0.3203	0.730
CC_CAUSE_NCEN ✻ (OTH – GRN)	0.1803	0.385	−0.5760	0.936	0.4680	0.640	0.1003	−0.3205	0.521
CC_CAUSE_NCEN ✻ (REF – GRN)	−0.4890	0.392	−1.2581	0.280	−1.2483	0.212	−0.2721	−0.7000	0.156

* Represents reference level

Model 3 Coefficient tables – Baseline LABOUR

Model Coefficients - RRCI_GF

Predictor	Estimate	SE	95% Confidence Interval		t	p	Stand. Estimate	95% Confidence Interval	
			Lower	Upper				Lower	Upper
Intercept *	−0.3346	0.131	−0.5925	−0.0768	−2.5477	0.011			
PAR_NAME:									
CON – LAB	0.5378	0.143	0.2580	0.8176	3.7735	< .001	0.5672	0.2721	0.8623
GRN – LAB	−0.1673	0.184	−0.5289	0.1942	−0.9086	0.364	−0.1765	−0.5579	0.2049
LD – LAB	0.1799	0.171	−0.1563	0.5160	1.0506	0.294	0.1897	−0.1648	0.5443
OTH – LAB	0.6225	0.149	0.3304	0.9146	4.1843	< .001	0.6566	0.3485	0.9647
REF – LAB	1.2399	0.167	0.9128	1.5670	7.4421	< .001	1.3078	0.9628	1.6528
CC_CAUSE_NCEN	0.8245	0.397	0.0442	1.6049	2.0745	0.038	0.4588	0.0246	0.8929
CC_CAUSE_NCEN ✻ PAR_NAME:									
CC_CAUSE_NCEN ✻ (CON – LAB)	−0.2448	0.414	−1.0583	0.5687	−0.5908	0.555	−0.1362	−0.5888	0.3164
CC_CAUSE_NCEN ✻ (GRN – LAB)	−0.2083	0.543	−1.2750	0.8584	−0.3834	0.702	−0.1159	−0.7094	0.4776
CC_CAUSE_NCEN ✻ (LD – LAB)	0.1595	0.502	−0.8254	1.1444	0.3180	0.751	0.0887	−0.4592	0.6367
CC_CAUSE_NCEN ✻ (OTH – LAB)	−0.0280	0.411	−0.8354	0.7793	−0.0682	0.946	−0.0156	−0.4648	0.4336
CC_CAUSE_NCEN ✻ (REF – LAB)	−0.6973	0.417	−1.5167	0.1221	−1.6707	0.095	−0.3880	−0.8439	0.0679

* Represents reference level

Model 3 Coefficient tables – Baseline LIBERAL DEMOCRAT

Model Coefficients - RRCI_GF

Predictor	Estimate	SE	95% Confidence Interval		t	p	Stand. Estimate	95% Confidence Interval	
			Lower	Upper				Lower	Upper
Intercept *	−0.155	0.110	−0.370	0.0609	−1.409	0.159			
PAR_NAME:									
CON – LD	0.358	0.123	0.116	0.5993	2.910	0.004	0.3775	0.123	0.6321
GRN – LD	−0.347	0.169	−0.680	−0.0144	−2.048	0.041	−0.3662	−0.717	−0.0152
LAB – LD	−0.180	0.171	−0.516	0.1563	−1.051	0.294	−0.1897	−0.544	0.1648
OTH – LD	0.443	0.130	0.187	0.6982	3.400	< .001	0.4669	0.197	0.7364
REF – LD	1.060	0.150	0.765	1.3550	7.056	< .001	1.1181	0.807	1.4292
CC_CAUSE_NCEN	0.984	0.306	0.383	1.5849	3.215	0.001	0.5475	0.213	0.8818
CC_CAUSE_NCEN ✻ PAR_NAME:									
CC_CAUSE_NCEN ✻ (CON – LD)	−0.404	0.328	−1.048	0.2391	−1.234	0.218	−0.2250	−0.583	0.1330
CC_CAUSE_NCEN ✻ (GRN – LD)	−0.368	0.481	−1.311	0.5756	−0.765	0.444	−0.2046	−0.730	0.3203
CC_CAUSE_NCEN ✻ (LAB – LD)	−0.160	0.502	−1.144	0.8254	−0.318	0.751	−0.0887	−0.637	0.4592
CC_CAUSE_NCEN ✻ (OTH – LD)	−0.188	0.324	−0.823	0.4480	−0.579	0.562	−0.1044	−0.458	0.2492
CC_CAUSE_NCEN ✻ (REF – LD)	−0.857	0.331	−1.508	−0.2060	−2.585	0.010	−0.4767	−0.839	−0.1146

* Represents reference level

Model 3 Coefficient tables – Baseline 'OTHER'

Model Coefficients - RRCI_GF

Predictor	Estimate	SE	95% Confidence Interval		t	p	Stand. Estimate	95% Confidence Interval	
			Lower	Upper				Lower	Upper
Intercept*	0.2879	0.0699	0.151	0.4251	4.1201	< .001			
PAR_NAME:									
CON – OTH	−0.0847	0.0891	−0.260	0.0902	−0.9507	0.342	−0.0894	−0.274	0.0952
GRN – OTH	−0.7899	0.1468	−1.078	−0.5016	−5.3805	< .001	−0.8331	−1.137	−0.5291
LAB – OTH	−0.6225	0.1488	−0.915	−0.3304	−4.1843	< .001	−0.6566	−0.965	−0.3485
LD – OTH	−0.4426	0.1302	−0.698	−0.1871	−3.4004	< .001	−0.4669	−0.736	−0.1973
REF – OTH	0.6174	0.1241	0.374	0.8610	4.9767	< .001	0.6512	0.394	0.9081
CC_CAUSE_NCEN	0.7965	0.1054	0.589	1.0035	7.5540	< .001	0.4431	0.328	0.5583
CC_CAUSE_NCEN ✻ PAR_NAME:									
CC_CAUSE_NCEN ✻ (CON – OTH)	−0.2168	0.1576	−0.526	0.0927	−1.3753	0.169	−0.1206	−0.293	0.0516
CC_CAUSE_NCEN ✻ (GRN – OTH)	−0.1803	0.3852	−0.936	0.5760	−0.4680	0.640	−0.1003	−0.521	0.3205
CC_CAUSE_NCEN ✻ (LAB – OTH)	0.0280	0.4112	−0.779	0.8354	0.0682	0.946	0.0156	−0.434	0.4648
CC_CAUSE_NCEN ✻ (LD – OTH)	0.1876	0.3237	−0.448	0.8231	0.5794	0.562	0.1044	−0.249	0.4580
CC_CAUSE_NCEN ✻ (REF – OTH)	−0.6693	0.1653	−0.994	−0.3446	−4.0477	< .001	−0.3724	−0.553	−0.1918

* Represents reference level

Model 3 Coefficient tables – Baseline REFORM UK

Model Coefficients - RRCI_GF

Predictor	Estimate	SE	95% Confidence Interval		t	p	Stand. Estimate	95% Confidence Interval	
			Lower	Upper				Lower	Upper
Intercept*	0.905	0.103	0.704	1.107	8.832	< .001			
PAR_NAME:									
CON – REF	−0.702	0.116	−0.931	−0.473	−6.028	< .001	−0.7406	−0.9818	−0.499
GRN – REF	−1.407	0.165	−1.731	−1.084	−8.537	< .001	−1.4843	−1.8257	−1.143
LAB – REF	−1.240	0.167	−1.567	−0.913	−7.442	< .001	−1.3078	−1.6528	−0.963
LD – REF	−1.060	0.150	−1.355	−0.765	−7.056	< .001	−1.1181	−1.4292	−0.807
OTH – REF	−0.617	0.124	−0.861	−0.374	−4.977	< .001	−0.6512	−0.9081	−0.394
CC_CAUSE_NCEN	0.127	0.127	−0.123	0.377	0.999	0.318	0.0708	−0.0683	0.210
CC_CAUSE_NCEN ✻ PAR_NAME:									
CC_CAUSE_NCEN ✻ (CON – REF)	0.453	0.173	0.113	0.792	2.615	0.009	0.2518	0.0627	0.441
CC_CAUSE_NCEN ✻ (GRN – REF)	0.489	0.392	−0.280	1.258	1.248	0.212	0.2721	−0.1559	0.700
CC_CAUSE_NCEN ✻ (LAB – REF)	0.697	0.417	−0.122	1.517	1.671	0.095	0.3880	−0.0679	0.844
CC_CAUSE_NCEN ✻ (LD – REF)	0.857	0.331	0.206	1.508	2.585	0.010	0.4767	0.1146	0.839
CC_CAUSE_NCEN ✻ (OTH – REF)	0.669	0.165	0.345	0.994	4.048	< .001	0.3724	0.1918	0.553

* Represents reference level

APPENDIX 7.5: Logistic Regression Results

Relative English National Identity, Objective Rural Identity, Populism and Left-Right Alignment as predictors of Party Alignment.

Model Fit Measures

				Overall Model Test		
Model	Deviance	AIC	R^2_{McF}	χ^2	df	p
1	2462	2482	0.0210	52.8	5	< .001
2	2419	2449	0.0381	95.7	10	< .001
3	2291	2331	0.0888	223.3	15	< .001
4	1766	1816	0.2974	747.9	20	< .001

Note. Models estimated using sample size of N=707

Model Comparisons

Comparison					
Model		Model	χ^2	df	p
1	-	2	42.9	5	< .001
2	-	3	127.6	5	< .001
3	-	4	524.6	5	< .001

Model 4 Coefficient tables – Baseline CONSERVATIVE

Model Coefficients - PAR_NAME

			95% Confidence Interval						95% Confidence Interval	
PAR_NAME	Predictor	Estimate	Lower	Upper	SE	Z	p	Odds ratio	Lower	Upper
GRN - CON	Intercept	−0.1565	−0.5701	0.2570	0.211	−0.742	0.458	0.8551	0.56545	1.2931
	ZS_ENG_REL	−0.2534	−0.5940	0.0872	0.174	−1.458	0.145	0.7762	0.55214	1.0912
	ZS_RUR_CEN	−0.2273	−0.5563	0.1017	0.168	−1.354	0.176	0.7967	0.57334	1.1070
	ZS_POP	0.3801	0.0188	0.7413	0.184	2.062	0.039	1.4624	1.01897	2.0987
	ZS_LR_CEN	−4.0814	−4.7293	−3.4334	0.331	−12.346	< .001	0.0169	0.00883	0.0323
LAB - CON	Intercept	−1.0679	−1.6055	−0.5303	0.274	−3.893	< .001	0.3437	0.20080	0.5884
	ZS_ENG_REL	−0.3491	−0.7221	0.0238	0.190	−1.835	0.067	0.7053	0.48574	1.0241
	ZS_RUR_CEN	−0.7480	−1.1750	−0.3211	0.218	−3.434	< .001	0.4733	0.30883	0.7253
	ZS_POP	0.0515	−0.3383	0.4414	0.199	0.259	0.796	1.0529	0.71295	1.5548
	ZS_LR_CEN	−4.5647	−5.2645	−3.8648	0.357	−12.784	< .001	0.0104	0.00517	0.0210
LD - CON	Intercept	0.1932	−0.1794	0.5659	0.190	1.016	0.309	1.2132	0.83575	1.7611
	ZS_ENG_REL	−0.4464	−0.7722	−0.1205	0.166	−2.685	0.007	0.6399	0.46200	0.8864
	ZS_RUR_CEN	−0.1910	−0.4818	0.0998	0.148	−1.287	0.198	0.8261	0.61766	1.1050
	ZS_POP	0.0691	−0.2703	0.4085	0.173	0.399	0.690	1.0715	0.76312	1.5045
	ZS_LR_CEN	−2.7147	−3.2894	−2.1401	0.293	−9.259	< .001	0.0662	0.03728	0.1176
OTH - CON	Intercept	0.2668	−0.1001	0.6338	0.187	1.425	0.154	1.3058	0.90473	1.8848
	ZS_ENG_REL	−0.1878	−0.4706	0.0950	0.144	−1.302	0.193	0.8288	0.62464	1.0996
	ZS_RUR_CEN	−0.2162	−0.4575	0.0252	0.123	−1.756	0.079	0.8056	0.63284	1.0255
	ZS_POP	0.8952	0.5889	1.2015	0.156	5.729	< .001	2.4478	1.80205	3.3250
	ZS_LR_CEN	−1.1035	−1.5444	−0.6625	0.225	−4.905	< .001	0.3317	0.21343	0.5156
REF - CON	Intercept	−0.5973	−1.0410	−0.1535	0.226	−2.638	0.008	0.5503	0.35311	0.8577
	ZS_ENG_REL	−0.1286	−0.4168	0.1596	0.147	−0.874	0.382	0.8794	0.65917	1.1731
	ZS_RUR_CEN	−0.3313	−0.5846	−0.0781	0.129	−2.565	0.010	0.7180	0.55736	0.9248
	ZS_POP	1.2385	0.9234	1.5535	0.161	7.705	< .001	3.4503	2.51788	4.7281
	ZS_LR_CEN	0.1163	−0.2936	0.5262	0.209	0.556	0.578	1.1233	0.74558	1.6925

Model 4 Coefficient tables – Baseline GREEN

Model Coefficients - PAR_NAME

			95% Confidence Interval						95% Confidence Interval	
PAR_NAME	Predictor	Estimate	Lower	Upper	SE	Z	p	Odds ratio	Lower	Upper
CON - GRN	Intercept	0.1565	−0.2571	0.57005	0.211	0.7414	0.458	1.169	0.773	1.768
	ZS_ENG_REL	0.2533	−0.0873	0.59393	0.174	1.4578	0.145	1.288	0.916	1.811
	ZS_RUR_CEN	0.2273	−0.1016	0.55629	0.168	1.3544	0.176	1.255	0.903	1.744
	ZS_POP	−0.3800	−0.7413	−0.01878	0.184	−2.0619	0.039	0.684	0.476	0.981
	ZS_LR_CEN	4.0814	3.4334	4.72928	0.331	12.3461	< .001	59.226	30.983	113.214
LAB - GRN	Intercept	−0.9114	−1.4290	−0.39376	0.264	−3.4510	< .001	0.402	0.240	0.675
	ZS_ENG_REL	−0.0958	−0.3709	0.17933	0.140	−0.6824	0.495	0.909	0.690	1.196
	ZS_RUR_CEN	−0.5207	−0.8926	−0.14888	0.190	−2.7446	0.006	0.594	0.410	0.862
	ZS_POP	−0.3285	−0.6117	−0.04542	0.144	−2.2744	0.023	0.720	0.542	0.956
	ZS_LR_CEN	−0.4833	−0.9124	−0.05423	0.219	−2.2077	0.027	0.617	0.402	0.947
LD - GRN	Intercept	0.3497	−0.0366	0.73604	0.197	1.7744	0.076	1.419	0.964	2.088
	ZS_ENG_REL	−0.1930	−0.4830	0.09691	0.148	−1.3048	0.192	0.824	0.617	1.102
	ZS_RUR_CEN	0.0363	−0.2835	0.35614	0.163	0.2226	0.824	1.037	0.753	1.428
	ZS_POP	−0.3110	−0.6185	−0.00351	0.157	−1.9824	0.047	0.733	0.539	0.996
	ZS_LR_CEN	1.3666	0.8923	1.84079	0.242	5.6480	< .001	3.922	2.441	6.302
OTH - GRN	Intercept	0.4233	0.0387	0.80796	0.196	2.1572	0.031	1.527	1.039	2.243
	ZS_ENG_REL	0.0655	−0.2584	0.38949	0.165	0.3964	0.692	1.068	0.772	1.476
	ZS_RUR_CEN	0.0111	−0.3245	0.34679	0.171	0.0650	0.948	1.011	0.723	1.415
	ZS_POP	0.5152	0.1566	0.87374	0.183	2.8159	0.005	1.674	1.170	2.396
	ZS_LR_CEN	2.9778	2.3708	3.58487	0.310	9.6145	< .001	19.645	10.706	36.049
REF - GRN	Intercept	−0.4408	−0.9113	0.02981	0.240	−1.8358	0.066	0.644	0.402	1.030
	ZS_ENG_REL	0.1248	−0.2322	0.48178	0.182	0.6850	0.493	1.133	0.793	1.619
	ZS_RUR_CEN	−0.1040	−0.4678	0.25979	0.186	−0.5603	0.575	0.901	0.626	1.297
	ZS_POP	0.8584	0.4612	1.25567	0.203	4.2355	< .001	2.359	1.586	3.510
	ZS_LR_CEN	4.1976	3.5236	4.87166	0.344	12.2057	< .001	66.527	33.905	130.537

Model 4 Coefficient tables – Baseline LABOUR

Model Coefficients - PAR_NAME

			95% Confidence Interval						95% Confidence Interval	
PAR_NAME	Predictor	Estimate	Lower	Upper	SE	Z	p	Odds ratio	Lower	Upper
CON - LAB	Intercept	1.0678	0.5303	1.605	0.274	3.893	< .001	2.909	1.699	4.98
	ZS_ENG_REL	0.3491	−0.0238	0.722	0.190	1.835	0.067	1.418	0.976	2.06
	ZS_RUR_CEN	0.7481	0.3211	1.175	0.218	3.434	< .001	2.113	1.379	3.24
	ZS_POP	−0.0515	−0.4414	0.338	0.199	−0.259	0.796	0.950	0.643	1.40
	ZS_LR_CEN	4.5647	3.8648	5.265	0.357	12.784	< .001	96.032	47.696	193.35
GRN - LAB	Intercept	0.9113	0.3937	1.429	0.264	3.451	< .001	2.488	1.482	4.17
	ZS_ENG_REL	0.0958	−0.1793	0.371	0.140	0.682	0.495	1.101	0.836	1.45
	ZS_RUR_CEN	0.5207	0.1489	0.893	0.190	2.745	0.006	1.683	1.161	2.44
	ZS_POP	0.3285	0.0454	0.612	0.144	2.274	0.023	1.389	1.046	1.84
	ZS_LR_CEN	0.4833	0.0542	0.912	0.219	2.208	0.027	1.621	1.056	2.49
LD - LAB	Intercept	1.2611	0.7456	1.777	0.263	4.795	< .001	3.529	2.108	5.91
	ZS_ENG_REL	−0.0972	−0.4147	0.220	0.162	−0.600	0.548	0.907	0.661	1.25
	ZS_RUR_CEN	0.5571	0.1480	0.966	0.209	2.669	0.008	1.746	1.160	2.63
	ZS_POP	0.0176	−0.3108	0.346	0.168	0.105	0.917	1.018	0.733	1.41
	ZS_LR_CEN	1.8500	1.3193	2.381	0.271	6.833	< .001	6.360	3.741	10.81
OTH - LAB	Intercept	1.3347	0.8190	1.850	0.263	5.073	< .001	3.799	2.268	6.36
	ZS_ENG_REL	0.1613	−0.1968	0.519	0.183	0.883	0.377	1.175	0.821	1.68
	ZS_RUR_CEN	0.5319	0.1001	0.964	0.220	2.415	0.016	1.702	1.105	2.62
	ZS_POP	0.8437	0.4551	1.232	0.198	4.256	< .001	2.325	1.576	3.43
	ZS_LR_CEN	3.4612	2.7989	4.123	0.338	10.244	< .001	31.855	16.427	61.77
REF - LAB	Intercept	0.4706	−0.1118	1.053	0.297	1.584	0.113	1.601	0.894	2.87
	ZS_ENG_REL	0.2206	−0.1682	0.609	0.198	1.112	0.266	1.247	0.845	1.84
	ZS_RUR_CEN	0.4167	−0.0376	0.871	0.232	1.798	0.072	1.517	0.963	2.39
	ZS_POP	1.1870	0.7623	1.612	0.217	5.478	< .001	3.277	2.143	5.01
	ZS_LR_CEN	4.6809	3.9567	5.405	0.370	12.667	< .001	107.872	52.283	222.57

Model 4 Coefficient tables – Baseline LIBERAL DEMOCRAT

Model Coefficients - PAR_NAME

			95% Confidence Interval						95% Confidence Interval	
PAR_NAME	Predictor	Estimate	Lower	Upper	SE	Z	p	Odds ratio	Lower	Upper
CON - LD	Intercept	−0.1933	−0.56594	0.1794	0.190	−1.016	0.309	0.824	0.5678	1.196
	ZS_ENG_REL	0.4463	0.12053	0.7722	0.166	2.685	0.007	1.563	1.1281	2.164
	ZS_RUR_CEN	0.1910	−0.09984	0.4818	0.148	1.287	0.198	1.210	0.9050	1.619
	ZS_POP	−0.0691	−0.40846	0.2703	0.173	−0.399	0.690	0.933	0.6647	1.310
	ZS_LR_CEN	2.7147	2.14011	3.2894	0.293	9.259	< .001	15.101	8.5004	26.826
GRN - LD	Intercept	−0.3498	−0.73610	0.0365	0.197	−1.775	0.076	0.705	0.4790	1.037
	ZS_ENG_REL	0.1930	−0.09692	0.4830	0.148	1.305	0.192	1.213	0.9076	1.621
	ZS_RUR_CEN	−0.0363	−0.35613	0.2835	0.163	−0.223	0.824	0.964	0.7004	1.328
	ZS_POP	0.3110	0.00350	0.6185	0.157	1.982	0.047	1.365	1.0035	1.856
	ZS_LR_CEN	−1.3666	−1.84086	−0.8924	0.242	−5.648	< .001	0.255	0.1587	0.410
LAB - LD	Intercept	−1.2611	−1.77662	−0.7456	0.263	−4.795	< .001	0.283	0.1692	0.474
	ZS_ENG_REL	0.0972	−0.22027	0.4148	0.162	0.600	0.548	1.102	0.8023	1.514
	ZS_RUR_CEN	−0.5571	−0.96610	−0.1480	0.209	−2.669	0.008	0.573	0.3806	0.862
	ZS_POP	−0.0175	−0.34585	0.3108	0.168	−0.105	0.917	0.983	0.7076	1.364
	ZS_LR_CEN	−1.8499	−2.38061	−1.3193	0.271	−6.833	< .001	0.157	0.0925	0.267
OTH - LD	Intercept	0.0736	−0.26146	0.4086	0.171	0.430	0.667	1.076	0.7699	1.505
	ZS_ENG_REL	0.2585	−0.05771	0.5748	0.161	1.602	0.109	1.295	0.9439	1.777
	ZS_RUR_CEN	−0.0252	−0.33149	0.2811	0.156	−0.161	0.872	0.975	0.7178	1.325
	ZS_POP	0.8261	0.47907	1.1732	0.177	4.665	< .001	2.284	1.6146	3.232
	ZS_LR_CEN	1.6112	1.06735	2.1551	0.277	5.806	< .001	5.009	2.9077	8.629
REF - LD	Intercept	−0.7905	−1.22463	−0.3564	0.221	−3.569	< .001	0.454	0.2939	0.700
	ZS_ENG_REL	0.3178	−0.02854	0.6641	0.177	1.798	0.072	1.374	0.9719	1.943
	ZS_RUR_CEN	−0.1403	−0.47350	0.1928	0.170	−0.826	0.409	0.869	0.6228	1.213
	ZS_POP	1.1694	0.78697	1.5518	0.195	5.993	< .001	3.220	2.1967	4.720
	ZS_LR_CEN	2.8310	2.22395	3.4381	0.310	9.140	< .001	16.963	9.2438	31.127

Model 4 Coefficient tables – Baseline 'OTHER'

Model Coefficients - PAR_NAME

			95% Confidence Interval						95% Confidence Interval	
PAR_NAME	Predictor	Estimate	Lower	Upper	SE	Z	p	Odds ratio	Lower	Upper
CON - OTH	Intercept	−0.2668	−0.6338	0.1001	0.187	−1.4252	0.154	0.7658	0.5306	1.1053
	ZS_ENG_REL	0.1878	−0.0950	0.4706	0.144	1.3017	0.193	1.2066	0.9094	1.6009
	ZS_RUR_CEN	0.2162	−0.0252	0.4575	0.123	1.7555	0.079	1.2413	0.9751	1.5802
	ZS_POP	−0.8952	−1.2015	−0.5889	0.156	−5.7288	< .001	0.4085	0.3008	0.5549
	ZS_LR_CEN	1.1035	0.6625	1.5445	0.225	4.9047	< .001	3.0147	1.9397	4.6856
GRN - OTH	Intercept	−0.4234	−0.8080	−0.0387	0.196	−2.1574	0.031	0.6548	0.4457	0.9620
	ZS_ENG_REL	−0.0656	−0.3895	0.2584	0.165	−0.3966	0.692	0.9365	0.6774	1.2949
	ZS_RUR_CEN	−0.0111	−0.3468	0.3245	0.171	−0.0650	0.948	0.9889	0.7070	1.3834
	ZS_POP	−0.5151	−0.8737	−0.1566	0.183	−2.8158	0.005	0.5974	0.4174	0.8551
	ZS_LR_CEN	−2.9778	−3.5849	−2.3708	0.310	−9.6146	< .001	0.0509	0.0277	0.0934
LAB - OTH	Intercept	−1.3347	−1.8504	−0.8190	0.263	−5.0727	< .001	0.2632	0.1572	0.4409
	ZS_ENG_REL	−0.1613	−0.5195	0.1968	0.183	−0.8829	0.377	0.8510	0.5948	1.2175
	ZS_RUR_CEN	−0.5319	−0.9636	−0.1001	0.220	−2.4145	0.016	0.5875	0.3815	0.9047
	ZS_POP	−0.8437	−1.2322	−0.4551	0.198	−4.2557	< .001	0.4301	0.2916	0.6344
	ZS_LR_CEN	−3.4612	−4.1234	−2.7989	0.338	−10.2437	< .001	0.0314	0.0162	0.0609
LD - OTH	Intercept	−0.0736	−0.4087	0.2614	0.171	−0.4306	0.667	0.9290	0.6645	1.2988
	ZS_ENG_REL	−0.2586	−0.5748	0.0577	0.161	−1.6025	0.109	0.7722	0.5628	1.0594
	ZS_RUR_CEN	0.0252	−0.2811	0.3315	0.156	0.1612	0.872	1.0255	0.7549	1.3930
	ZS_POP	−0.8261	−1.1732	−0.4791	0.177	−4.6653	< .001	0.4377	0.3094	0.6194
	ZS_LR_CEN	−1.6112	−2.1551	−1.0673	0.277	−5.8063	< .001	0.1996	0.1159	0.3439
REF - OTH	Intercept	−0.8641	−1.2872	−0.4410	0.216	−4.0026	< .001	0.4214	0.2760	0.6434
	ZS_ENG_REL	0.0592	−0.2287	0.3472	0.147	0.4032	0.687	1.0610	0.7955	1.4151
	ZS_RUR_CEN	−0.1152	−0.3906	0.1603	0.141	−0.8193	0.413	0.8912	0.6766	1.1739
	ZS_POP	0.3433	0.0180	0.6685	0.166	2.0687	0.039	1.4095	1.0182	1.9513
	ZS_LR_CEN	1.2198	0.7657	1.6739	0.232	5.2648	< .001	3.3865	2.1505	5.3329

Model 4 Coefficient tables – Baseline REFORM UK

Model Coefficients - PAR_NAME

			95% Confidence Interval						95% Confidence Interval	
PAR_NAME	Predictor	Estimate	Lower	Upper	SE	Z	p	Odds ratio	Lower	Upper
CON - REF	Intercept	0.5973	0.1536	1.0410	0.226	2.638	0.008	1.81716	1.16597	2.8320
	ZS_ENG_REL	0.1286	−0.1596	0.4168	0.147	0.874	0.382	1.13720	0.85245	1.5171
	ZS_RUR_CEN	0.3313	0.0781	0.5846	0.129	2.565	0.010	1.39283	1.08126	1.7942
	ZS_POP	−1.2385	−1.5535	−0.9234	0.161	−7.705	< .001	0.28983	0.21150	0.3972
	ZS_LR_CEN	−0.1163	−0.5262	0.2936	0.209	−0.556	0.578	0.89022	0.59086	1.3412
GRN - REF	Intercept	0.4408	−0.0298	0.9113	0.240	1.836	0.066	1.55389	0.97062	2.4877
	ZS_ENG_REL	−0.1247	−0.4818	0.2323	0.182	−0.685	0.493	0.88272	0.61770	1.2615
	ZS_RUR_CEN	0.1041	−0.2597	0.4679	0.186	0.561	0.575	1.10967	0.77126	1.5966
	ZS_POP	−0.8584	−1.2557	−0.4612	0.203	−4.236	< .001	0.42382	0.28488	0.6305
	ZS_LR_CEN	−4.1977	−4.8718	−3.5236	0.344	−12.206	< .001	0.01503	0.00766	0.0295
LAB - REF	Intercept	−0.4706	−1.0530	0.1118	0.297	−1.584	0.113	0.62464	0.34891	1.1183
	ZS_ENG_REL	−0.2205	−0.6093	0.1682	0.198	−1.112	0.266	0.80210	0.54374	1.1832
	ZS_RUR_CEN	−0.4167	−0.8710	0.0377	0.232	−1.797	0.072	0.65924	0.41853	1.0384
	ZS_POP	−1.1870	−1.6117	−0.7623	0.217	−5.478	< .001	0.30514	0.19955	0.4666
	ZS_LR_CEN	−4.6810	−5.4053	−3.9567	0.370	−12.667	< .001	0.00927	0.00449	0.0191
LD - REF	Intercept	0.7905	0.3564	1.2247	0.222	3.569	< .001	2.20460	1.42819	3.4031
	ZS_ENG_REL	−0.3178	−0.6641	0.0286	0.177	−1.798	0.072	0.72777	0.51474	1.0290
	ZS_RUR_CEN	0.1404	−0.1928	0.4735	0.170	0.826	0.409	1.15070	0.82466	1.6056
	ZS_POP	−1.1694	−1.5519	−0.7870	0.195	−5.993	< .001	0.31055	0.21185	0.4552
	ZS_LR_CEN	−2.8311	−3.4382	−2.2240	0.310	−9.140	< .001	0.05895	0.03212	0.1082
OTH - REF	Intercept	0.8641	0.4410	1.2873	0.216	4.003	< .001	2.37296	1.55429	3.6228
	ZS_ENG_REL	−0.0592	−0.3472	0.2287	0.147	−0.403	0.687	0.94249	0.70666	1.2570
	ZS_RUR_CEN	0.1152	−0.1603	0.3907	0.141	0.819	0.413	1.12205	0.85186	1.4779
	ZS_POP	−0.3433	−0.6685	−0.0181	0.166	−2.069	0.039	0.70943	0.51246	0.9821
	ZS_LR_CEN	−1.2198	−1.6739	−0.7657	0.232	−5.265	< .001	0.29529	0.18751	0.4650

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1 ANNEX: Methods Tutorial

"*As to the distribution between causal and predictive inferences, causal relations are always predictive, but predictive relations are not necessarily causal. The question whether an explanatory variable is not only predictive, but also causal, belongs to the subject matter of the model*." (Wold, 1980).

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The second half of this thesis uses Structural Equation Modelling and Factor Analysis techniques. This Annex does not form part of the assessed body of the Thesis, but is included here in the hope that it provides a detailed but accessible overview of these techniques to readers from non-quantitative research backgrounds so that they can better understand the analytical and reporting choices I made in the final two results chapters. It is largely written without mathematical notation, because it is principally aimed at anyone who is entirely unfamiliar with these methods (as I was at the start of this PhD). It also positions the research as recognising and responding to the methodological quagmire that surrounds SEM research, particularly as regards model evaluation. It is useful background for interpreting:

- Chapter 6, which details the development of a new scale to measure resistance to rural change from climate policy, which uses both Exploratory and Confirmatory Factor Analysis techniques in the testing and refining of the measurement instrument.
- Chapter 7, which describes the development and testing of a hypothesised model of how a set of core identity values may influence resistance to landscape change from climate policy, and how the influence of those values is mediated through political affiliations. The analysis in Chapter 7 moves from Regression model approaches to Path Analysis, which is a subset of Structural Equation Modelling.

The Annex illustrates how SEM subsumes a number of other different statistical techniques, including regression models, path models and confirmatory factor analysis, combining them into a very powerful, flexible method for modelling multifaceted social and behavioural phenomena. Unfortunately, "*methods and notions that are widely available and that are represented in user-friendly software packages tend to be quickly abused. Structural equations modelling may be the best example of this phenomenon*". (Cortina, 2002). The 'model evaluation' section of this chapter in particular aims to demonstrate how relying on rules of thumb and the unthinking application of standard software settings has resulted in "*journals*

littered with…a plethora of forgettable, non-replicable, and largely 'of no actual measurable consequence' models." (Barrett, 2007), a problem which I have tried to make no further contribution to.

1.1 From explaining structure to imposing structure

To the uninitiated, it isn't straightforward to differentiate between Structural Equation Modelling (SEM) and other statistical techniques used in the social sciences, in particular the more commonly encountered Linear Regression Model. Interpreting the results from each feels superficially similar. Both methods produce results tables filled with regression coefficients (raw and standardised), standard errors and p-values, and both tell us something about relationships between predictor and outcome. The overall utility of each model type can be expressed in an R^2 measure, one interpretation of which is that it describes percentage of variance in the outcome variable that is explained by the combined predictor variables.

The crucial distinction, however, is how the two methods differ in their approach to causal inference. "*In a regression model, each equation represents the conditional mean of a dependent variable as a function of explanatory variables"* (Bollen and Pearl, 2013). In a Structural Equation Model, on the other hand*, "each equation represents a causal link rather than a mere empirical association*." (Goldberger, 1972).

In other words, Linear Regression measures how two things appear to move together, and the regression equation simply describes this association: "When X increases, Y tends to increase by this much." It doesn't tell us why they move together, just that they do.

Structural Equation Modelling goes deeper by proposing and testing cause-and-effect relationships. Though the equations look similar, in a SEM they represent specific causal pathways, rather than just an observed association between variables. In SEM, the resulting equation whereby one would predict a value of Y from a known value of X cannot simply be rearranged so that one can also predict a

value of X from a known value of Y (Bollen and Pearl, 2013). As soon as the concept of causality has been introduced, the researcher has imposed upon the equations a one-way relationship. "*Structural equations attain their causal interpretation prior to, and independently of, any statistical relationships among their constituents*" (Pearl, 2009; Tarka, 2018), meaning that the causal inference comes from theory, and the model is used to confirm this. By making explicit assumptions about all relationships in the model, including error relationships, a researcher makes claims about the causal structure of the system. When done well, this is invaluable for policy recommendations. (Pearl, 2012; Bollen and Pearl, 2013).

SEM therefore represents a blend of theory and statistics, with an important hierarchy.

1. theory comes first;
2. equations are written as causal statements (even though they superficially look the same as regression equations, which make no such causal claims);
3. causality is inferred from the evaluation and interpretation of the model fit; and then
4. the theory is either considered credible, or is (wholly or partially) amended as a result.

It is the focus on causality which sets SEM apart from other statistical modelling techniques, and which forms the basis of so much of the critique of the method, especially from those corners of academia that hold with the idea that causation can only be shown where predictor variables are isolated and manipulated in some way, (Holland, 1986) so that the change in effect on the outcome variable can be measured, or where the entire model is 'self-contained' (i.e. all variables that could affect the outcome are within the model), (James et al, 1982). This is, of course, the experimental method that underpins research in the natural and physical sciences, an approach which can be impossible (and sometimes unethical) to try to replicate in the social sciences.

Bollen and Pearl, (2013), address this critique, along with a range of other 'myths' about Structural Equation Modelling, concluding that, despite the fact that "*SEMs*

have had a long and turbulent encounter with causality", the method has now secured its place as a "*universal formalism that unifies nearly all approaches to causation around simple and transparent principles,*" a view echoed by Ropovik, (2015), who states that SEM has become the "*standard in solving multivariate research problems in most of the social sciences*".

Structural Equation Modelling subsumes several other analytical techniques, and this chapter provides an overview of how these fit together to create a full Structural Equation Model. The development of a full SEM follows 6 distinct steps (Hoyle, 2012; Whittaker and Schumaker, 2022):

1. **Specification**: defining the model structure, including all variables, and the paths and covariances between them.
2. **Identification**: determining whether the information we have in our sample is adequate to ensure that a *unique* value can be calculated for everything that the model needs to estimate, and to test whether our theoretical structure makes sense.
3. **Estimation**: using the information from our sample data to produce the estimates for the unique values in our model.
4. **Evaluation**: an empirically-informed examination of whether our specified model structure is a close match to our sample data, using measures of fit.
5. **Modification/Re-Specification**: Modifying and comparing different forms of the model to improve fit.
6. **Interpretation/Reporting**: telling the story of the model – what is its substantive contribution to understanding social or behavioural processes?

In this chapter, we will build up to a full SEM by looking at some of its constituent parts. Reference to the six stages are noted with numbered superscripts $^{(n...)}$ to help with navigation. First, we look at linear regression models (used as the precursor to further analysis in Chapter 7). We see how even these can be 'specified' in the same way as a SEM, using a Path Diagram.

1.2 Multiple Linear Regression as a restricted form of SEM

Linear regression models are a familiar place to introduce some elements of SEM, though they do not ultimately do the same thing. Linear Regression models find the line of best fit through a cloud of data points, where each point represents one case in a sample, for at least two variables that we believe to have a linear relationship. The line is a 'best fit', not a 'perfect fit'. Not all points are on the line; some are above or below, and those differences from the score predicted by the line are called the 'error term' (ε). The error term accounts for the differences caused by the following, which are important in understanding model fit:

- *measurement errors* (systematic bias in the data, caused by issues with data collection, survey design, consistent bias in sensitive responses etc)
- *random error* (natural, truly random variations between subjects, or genuinely random errors in data collection)
- *omitted variables* (predictor variables that have not been included in the model, but which will be affecting the scores of the outcome variable)
- *model mis-specification* (for example, assuming a linear relationship where the true relationship is non-linear).

1.2.1 Specification(1) – describing relationships with a path diagram

The relationship between predictor and outcome variables[47] in a Linear Regression Model can be expressed as a **Path Diagram**, which expresses the relationships between the variables. An example is given in Figure 27, below.

This could be a simple model, for example, predicting the adult height of a child. There are no assumptions made by the researcher in this model beyond which variables to include and whether to include interaction terms between variables. All four predictor variables, A-D (which we could imagine as mother's height, father's

[47] 'Predictor and Outcome variable' is the convention followed here. Note though that these also go by other names, such as 'Independent and Dependent' variables, 'Explanatory and Response variables', 'Manipulated and Measured variables' and 'Regressor and Regressand'.

height, ethnicity, and daily calorie intake) simultaneously predict the outcome, Z (final height).

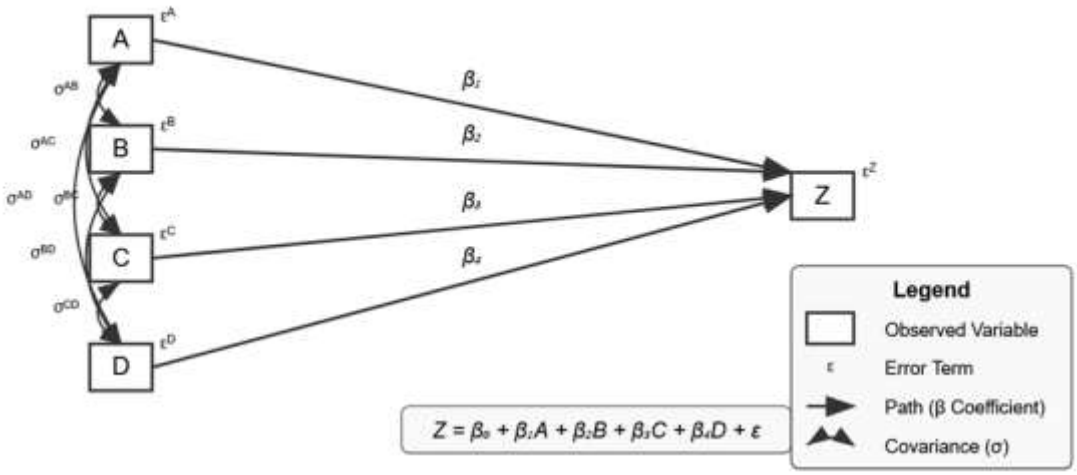


Figure 27: Multiple Linear Regression expressed as a Path Diagram.

Figure 27 is a *multiple* linear regression. It contains more than one predictor, and the model estimates the relationships between all the predictors and the outcome *simultaneously*. Thus, in our example, the model estimates would not sequentially look at the effect of mothers' height, then fathers' height and so on. Instead, the process estimates how the predictors work together, and accounts for the fact that the predictors may also correlate (covary) with each other. Because there are multiple predictors, the 'line of best fit' is actually a 'hyperplane of best fit'. This can be visualised with three predictors (Figure 28), but beyond three predictors, visualisation becomes very difficult.

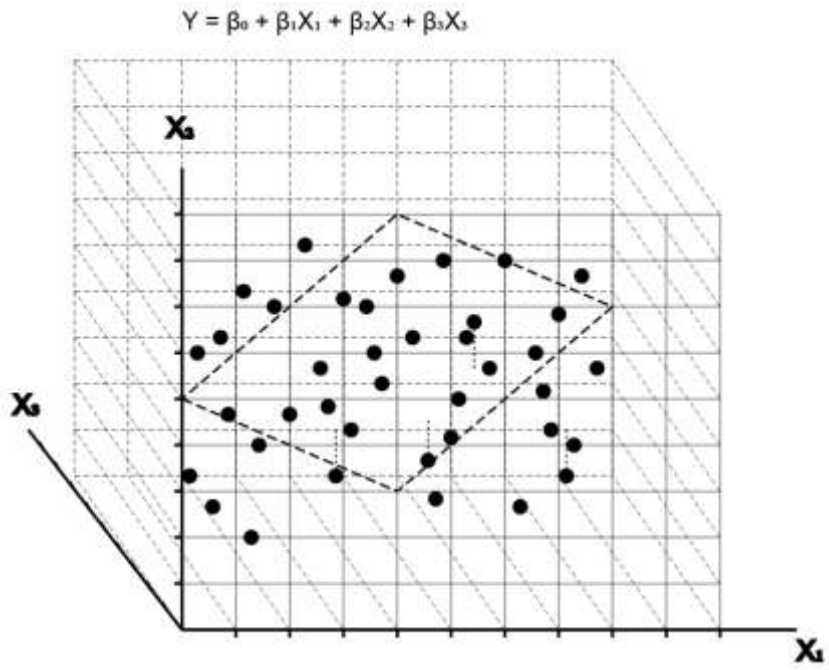


Figure 28: Hyperplane of best fit in multiple linear regression. The plane is the best fit through the cloud of data points from several variables, visualised in 3D data space.

In practice, there is seldom any utility in drawing a path diagram of a basic regression model. Any linear regression model would look similar to Figure 27, since every possible relationship is 'specified' (marked by arrows), and a value for every relationship will be estimated by the model. However, since Path Diagrams are central to the 'structure' element of Structural Equation Modelling, it is useful to visualise a simple linear regression model expressed this way, since regression is the more familiar concept.

This path diagram brings us to the importance of the second stage of Structural Equation Modelling: Identification.

1.2.2 Identification(2) – showing that sufficient information exists to estimate model parameters

In SEM, we *first* hypothesise and specify the structure of causal relationships that we believe exists in the population, and *then* we turn to our sample data to assess whether this structure is plausible.

Every path that we have specified with an arrow in our path diagram is a parameter that needs to be estimated. The information we have at our disposal to estimate these parameters comes from our sample data, specifically, the variances (how much each variable's values spread out around its mean) and covariances (how much two variables move together). Together, these make up the sample's **variance-covariance matrix**. When we look at tests of fit, we are assessing whether the variance-covariance matrix implied by our model matches that of our sample, thus confirming the plausibility of our theory. First though, we need to know if we have enough information to do so.

An 'identified' model is one where (paraphrasing Schumaker and Lomax, 2010 p 56) we can answer the question 'do we have enough information in our sample to calculate a unique estimate for everything we want to calculate in our model'? This does not mean 'do we have a big enough sample with lots of cases in it?', rather it means 'is there enough *unique statistical information* in our data structure to match or exceed the number of parameters we want to estimate in our model'?

For any path diagram we have specified, we can determine whether it is identified by applying **Path Tracing Rules**, first developed by geneticist Sewall Wright in the 1920's. (Curran and Bauer, 2023).

The goal of path tracing is to allow the researcher to compute the sum of all pathways in the model. Each variable in our sample data contributes its own variance and several covariances to the pool of unique statistical information we have available to calculate the parameters in our model. For a model to be 'identified', each unknown parameter must be solvable. Unlike simple algebraic problems that can be solved sequentially, in SEMs we must solve all equations simultaneously, because the parameters are interdependent. Each piece of information in our sample variance-covariance matrix therefore represents 'statistical currency' that can only be spent once. When we need to use the same variance or covariance value in several calculations at the same time, we cannot produce a unique value for each parameter. Such a model is 'under-identified', and we are unable to derive stable estimates, or test the model's fit.

Linear Regression Models, can be viewed as a special, restricted form of SEM. They are always '**just-identified**' or 'saturated' models. The model uses every possible path and relationship between the variables (significant or otherwise) to estimate the effects of the predictors on the outcome. Saturated models cannot be subjected to tests of *causal* (or structural) fit, not because they are inherently 'right', but because that maximised availability of coefficients and covariances is always sufficient for reproducing the data. (Hayduk and Glaser, 2000). For this reason, linear regression models can tell us about correlations but should never be interpreted to mean causation.

Take the common illustration that good weather predicts an increase in ice cream sales, and good weather also predicts an increase in drownings. Now imagine a simpler model that omits the role of the weather. The underlying relationship between the three variables can largely be mathematically reproduced through the correlated relationship between ice cream sales and drowning. Common sense in this case tells us that while this correlation may be mathematically correct, to describe the relationship as 'ice cream causes people to drown' would be causally suspect. In more complex models, we must have more than common sense to help us confirm if proposed causal structures are plausible, to suggest missing variables, or to alter relationships.

In Structural Equation Modelling we aim to test the structural plausibility of the model we have specified (the 'causal paths'). To do so, we must go beyond a 'just-identified' model and aim for 'over-identification'. An **over-identified** model is one where we have enough leftover statistical information in our sample variance-covariance matrix to carry out tests of *structural* fit *in addition to* obtaining unique estimates for each of our parameters[48]. This statistical spare capacity is known as **degrees of freedom[49]**, and plays a part in most tests of fit.

[48] In an '**under-identified**' model, by contrast, not only do we not have enough information to carry out tests of structural fit, we cannot even produce a *unique* value for every parameter.
[49] Degrees of Freedom are explained further in section 1.6.5.2 under model fit

1.3 Structural Models: imposing structure with path diagrams

Recall the Linear Regression Model in Figure 27. The researcher, drawing on theory, now reimagines the model. She posits that there is a mediating relationship between variables A and B, through C, to the outcome variable Z, and that variable D both directly influences Z, and is also mediated through C.

Such a model would have a Path Diagram like the one shown in Figure 29, below. Here we see some new terminology (not used in Linear Regression), in the use of '**Exogenous**' variables (for things that are not predicted by anything else in the model), and '**Endogenous**' variables, for things that are. Endogenous variables can act like traditional outcome variables (dependent in all relations), or as **mediator** variables (dependent in some but not in all relations). These predict, while at the same time themselves being predicted by other variables in the model (Israëls, 1987). Some variables have no direct path to the final outcome at all. This more obviously represents the sort of complex system found in the social sciences. Linear Regression cannot cope with this sort of structure. Though not shown in the model, the researcher could also include **moderator** variables. These act like interaction terms in a linear regression model, where the effect of one variable on another is conditional upon the level of a third variable (for example, caffeine affects alertness, but its effect is moderated by a third variable, time of day).

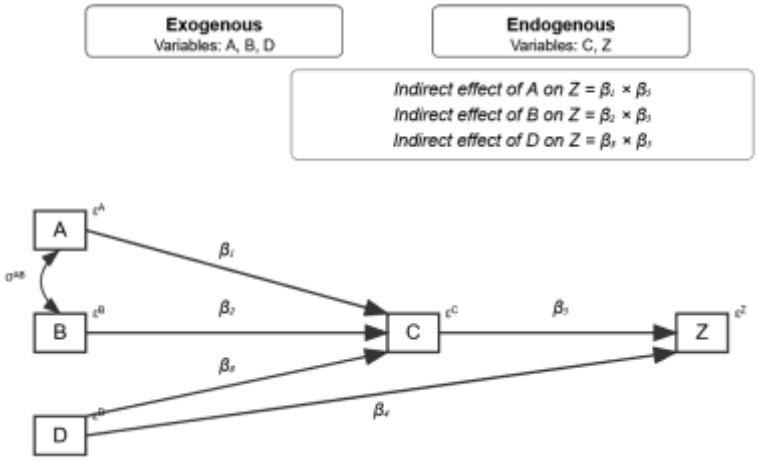


Figure 29: Path Diagram showing hypothesised mediated relationships between predictors and outcome.

Structural Equation Modelling allows us to develop an *a priori* specification for how we think our variables affect the outcome *and* to specify hypothesised causal paths, including those where some variables mediate or amplify the effect of others. The power and flexibility of SEM comes from the ability of the researcher to specify both weak and strong **causal assumptions** for the model's parameters, which are the specific numerical values (like coefficients, intercepts, or variances) that the model estimates. These are the quantitative measures of the relationships between the variables.

A 'strong causal assumption' forces a given parameter to take on a specific value, most commonly, zero, when the researcher specifies no path at all between two or more variables in the model. This is a strong assumption because incorrectly removing a relationship doesn't eliminate pressure for the calculation process to try to calculate that path, leading to biased estimates elsewhere in the model. (Cole and Preacher, 2014). The theory underpinning such choices must be sound.

'Weak causal assumptions' are those that limit the range of values that a parameter can take. The weakest, most common form of weak assumption comes from merely specifying that the value of a given parameter is 'not zero', (i.e. specifying that there *is* a relationship between one variable and another), then allowing the model to estimate the value. But weak assumptions can be a little stronger than this, for example by forcing parameters to take on only positive values. (Bollen and Pearl, 2013; Curran and Bauer, 2023).

Our model in Figure 29 contains only **observed variables** (those which can be measured directly, which are generally represented by rectangles in path diagrams.) There are no **latent variables** (those which have to be measured through other indicators, such as attitudes, beliefs or behaviours). As such, it is not yet a full Structural Equation Model. It is the 'structure' half of a SEM, representing a subset of SEM called '**Path Analysis**'.

1.3.1 From 'just-identified' to 'over-identified' models

By proposing causal mechanisms in Path Analysis, we move away from the data-driven approach of the Linear Regression model, in which we were simply asking whether our collection of dependent variables has an association with a dependent variable, and in which all relationships were estimated (significant or not).

Unlike the Linear Regression Model in Figure 1, not all possible paths in Figure 29 are used. There is no direct hypothesised path from A to Z, and only one pair of variables (A and B) is allowed to covary. It is this removal of paths (the 'strong assumptions', mathematically constraining the coefficients of those regression paths to zero), which allows for such models to be 'unsaturated' or 'over-identified'. In an over-identified model, "*there is more than one possible solution, and the task is to select the one that comes closest to explaining the observed data*" (Kelloway, 1998, pg 15). In such a model, there are more parameters that *could* be estimated than actually *are* being estimated. This results in a certain number of degrees of freedom in the model, which allows for tests of model fit, and ultimately, for different models to be compared. (Schumaker, 2010; Bollen and Pearl, 2013; Curran and Bauer, 2023).

1.4 Measurement Models: measuring the unmeasurable

1.4.1 Latent variables

Behavioural and attitudinal research in the social sciences often requires measurement of constructs or **latent variables** that cannot themselves be directly measured. Moods and personality traits such as 'happiness', 'introversion' or 'loyalty' are classic examples, as are attitudes, such as 'trust in civil society institutions'.

Latent variables are described by Bollen and Pearl (2013), as those which are "*part of our theory, but not in our dataset*." Measuring such constructs such requires the researcher to operationalise those unmeasurable variables, to make them measurable in some way. The first stage of this is normally through the

development of 'Survey Instruments'; batteries of questions, often Likert-type items. It is the responses to *those* items which *are* in our dataset. Responses to those items reveal the underlying construct and allow us to estimate a score for each respondent on the latent construct. (Willits *et al* , 2016; DeVellis, 2017).

Many well-tested scales for common latent variables (such as IQ, depression, job satisfaction *etc*.) already exist, and researchers studying those constructs can re-use these scales (the structure of which must still be verified using Confirmatory Factor Analysis, which is discussed later in this section).

Researchers studying novel or niche latent constructs face the more difficult task of first needing to construct, pilot, test and refine a list of items, ensuring a final structure with enough items (usually at least four) to reliably measure their theorised construct. (Diamantopoulos *et al.*, 2012; Willits *et al*, 2016). This does not always mean developing a set of items entirely from scratch. Consulting the literature for items and scales that measure a close analogue of the construct of interest, and adapting those for use in a new scale is a common approach, as is combining existing items with new items. (DeVellis, 2017).

1.4.2 Exploratory Factor Analysis

Any new or modified collection of items being proposed as a scale needs to be demonstrated to be reliable, and this requires the application of **Factor Analysis** techniques.

Here we must distinguish between **Exploratory Factor Analysis** (EFA), and **Confirmatory Factor Analysis** (CFA). Both of these techniques stem from the work of L.L. Thurstone in the 1930's and '40's, whose Common Factor Model, (building on Charles Spearman's work on correlation), developed the method for understanding how 'manifest indicators' (things that *can* be measured), can be used to "*uncover the smallest number of interpretable factors needed to explain the correlations among them*" (Brown, 2015, p.18).

An EFA reveals the strongest correlations between the 'manifest indicators' (such as survey responses), exposing the likely latent factors that cause the correlations. The results are presented in the form of 'loadings', a measure of how much a particular indicator, or item, is contributing to a given factor. The square of a loading (when expressed as a percentage) can be thought of as the amount of variance in that item that can be attributed to the factor (Blaikie, 2003). Thus, for an item with a loading of 0.4, we can attribute 16% of its variance to the Factor. For an item with a loading of 0.85, the attributable variance would be 72%.

Thurstone's Common Factor Model showed that the variance of every manifest indicator (item) can be partitioned into (a) that variance shared with other items which is caused by the common factor(s), and (b) that variance which is unique to that indicator, or a result of random error (Gallagher and Brown, 2013). The **shared variance** is known as the **communality** of the item. It is the sum of its squared loadings across all factors in the solution. The remainder is the item's **specific variance** or **uniqueness**.

That Thurstone's Common Factor Model is the methodological bedrock of EFA is not reflected in analytic choices as much as it should be. EFA carried out for the purpose of identifying latent variables for scale development requires an informed choice of which factor extraction technique to deploy. Researchers should use techniques that really are uncovering latent factors, rather than merely 'boiling down' correlated items into a smaller, more manageable number. Bandalos and Boehm-Kaufman (2009) provide a helpful illustration – perhaps we want to predict final year exam grades from a large collection of prior tests and other measurements such as attendance, overdue homework etc. We might use Principal Components Analysis to boil these down into a smaller set of composite variables (which we could call 'components'). Perhaps all the scores for science subjects are highly correlated and could combine into a single 'science' predictor, for example. This is a very different mathematical operation to subjecting the same set of items to a Common Factor Analysis (using other extraction methods such as Maximum Likelihood or Principal Axis Factoring). Here, instead of maximising predictive power with minimal components, we are looking for hidden constructs that explain

the reasons that some items always move together. Their shared common variance, partitioned from their unique variances, is key to this process. Choosing PCA instead of a more appropriate technique leads to potentially misleading factor structures (Preacher and MacCallum, 2003; Kim, 2008). Unfortunately, since the choice of ML, PAC, and PCA is often in the same dropdown menu in software, and results outputs look the same, this methodological incompatibility is not obvious to novice EFA practitioners.

Researchers administer a survey with their test items and then use EFA to explore the structure of the responses, to identify the factors within it. In an EFA, it is the researcher's job to decide how many factors to extract, what their substantive importance is, and how they should be named and used in practice. This is based on a combination of theoretical (qualitative) understanding of the field, as well as an empirical assessment of whether the derived factor(s) will remain stable in future studies, allowing the instrument to be used by others, and as a variable in further analytical models. The principal decision here is whether there are enough indicators strongly loading onto a factor, usually taken to be a minimum of three, preferably four, loading to least 0.4, with minimal cross-loading onto other factors. (Watkins, 2018; Whittaker and Schumacker, 2022; Birmingham City University, 2017).

Both EFA and CFA share the same basic model for how latent variables relate to observed variables (the items or questions that make up the survey instrument used to gather data). They differ, however, in emphasis.

An EFA is primarily data-driven, and the main purpose is to empirically derive the number and nature of latent factors revealed by the set of item scores across the sample. In statistical terms, an EFA is a saturated model, and this rules out most methods of evaluating model fit. Since *all* the observed variables in the dataset are regressed on *all* the possible factors, there are effectively no degrees of freedom 'left over' with which to evaluate model fit. An EFA essentially repackages all of the observed variances, covariances and means in the sample set as model parameters. (Curran and Bauer, 2023).

In an EFA, items that cross-load heavily across multiple factors, or that load at a low level on all factors are usually discarded. The convention is to drop any item with loadings lower than 0.4 (Guadagnoli and Velicer, 1988; Blaikie, 2003), removing items through a stepwise process that begins with the weakest items with the highest cross-loadings onto more than one factor. (Birmingham City University, 2017). Eventually, a stable collection of items with high loadings on single factors remains, giving the 'Approximate Simple Structure' that is easiest to interpret. (Blaikie, 2003; Whittaker and Schumacker, 2022). Once the EFA solution has stabilised, the regression slopes of each item on their factors (the factor loadings) can be interpreted by the researcher to determine and name the factors that they likely represent.

By contrast, a CFA is primarily theory-driven. The emphasis is on the formal testing of a pre-expected theoretical factor structure. As such, all items are *not* permitted to freely correlate with all other items. The researcher suggests the number of factors and permits only those items that they expect to be associated with a given factor to freely relate to it.

The literature describes the two approaches as entirely separate. In reality, EFA on new scales is never *entirely* data-driven and theory-free, since any new scale has been constructed from a search of the literature and reasoned consideration of the construct that the researcher is aiming to measure. Thus, the novel scale *is* theory-driven to some degree and there is often some expectation that certain items will cluster together in the factor structure. In the same way, CFA is never *entirely* theory-driven, especially since many researchers use Modification Indices to improve the fit of their model (which are returned to in Section 1.7). (Curran and Bauer, 2023)

It is useful to think of EFA as a cousin, rather than sibling, to the Structural Equation Model family. Its relevance here is that it is usually the first step in the development of the **Measurement Model** part of a SEM, but it does not follow exactly the same conventions with regard to assessing model fit.

1.4.3 Confirmatory Factor Analysis

By contrast to EFA, CFA requires the researcher to pre-specify the factors in a model, and mandate which items should load onto which factors. This is a crucial distinction because it means that instead of *exploring* data to find structure, as in an EFA or linear regression, in a CFA we *impose* a hypothesised structure and then compare that structure to the structure of our data, to see if it matches (fits). This emphasis on imposing rather than exploring structure is central to Structural Equation Modelling, and is the reason why measures of model fit are so crucial; the theoretical expectation of causal relationships in the population can only be empirically confirmed as plausible by comparing a proposed model structure to sample data drawn from that population.

A basic CFA structure might look something like Figure 30 below, which represents a single latent factor measured by five manifest indicators (such as survey questions). The factor itself is an unmeasurable attitudinal construct, and the indicators are usually survey questions that are already proven via EFA (and possibly prior CFA) to reliably measure this, in at least one prior study. The double-headed arrow represents the variance (ψ) of the factor itself. Factor scores for each respondent are estimated in the model based on their responses to the indicators, with each indicator weighted according to its loading on the factor. These scores represent each person's position on the underlying construct, as inferred from their pattern of responses.

The small circles represent the error term (Θ) for each indicator (that part of its variance that is not explained by the latent factor). The single-headed arrows from the factor to each indicator represent the factor loadings, rendered here in different line thicknesses to illustrate that not every item loads as strongly onto the factor.

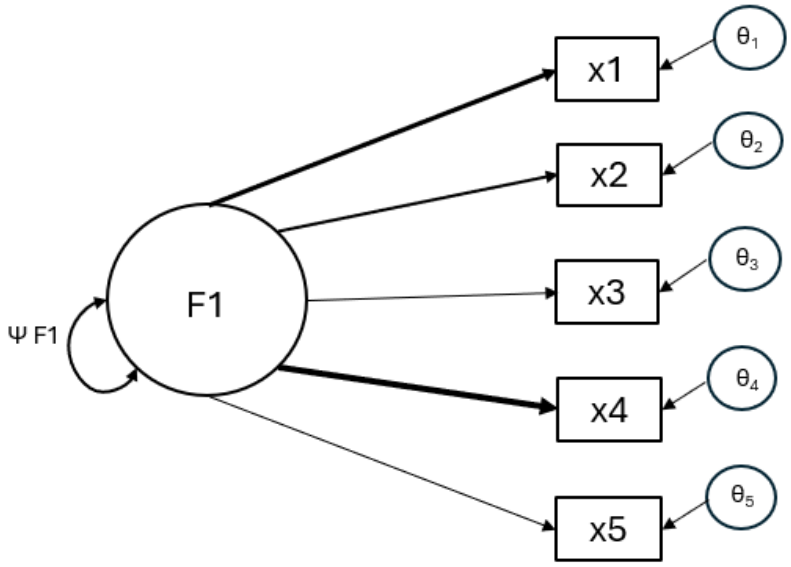


Figure 30: Example schematic for a CFA, hypothesising a single latent factor measured by 5 indicators. Line weights represent different loading strengths of each indicator on the factor.

Figure 30 bears a passing resemblance to Figure 27, the Path Diagram of a multiple linear regression model, but the similarity is only superficial. In Figure 27 we had predictor variables A-D, which are observed variables (like physical measurements). Knowing a score on A-D helps us predict a likely value of Z (the outcome) for a given respondent. In Figure 27, the arrows run from the predictors to the outcome.

Figure 30, by contrast, represents a completely different approach. The Factor (F1) is something that cannot be measured directly, but which we hypothesise is responsible for causing the patterns we see in our observed variables (x1 to x5). The arrows therefore flow *from* the factor *to* the indicators. This distinction is crucial when we come to tests of model fit because there are no outcome variables in a measurement model (the CFA). The latent variable is a hypothetical causal variable which cannot itself be directly measured. Therefore, the only way to assess the fit of a CFA (and confirm that the existence of the latent variable is plausible) is through comparing the structure we have imposed to the structure of the data we have in a sample we can compare it to. (Barrett, 2007).

1.4.4 Correlated Factor, Higher Order, and Bifactor Models

A CFA can also propose and test more complex structures of multiple latent variables and their indicators, including the extent to which multiple factors themselves may be correlated (Schreiber *et al.*, 2006; Quinn, 2014). Figure 31, below, represents a correlated factor model. Note that the factors themselves are at the same level as each other – neither has 'dominance' over the other, both have specific sets of items associated with them.

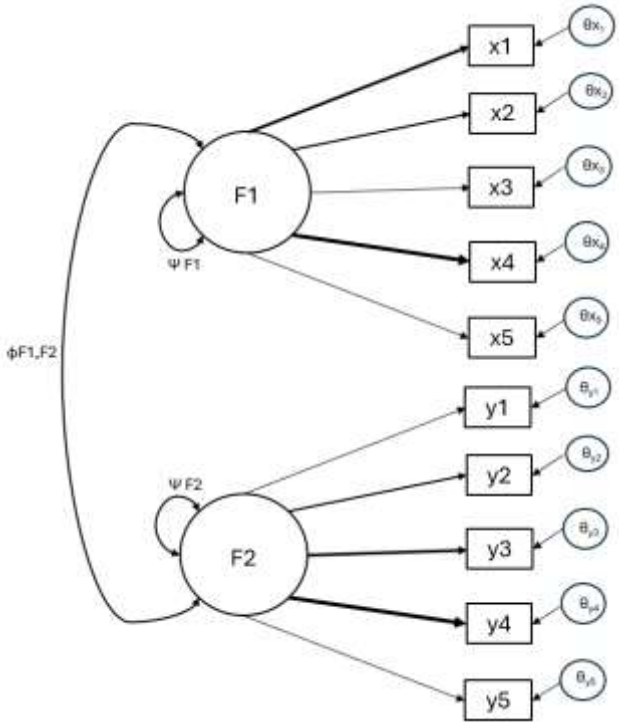


Figure 31: Correlated Factor Model (adapted from Quinn, 2014).

Beyond simple **correlated factor models** are those where latent variables are hierarchically structured (Brunner *et al*, 2012; Chen *et al.*, 2012); for example, a researcher trying to understand levels of citizen trust in civil society institutions may be concerned with trust in community-based institutions and trust in national NGO's (which might form two sub-factors), while also incorporating the idea of an overall 'civil society trust scale' that includes attitudes to the general idea of civil society institutions as a whole.

In a hierarchical model (also known as a **higher-order model**), there is a General Factor that acts through other sub-factors. "*The subordinate factors in a higher-order model mediate the relationship with the more general [second-order] factor*" (Dunn and McCray, 2020), as illustrated in the example diagram in Figure 32, below.

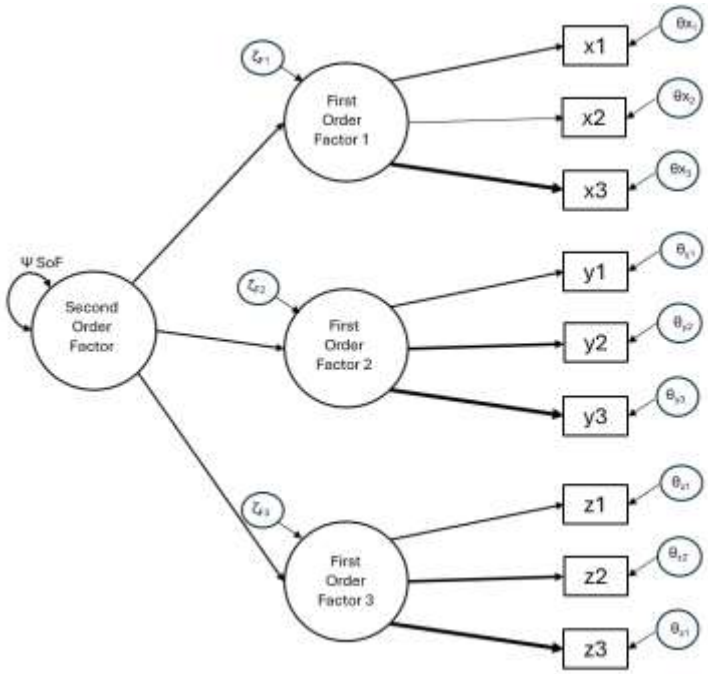


Figure 32: Higher Order Factor Model. (Adapted from Quinn, 2014).

By contrast, in a **bifactor model** there exists a General Factor *onto which all items load directly*, which has measurement utility in and of itself, and which often drives the bulk of the item-response variance. Beyond the General Factor, the model includes a number of sub-scales ('Specific Factors'), onto each of which a subset of the measurement items also load, as expressed in Figure 33, below.

A bifactor model should be understood as modelling "*the general commonality between all items on the test/survey and the residual variance for each* [topic] *area beyond that* [of the general factor], *with equal weight*" (Dunn and McCray, 2020). There is no hierarchy to the factors, and the bulk of the data variation is explained by the General Factor.

In statistical terms, a higher order model is actually nested within the bifactor model, (Yung, Thissen and McLeod, 1999; Rijmen, 2010; Markon, 2019), but the

bifactor model is more flexible (Dunn and McCray, 2020, Chen *et al.*, 2012). "*Due to the orthogonality of general and group factors, it is only [the bifactor] model that allows researchers to easily partition item response variance into two common sources, which are that item variance that is due to the General Factor, and that which is due to the sub-factors*". (Reise, 2012).

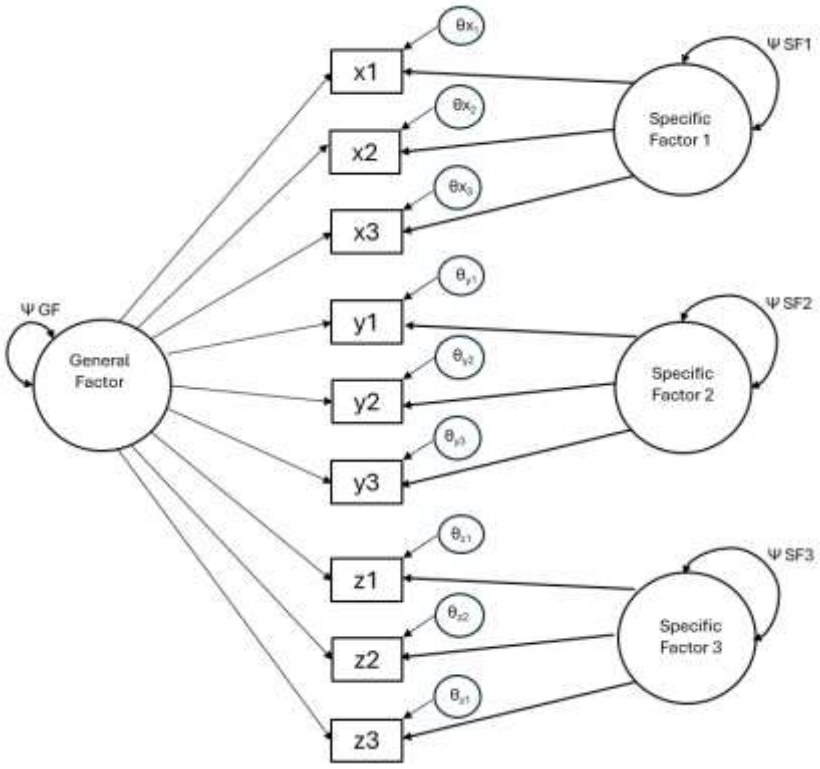


Figure 33: Bifactor Model (Adapted from Quinn, 2014).

When we speak of the Specific Factors in the bifactor model being 'orthogonal' to the General Factor, we mean they are uncorrelated; they capture that variance in the indicators which is *not* explained by the General Factor. They are not 'statistical leftovers'; rather, they are meaningful explanatory constructs in their own right.

Orthogonality is represented in Figure 34. In this schematic of a cloud of data points, the primary dimension of the variation in the data (the direction where the data 'stretches out' the most) is represented by the long axis and is the General Factor. The shorter line would represent a Specific Factor, a completely independent dimension in the data variation. There is no correlation between the Specific Factor scores and the General Factor scores.

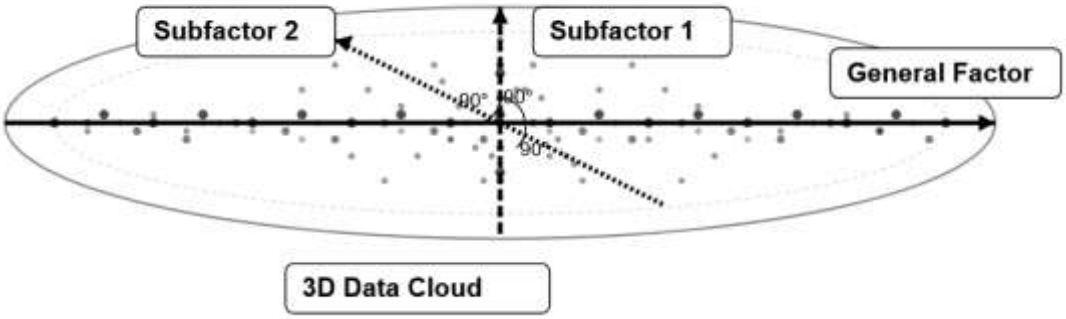


Figure 34: Orthogonal factors in multivariate space.

Many IQ tests are bifactor models. The test provides an overall score that could be called a 'General Intelligence Score', but there is often also utility in reporting the scores of subsets of the test questions, which measure specific facets of mathematical, verbal, or spatial ability unrelated to the overall IQ dimension. Bifactor models have the great advantage of showing whether the facets of a multi-dimensional trait such as IQ can really stand alone as useable measures in their own right, because the reliability of the subscales can be independently tested, which is not possible in higher order models. (Chen *et al.*, 2012; Rodriguez *et al*, 2016b).

Within a bifactor model, although the specific factors are hypothesised to be orthogonal (uncorrelated) with the General Factor, they can still be correlated among themselves. (Dunn and McCray, 2020).

A long-standing debate in the development of measurement models is to what extent such multi-dimensional models can, or even should, be treated as **unidimensional** for practical purposes (i.e. when can the General Factor score be used as a single measure), and what statistical criteria can be used to answer these questions. (Quinn, 2014; Rodriguez *et al*, 2016b, 2016a). In addition, understanding the **Factor Determinacy** of the scale (how well the factor scores correlate with the true underlying factor measure), and the **Construct Replicability** of the scale (how well-defined the underlying factor construct is) all have a bearing on minimising

bias when factor scores are used directly in causal models. These considerations are explained further in the section on measures of fit (1.6.3.1).

1.5 Full Structural Equation Models: combining structure and measurement

A full SEM does two things simultaneously. The first part is the 'measurement model', where the full statistical relationship of any *latent* variables to their indicators is defined and estimated; essentially, a CFA for each latent variable. The 'structure model' then proposes the hypothesised causal paths between the variables and any covariances between them; essentially, a path analysis of the relationships between each variable, (latent or otherwise).

1.5.1 Visualising a full Structural Equation Model

Figure 35, below shows the specification of a full structural equation model, expressed as a path diagram.

- Variables A, B and C are *exogenous*; they are not predicted by anything in the model.
- Variables A, B, V and Z are latent variables, each measured via 3 observed indicators (in practice, latent variables usually have more indicators than this).
- Variables C, W and Y are observed variables, (measured directly).
- Variables V, W, X, Y and Z are all *endogenous* variables; they are predicted by something else in the model.
- In this model, V, W and X each predict Y, which predicts the final outcome variable Z.
- V and X also have direct predictive paths to Z.

In this model, none of our exogenous variables directly predict the final outcome, Z, but this is not always the case. It is perfectly possible to have exogenous variables that predict the final outcome directly, as well as having mediated paths to it via

other variables in the model. It all depends on the theory that has been developed to explain the relationships.

Finally, the curved, double headed arrow shows that B and C in this model covary with each other. Since these are exogenous variables, they *directly* covary (their variances move together in some way). If they were endogenous variables, this arrow would indicate that their *residuals* covary; that is, something in their unexplained variance *within* this model is correlated, and explained by a common factor that is *outside* the model. (Whittaker and Schumacker, 2022 p.4).

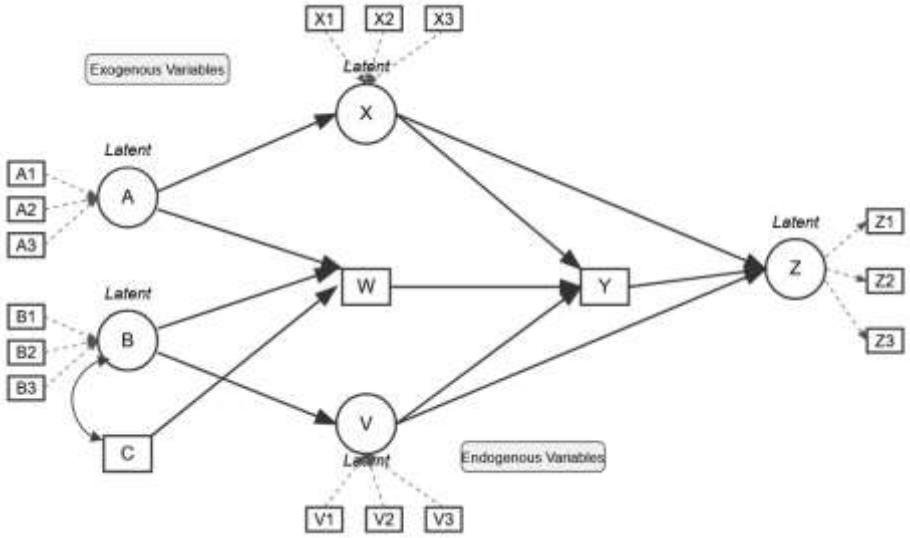


Figure 35: Full Structural Equation Model

The hypothesised paths between the variables represent the **structure** part of the model, and look no different to the Path Analysis model in Figure 29 (nor indeed to the Linear Regression Model in Figure 27, which is simply an unconstrained Path Analysis).

The relationships between each latent variable and its indicators represents the **measurement** part of the model. Each latent variable should be thought of as a CFA which is being estimated at the same time as the structural (regression-like) paths between the variables. A great strength this brings to SEM is that the scores for the latent variables themselves, shown in the circles, are considered to be completely free of measurement error. This is because any measurement error is estimated as

part of the residual terms associated with each observed indicator variable. Since these measurement errors are separated from the latent constructs, and are not directly part of the hypothesised paths in the model, this error does not bias the estimates of the relationships between the variables. This is one of SEM's major advantages over traditional regression techniques. (Pike, 1991; Lance *et al.*, 2016; Curran and Bauer, 2023).

1.5.2 Estimation(3) of parameters in SEM

Up to this point, SEM researchers are working at the level of what we believe to be true in the population. We have specified, from theory, the variables in our model and the network of hypothesised relationships between them. We have identified the model by working out how many parameters we need to estimate, and whether we have enough data to do this.

Now we must turn to the sample data we have to calculate the model parameters (the strengths of the predictive relationships and covariances in the model), which first requires choosing the appropriate method of estimation.

1.5.2.1 Choice of estimator

Choice of model estimator is a major source of result variability. The same model specification can yield different parameters with different estimators. Some estimation techniques may flag a particular indicator as unreliable that would not be problematic by another. (Sarstedt *et al.*, 2024).

Ordinary Least Squares (OLS) estimation is the traditional approach taken in linear regression models (which, recall, are exploring data to find the best fitted line or plane through a cloud of data points). The name is derived from the method of finding the line that produces the smallest value for the sum of squared errors, visualised in Figure 36, below, where the squares represent the sum of the squares of the individual error distances, shown by grey arrows. Various SEM estimators are based on the least squares approach.

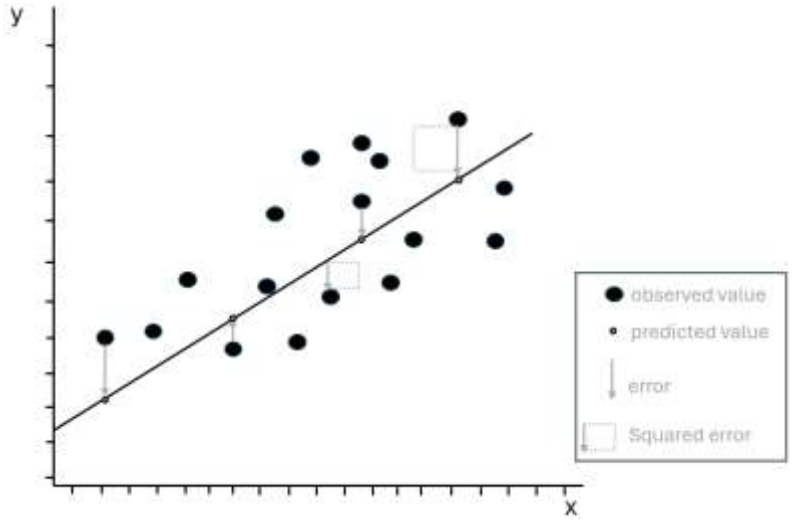


Figure 36: Visualisation of Ordinary Least Squares estimation

However, most SEM software defaults to **Maximum Likelihood Estimation** (ML), which takes a different approach. Instead of focusing on minimising error, it uses a likelihood function to ask the question "what model parameters would make it most likely to see data like ours"? Most introductory guidance recommends using an ML estimator for good reason, since in large datasets of normally distributed data, it will produce the most precise parameter estimates with the smallest confidence intervals. (Curran and Bauer, 2023).

Maximum Likelihood estimators assume data are drawn from a normal (bell-shaped) distribution. This means the process expects the data to be symmetrical and centred around a mean, with most values close to the mean and fewer in the tails. The problem of using ML estimators on non-normal data is illustrated in Figure 37, (Adapted from Starmer, 2017).

In Panel 1, the fit function correctly assumes a normal distribution. The curve is centred over the mean of the sample data (vertical dotted line) there are equal standard deviation lines (vertical solid grey lines) either side of that mean. The fit function correctly assigns high probabilities to finding data in that peaked region. In Panel 2, the distribution is bimodal. The normal curve is a poor representation of this data, and the fit function assigns low probabilities to the actual data points, which are out in the tails. In Panel 3, the data is skewed. The mean is low because

of the skew. The normal curve, being symmetrical, cannot extend far enough to the right to capture all the data, assigning low (or even zero) probability to those values.

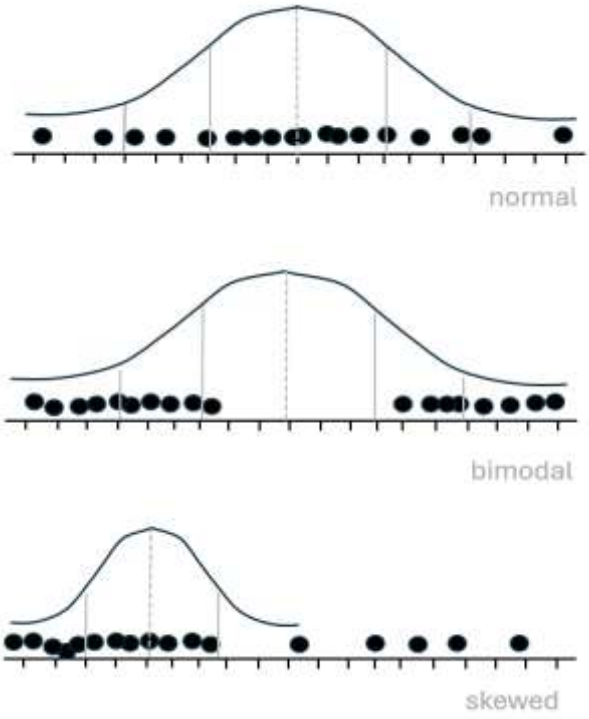


Figure 37: Simple illustration of Maximum Likelihood Estimation with normal and non-normal data.

Using ML estimators with non-normal data can produce negatively biased global fit measures that lead researchers to reject good models (Curran *et al*, 1996), while conversely producing positively-biased significance estimates of individual paths in the model. (Newsom, 2025). Various adjustments such as the Satorra-Bentler correction, and other robust versions of ML have been developed, but these do not deal with extreme non-normality, and are not offered in all software packages. ML also assumes continuous data; it copes effectively with variables with high numbers of response categories (>5 choices), but is not suitable for truly categorical or low ordinal data.(Beauducel and Herzberg, 2006).

With normally distributed data, ML's efficiency is apparent at samples as low as 200 cases, which is often taken to be the rule of thumb for a 'large sample' (Kline, 2015). Where models are complex or data is not normally distributed, the ability of ML to

produce unbiased estimates is compromised and even under corrected estimators such as Satorra-Bentler, non-normal data will need larger sample sizes. (Hu and Bentler, 1999; Newsom, 2025). Even at the largest sample sizes, ML estimates may be more biased than those from other estimators where the data is highly deviated from normality (where skew is >2 and/or kurtosis is >7) (Whittaker and Schumacker, 2022). Simply assuming a that very large sample size will overcome distributional deviations is a common, but flawed, approach.

Another consideration is the nature of the data – several studies (Muthen and Kaplan, 1992; Flora and Curran, 2004; Shi *et al.*, 2018) show that ML is not as efficient as other approaches when the data are ordinal, rather than continuous. This is often the case with Likert-style data, though the issue is only problematic when there are fewer than 6 response categories (Rhemtulla et al, 2012). For such data, and especially where the distribution is not normal, researchers may need to consider alternative estimators. The best alternatives in these situations will tend to be Weighted Least Squares (WLS), Weighted Least Squares Mean & Variance Adjusted (WLSMV), or Diagonally Weighted Least Squares, (DWLS). (Beauducel and Herzberg, 2006; DiStefano and Morgan, 2014; Shi *et al.*, 2018).

WLS requires extremely large sample sizes, making it an unrealistic choice for many researchers. The ideal estimation approach for non-normal data with moderate samples (>150) is what Flora and Curran (2004) call 'Robust WLS' - termed 'WLSMV' (Weighted Least Squares Mean and Variance adjusted) in some software. WLSMV is robust to non-normality. When trying to find parameters that minimise the difference between the model-implied structure and the actual data structure (the variance-covariance matrices), the method creates a weighting matrix that reflects how precisely each part of the data can be estimated. Variances and covariances that are harder to estimate, perhaps because their sample values are more spread out, or skewed, are 'down-weighted' in the calculations. This is not to say that it treats this data as less valuable, merely that the uncertainty in estimates involving those elements is higher, which leads to wider confidence intervals, larger standard errors, and potentially higher p-values for those parts of the model.

Both WLSMV and DWLS use the 'diagonals only' elements of this weighting matrix, which contain information about how precisely each variance and covariance is estimated. They pragmatically avoid also using the off-diagonal elements, (which reflect how errors in estimating one relationship might correlate with errors in estimating another relationship), because doing so adds huge complexity to the estimation process, requires enormous samples and contributes relatively little extra to estimation accuracy. WLSMV does go further than DWLS by then using the full matrix information to make some adjustments to the final test statistic, but is not available in all software packages. DWLS is a suitable, though marginally less optimal solution where WLSMV is not available. DWLS generally performs well for non-normal data where samples are larger than 200, with the exception of highly skewed categorical data. (Kline, 2015 pg 258.)

1.5.2.2 Estimation error in mis-specified models

Consider again the model in Figure 29, and note that there is no path specified directly between variables A and Z.

Imagine that the true relationship in the population (reflected in our sample), is that 60% of the variation in Z can be explained by the path C→Z, 25% by D→Z, and 15% by A→Z. The estimator is not able to calculate that final parameter, because the path is not shown (we have incorrectly constrained that parameter to zero). In such a situation, the estimator will find the best results it can but will not be able to make the calculated model parameters match the data closely enough. To make the relationships between the variables work, it will have to try to recreate that missing pathway by inflating relationships in the model elsewhere, meaning that the path from A→C→Z, for example, may have oversized estimates.

Whichever estimator we have used, it will have done its best, statistically. If based on LS, it will have attempted to minimise the errors between the model structure and the sample structure. If based on ML, it will have attempted to create model parameters that maximise the likelihood of seeing the results we have in our sample (which in cases where the sample is big enough and the data are normal enough, will have also minimised error).

The mis-specification will most likely reveal itself in poor fit indices, the understanding of which is covered in Section 1.6 on model evaluation.

1.5.2.3 Estimation error in models with Factor Scores as observed variables

Researchers often use factor scores directly as observed variables in their models, rather than including the full latent variables with all their indicators. An often-overlooked effect of using Factor Scores as observed variables in this way is the impact of low **scale reliability** on estimates, resulting in attenuated (deflated) values between variables.

Scale reliability**,** in statistical terms is "*the proportion of the observed score variance that is due to true score variance*" (Zickar and Broadfoot, 2009), which, in plain English, means that "*the more the score we obtain from a scale represents the true score of the [latent] variable and the less it reflects other extraneous factors, the more reliable it is*."(DeVellis, 2017 p39). Common methods of measuring reliability of scales, such as Cronbach's Alpha or McDonald's Omega, (covered briefly in Section 1.6.2.6) give a reliability rating between 0.0-1.0.

When using factor scores directly as observed variables in a path model, lower levels of underlying scale reliability (in predictor variables in particular) can create under-estimates on certain paths, which may lead researchers to assume a given relationship between variables is not significant, and consequently rejecting well-specified models. (Bollen, 1989 p159-160; Cole and Preacher, 2014). Corrections for known reliability shortcomings can partially mitigate this risk; by calculating the degree of attenuation, researchers can infer whether it is likely to have a meaningful impact on how they interpret model fit. Unfortunately, this is not as common a practice as it should be.

Low-reliability modelled variables can seriously affect the estimates in the structural parts of the model (Skrondal and Laake, 2001; Devlieger and Rosseel, 2017; Lai and Hsiao, 2022). Though reliability scores (alpha/omega) in excess of 0.7 have traditionally been considered to indicate adequate reliability, more recent

studies suggest that measures with reliability approaching 1.0 will be needed if the risk of rejecting correctly specified models is to be minimised, and even reliability values as high as 0.8-0.9 can be problematic. (Cole and Preacher, 2014).

In multifaceted constructs, use of scores derived from the General Factor of a bifactor model can help mitigate against biased estimates, since they will tend to have high **Factor Determinacy** (see section 1.6.3.4), indicating that they are likely to be very close to the 'true' (but unobservable) factor values implied by the model. (Ferrando and Lorenzo-Seva, 2018). By contrast, the Specific Factors from the same bifactor model tend to have much lower determinacy, and none of the factor scores from higher order models can be adequately disentangled from the multifaceted nature of the wider model. (Rodriguez *et al*, 2016a). A bifactor model's General Factor alone gives a cleaner measure for each participant, as it *"estimates a general latent variable with greater content validity than any of its facets*" (Chen *et al., 2012*).

1.5.2.4 Simultaneous estimation of structure and measurement models

Given the downsides of using factor scores as observed variables it's reasonable to wonder why researchers might chose this approach. There are pragmatic reasons for doing so: some models are so complex that the estimator cannot converge on a solution, and including the factor score rather than the full latent variable can make the model estimation process more tractable. (Lai and Hsiao, 2022; Lai, 2024).

Mixing latent and observed variables is a common cause of under-identification issues. Recall from Section 1.2.2 on identification that each variable in our sample data contributes its own variance and several covariances to the pool of unique statistical information we have available to calculate the parameters in our model. Mixing latent and structural variables often leads to 'structural imbalance', since the model must estimate, simultaneously, how the indicators relate to their latent construct *and* how that construct relates to all other variables in the model. The observed variables are greatly outnumbered by the number of indicators, and do not bring enough unique statistical information to their part of the model for all of those estimations to happen simultaneously; the model is under-identified.

Even where a model that mixes latent and observed variables *can* be over-identified, there is another concern. When simultaneously estimating the measurement and structure parts of a model with multiple latent variables, the imbalance means that the latent variables contribute most of the parameters to be estimated and tested for fit. The measurement model then overpowers the structure, which is often of the most theoretical interest. (Ropovik, 2015; Lance *et al.*, 2016; McNeish and Hancock, 2018; Kline, 2024). Global fit indices will be biased towards maximising the fit of the measurement part of the model, and the structure part may not be as good as the fit indices suggest. (Vandenburg and Grelle, 2009; Lance *et al.*, 2016; McNeish and Hancock, 2018; Lai, 2024).

If the measurement part of the model is so large as to obscure the structure in the analysis, two outcomes could occur. On the one hand, a poorly fitting measurement model that contributes most of the parameters to be estimated affects the results to such an extent that accurate causal assumptions are rejected, and an opportunity to implement good policy is missed. At the other extreme, a well-constructed (but very complex) measurement model allows a mis-specified causal structure to ride its coat-tails to excellent fit results, and policy is subsequently pursued based on faulty assumptions about causality.

1.6 Evaluation(4): Understanding Measures of Fit

Thus far, we have covered how models are specified, identified and estimated. We saw how linear regression models are a special 'just-identified' case of SEM, and how a full SEM contains both latent variable measurement models (from CFA) and other observed variables (which can be measured in different ways on different scales).

Now we need to understand the evaluation process. Is our model useful? The answer to this question depends on the kind of model we have built:

- In Linear Regression, we focus on explanatory value – does our collection of predictor variables explain a substantial proportion of the movement in our outcome variable?

- In EFA we also focus on explanatory value, but in a subtly different way – do the relationships between a set of observed variables reveal the presence of meaningful, but not directly measurable, constructs?
- In Path Analysis, CFA and a full SEM (which combines both) evaluation is not about explaining or exploring the data. Instead, it is about using the data to assess the plausibility of a structure we have hypothesised from theory. For a CFA where the researcher intends to use factor scores in further analysis, this also includes ensuring that the construct is being measured reliably, in a way that will remain stable across future studies, and which is uncontaminated with elements of other constructs.

Thus, though the phrase 'assessing model fit' is widely used, it is the context in which it is being used that tells us what is being fitted to what.

As we progress through the evaluation of different types of model, it will become clear that a form of 'research inertia' is a substantial contributor to poor analytic choices in factor analysis and SEM. Rules of thumb and standard measures persist, often decades after methodologists have shown their inadequacy or inflexibility. Their use is cemented by their embeddedness in easy-access software that requires little knowledge to use. (Cortina, 2002).

1.6.1 Measures of fit in Linear Regression Models

In linear regression, which is an unconstrained model that is unencumbered by theory, assessing the 'fit' of the model refers to how closely the regression line (or plane) aligns with the observed data points; 'the line/plane of best fit'. It is not testing structure or causal assumptions. The utility of a regression model is measured through a collection of metrics, including:

1.6.1.1 The F-test for overall utility of the model.

The F-test compares how well the model predicts (explains changes in) the outcome variable, when compared with just using the current mean outcome variable score to predict any new case.

It is a ratio of the amount of explained variance to the amount of unexplained variance in the model, which simultaneously takes account of how many predictors a model has (its complexity), and the size of the dataset being used (how much data the test has available to work with). These are represented as 'degrees of freedom' in the F-test calculation. The 'numerator degrees of freedom' is equal to the number of predictors, while the 'denominator degrees of freedom' equals the sample size minus the number of predictors, minus 1 (which is an allowance made for also calculating the intercept).

The F-statistic should be >1. This indicates that the explained variance is greater than the unexplained variance, and therefore at least one predictor in the model is useful for predicting the value of the outcome variable. But the size of the F-statistic alone is not enough to determine a useful model; it must be interpreted with a p-value that explains how likely it would be to produce an F-statistic (ratio score) of that size by chance.

In a dataset with very few cases, the F-statistic may well still be >1, but could have a non-significant p-value. This is because the unexplained variance in the outcome variable (also called 'residual variance', or 'error variance') is hard to calculate accurately in a sample with few observations. Therefore, the test can't be sure whether the results we have seen could be down to chance or not. However, in almost all research situations, an F-statistic greater than 2.5 would be statistically significant, especially with larger samples, unless there were some extreme peculiarities in the research design, such as a model with hundreds of predictors. (Dinov, 2020).

The results of the F-test will also give two separate degrees of freedom measures, with the statistic often reported in the form 'F(4, 102)=12'. This would represent a model with 4 predictors, 102 degrees of freedom for error, and an F-statistic of 12. Seeing these 'df' results is important for understanding why the p-value of a regression model may be non-significant, even with a large F-statistic. A model with more predictors needs to explain substantially more variance to achieve the same

statistical significance as a simpler model. This helps to prevent 'overfitted' models that won't generalise to other data.

1.6.1.2 The Coefficient of Multiple Determination (R^2)

The R^2 measure is the square of the value of R, which in turn is the strength of the linear relationship between the combined predictors and the outcome variable. When converted to a percentage, R^2 is taken to describe the percentage of variance in the outcome variable that is explained by the combined predictor variables. We would say 'the combined predictor variables explain 60% of the variance in the outcome variable' for a model that has an R^2 of 0.6.

The more complex the model (the more predictors are added), the higher R^2 will get, which can lead to overfitted models as researchers 'chase $R^{2'}$. Therefore, the 'Adjusted $R^{2'}$ measure (Goldberger, 1972; Greene, 2003 s 3.5.1) is used to assess the explanatory value of the models tested here. According to Greene, "*whether Adjusted R^2 rises or falls [as a new predictor variable is added] depends on whether the contribution of the new variable to the fit of the regression more than offsets the correction for the loss of an additional degree of freedom*".

There is much debate about what constitutes a good model in relation to R^2 values, which varies by field. Natural science and engineering models might look for values in excess of 0.9 to judge a model as good/strong. Ozili, (2023) details why the complexities of social science models mean that lower R^2 values can be acceptable, with values as low as 0.10 being acceptable so long as "most of the explanatory variables are statistically significant", and values over 0.5 generally being considered good. Similar guidance in linguistics research suggests thresholds of between 0.2 and 0.5 as moderate, with values greater than 0.5 being considered large, given complexities and overlapping predictors (Plonsky and Ghanbar, 2018). In clinical research, which again works with complex interactions of predictors, many of which will not be captured in any given model, R^2 values as low as 0.15 are considered 'probably meaningful' (Gupta et al 2024).

1.6.1.3 The coefficients of individual predictors

The raw coefficients for each predictor are in some ways easiest to interpret. They represent the predicted increase or decrease in score on the outcome variable that will result from a one-point increase in a given predictor variable, *holding all other predictors constant.* The raw estimate is interpreted in combination with the p-value, which indicates whether this is a significant effect, and the confidence interval, which indicates the likely range that the actual effect falls within.

The standardised coefficients for each predictor account for the fact that the original variables might be measured on different scales, especially important if the range of one scale is very wide, and the range of another is more restricted, where using the raw coefficient estimates can make relationships look more meaningful than they are. Standardised estimates represent the expected change in the outcome variable if a given predictor variable varies by one standard deviation from its mean, holding all other predictors constant. Note that standardised variables are, strictly-speaking, only meaningful for continuous variables, but most software will report standard deviations for all variables, so they should be interpreted with caution.

1.6.1.4 Residuals

The residuals in the model are the differences between the observed values of the outcome variable and the values that are predicted by the model for each case in the dataset.

Researchers inspect the residuals to make sure that they are normally distributed, and that there are no major outliers (results which, if removed, would significantly change the results of the whole regression). This is done using a statistic called Cook's Distance, which explains how much 'leverage' any given observation in the dataset has to change the overall result if removed. (Penn State University, 2018).

Highly correlated residuals can suggest a missing predictor variable that is such a powerful predictor that it alone can explain much of the unexplained variance in the model. A model with this characteristic is missing crucial information that should be identified and included. This can be diagnosed by plotting the residual values

against the predicted values. Uncorrelated residuals would result in a scatterplot where the residuals are randomly scattered above and below the line, appearing to have no relation to each other. Clustered, linear, funnel, or u-shaped patterns would suggest otherwise, and need further investigation. (Frost, 2017).

1.6.2 Measures of fit in EFA

In EFA, instead of *exploring* associations between observed variables, we *examine* the relationships between observed variables to reveal the presence of unmeasurable, hidden factors (such as attitudes and beliefs), often with the aim of developing a single, stable measure that can be used in future analysis. We impose only limited constraints (like the number of factors to extract, and whether we will allow the factors to correlate. These choices are informed by theory. We are fitting a network of relationships to the data, but the data still leads the way. We aim to work out how reliable overall set of items are at measuring the latent factor, and what items deserve a place in the final scale. (Williams, 2015). In this regard, interpreting loadings and deciding how many factors to extract is recognised to be as much an art as a science. (Henson and Roberts, 2006).

We begin by assessing our sample size and whether our items are even highly enough correlated with each other to support any form of Factor Analysis. Although correlations between items might be measurable at relatively small sample sizes, a minimum sample size will be needed for reliable outputs. Mundfrom *et al* (2005), developed guidance on appropriate sample sizes, which take account of the communalities of items (the variance of the item that is attributable to the factors in the solution that it loads on), and the number of items on each factor. With communalities above 0.6 and at least 5 items per factor, sample sizes of 200 are adequate. With higher communalities or items per factor, adequate sample size can be as low as 50 (Whittaker and Schumacker, 2022). In addition, since we expect to find that some items do not correlate as highly as expected, we also need a large enough item list to begin the process.

The conundrum here is that the likely communalities, the number of items per factor, and potential 'weak' items lost to attrition in the EFA process cannot be

known in advance. We therefore need to err on the side of larger samples when designing our research. Howard and Henderson's, 2023 review of EFA practices concluded that, "*together, modern researchers recommend larger absolute (e.g.,>300) and ratio (e.g., >10 participants per indicator) guidelines for EFA than older recommendations",* though recognising that nonetheless *"no universal guideline exists for the necessary sample size*." We must also ensure that our item list contains enough redundancy that we can afford to lose items that load only weakly onto the factor, and still retain a high enough item-to-factor ratio for final scale stability. (Tavakol and Wetzel, 2020).

1.6.2.1 Bartlett's Test of Sphericity and the KMO test of sampling adequacy

These are the first two tests recommended by most factor analysis software. Bartlett's Test of Sphericity (always afforded its full name to differentiate it from Bartlett's other tests) assesses the matrix of variances and covariances in our data. It determines whether it is sufficiently different from an 'identity matrix' to suggest that factor analysis is possible. An 'identity matrix' has ones on the diagonals and zeros everywhere else; it means that we have a collection of variables that have zero relationship to each other. The actual score is a chi-square (χ^2) value, which can be across a wide range. The absolute value is less important than the p-value, which tells us whether the correlations are significant for the type and size of data we have. It is normally reported alongside the KMO.

Given that (a) only a very peculiar research plan would lead to the development of a list of items the answers to which are truly uncorrelated and (b) even very weak correlations will result in a meaningful result in large samples, its value is questionable, but it's a useful first step. (Ludecke *et al.*, 2025).

KMO (the Kaiser-Meyer-Olkin measure of sampling adequacy) is more sophisticated. Where Bartlett's Sphericity tells us if there are any significant correlations at all, KMO tells us whether the pattern of correlations will make Factor Analysis worthwhile. It looks at both overall correlations, and then the partial correlations between items (how each pair correlates while controlling for the effect

of correlations with other variables). This helps diagnose if the items are likely to factor together in some meaningful groups, or whether the data is made up of many smaller (e.g pairwise) relationships but no clear constructs. Values range from 0-1 and it benefits from Kaiser's charmingly-named interpretation scale, broadly still applied: 0.90 to 1.00: Marvelous; 0.80 to 0.89: Meritorious; 0.70 to 0.79: Middling; 0.60 to 0.69: Mediocre; 0.50 to 0.59: Miserable; Below 0.50: Unacceptable.

1.6.2.2 Item-rest correlations

The item-rest correlation shows how highly correlated each item is with the other items in the scale combined. Items that do not correlate well with the overall distribution of the scores of other items in the scale may well be measuring something else, will result in a final scale that is not unidimensional. As a first pass, items with correlations lower than 0.3, or even 0.5 depending on the researcher's domain knowledge, should be dropped. (Blaikie, 2003; Williams, 2015; Watkins, 2018). The item-rest correlation is closely related to the reliability coefficients alpha and omega.

1.6.2.3 Item loadings and cross-loadings, and communalities

An item's loading on each factor in a solution is the correlation between the item and that factor (mathematically, the same as regression coefficients between predictor and outcome variables in a linear regression model (Cudeck, 2000)). Tavakol and Wetzel, (2020) note that factor loadings of more than 0.30 usually indicates a moderate correlation between the item and the factor. Recall from Section 1.4.2 that the squaring the loading tells us the proportion of variance in that item that is attributable to the factor. Tavakol and Wetzel's minimum meaningful loading of $0.3^2 \times 100$ would thus amount to 9% of variance explained. It is for the researcher to decide whether an item with such a high level of unexplained variance warrants inclusion, a decision that depends on the field of study, the number of other factors that the item loads onto (giving its total explained variance, or communality), and whether the researcher expects, or would accept, a multi-factor solution that would account for that total communality.

1.6.2.4 Initial solution and rotation

Once the initial factor structure has been produced, typically with Maximum Likelihood (ML) or Principal Axis Factoring (PAC)[50], the researcher must decide whether the solution is clear enough to be meaningful. Here again, the researcher's understanding of the domain is crucial, and the 'art' of EFA comes to the fore.

The initial solution of an EFA will usually result in more than one factor, where the first factor has the highest loadings, and the process has maximised the variance explained by each successive factor. This will be mathematically most efficient, but may not have strong theoretical value. Social science phenomena are complex, and initial solutions may result in a 'muddy' structure with items loading at moderate levels across multiple factors. (Blaikie, 2003).

Rotating the solution is the next step. Recall Figure 34, which illustrated the idea of orthogonality in data structures, with each dimension explaining additional variance not explained by the previous ones. Such orthogonal solutions where factors do not correlate with each other are simpler and often preferred to ease interpretation. (Whittaker and Schumacker, 2022). Whether this reflects reality in social constructs is debatable. (Bandalos and Boehm-Kaufman, 2009).

Researchers usually impose an orthogonal rotation first, selecting software options such as Varimax or Quartimax. The factors would be visualised as in Figure 34, a framework of 'wires' crossing at the centre, at right-angles (90°) to each other. If this rotation does not result in a more interpretable solution, we might instruct the software to rotate our wire frame again, to see if a more interpretable distribution of the items across the factors can be found (another orthogonal solution).

[50] EFA carried out for the purpose of identifying latent variables for scale development should ***never*** use PCA (Principal Components Analysis). Unlike ML and PAC, PCA does not follow Thurstone's Common Factor Model and therefore does not partition shared variance from unique (item-specific) variance. (Preacher and MacCallum, 2003). The results can differ substantially but since the choice of ML, PAC, and PCA is often in the same dropdown menu in software, and results outputs look the same, this methodological incompatibility is not obvious to novice EFA practitioners.

Sometimes, an orthogonal solution simply cannot be found, because the factors are indeed correlated (illustrated earlier in Figure 31). In fact, the strongly-held belief that an orthogonal structure is fundamentally best does not stand up to scrutiny, since many social constructs are inherently inter-related. Allowing the software to find an oblique solution (using software settings such as Promax or Direct Oblimin) can resolve this issue. The angles between our 'wires' are now allowed to vary from 90°, and we reconsider which items load on which factors. Do they make more conceptual sense this way? If so, we accept an oblique (correlated factors) solution, illustrated earlier in Figure 31. In fact, if our factors truly are uncorrelated, an oblique rotation would yield an orthogonal solution anyway. Orthogonal rotations often result in more generalisable measures, whereas oblique rotations maximise interpretability of the current sample. The researcher should therefore not lose sight of the aim of their study, and presenting both sets of results can be informative. (Rennie, 1997; Bandalos and Boehm-Kaufman, 2009).

1.6.2.5 How many factors to extract

Selecting the final number of factors to extract, as with the earlier decision on whether to remove items with low loadings, is not an exact science. It calls for both qualitative domain knowledge of the likely underlying constructs, and an examination of some quantitative measures.

As discussed in Section 1.4.2, the process assumes that the researcher understands that they should *not* be using Principal Components Analysis if their aim is to reveal latent factors. PCA will ignore the unique variances of the items, assuming all variance must be accounted for by the factors. This is unlikely to be true, and will result in the strength of the first 1 or 2 factors appearing to be stronger than they really are, increasing the likelihood of rejecting meaningful but weaker factors further down the hierarchy. (Kim, 2008; UCLA, 2024). Despite this, the choice of PCA is still worryingly high, with reviews of even recent practice suggesting that it is still the dominant choice in some fields (Howard and Henderson, 2023).

Two traditional methods for deciding how many factors to extract are offered in most EFA software (despite strong challenge to their use for over 30 years). Most

generalist 'rules of thumb' guides still recommend them, but most methods afficionados eschew them. The first is Kaiser's 'eigenvalues greater than 1' rule. The second is essentially a visual representation of that: the Scree Plot.

Eigenvalues measure the total variance in a set of items accounted for by each factor. Since the solutions (whether unrotated or rotated) aim for maximised explanation in the first factor, with each successive factor explaining something of the 'leftovers', the eigenvalue of the first factor tends to be much higher, with subsequent eigenvalues considerably lower. A factor with an eigenvalue <1 is often said to account for less variability than one of its single indicators, and the Kaiser Criterion is applied to reject it. However, this interpretation is not entirely accurate – the theory *actually* says that the *average* of all the eigenvalues is 1. Therefore, a factor with an eigenvalue <1 explains 'less than the average variance for a factor', rather than 'less variance than a particular item'. It does not necessarily follow that it is not an important factor. (Wilson and Cooper, 2008).

The maximised explanatory value of each successive factor explains the traditional shape (and name) of the Scree Plot, which shows a precipitous drop after the first factor, with smaller drops for the next few, tailing off thereafter. At the population level, the first few eigenvalues represent the shared variance that the common factors are responsible for, with the smaller eigenvalues reflecting the unique (unshared variances) remaining. (Braeken and Van Assen, 2017). The number of factors before the real flattening of a Scree Plot begins is the rule of thumb for the number of factors to retain. This is illustrated in Figure 38, below.

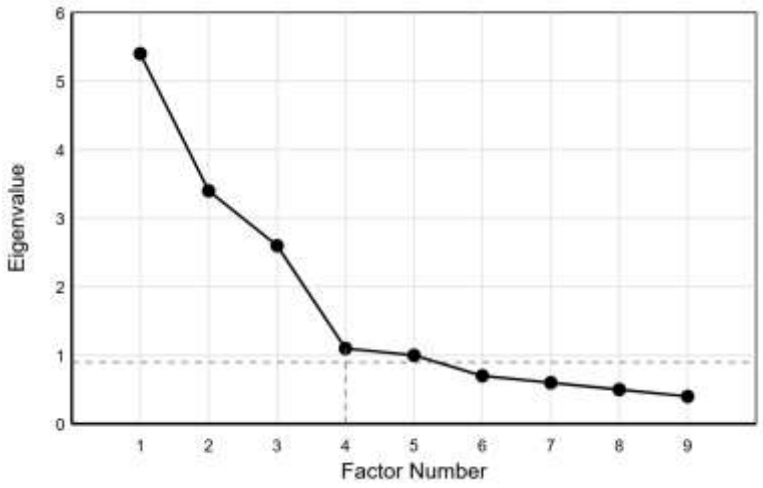


Figure 38: Scree Plot showing nine possible factors.

However, the proof on which both rules are based assumes the model perfectly represents the population, which will never be exactly true, and therefore the eigenvalues rule, though used as a cutoff by most researchers, should more accurately represent the *lower bound* of factors to retain. Indeed, Guttman's original 1954 paper from which the theory derives makes reference to this: *"In the present paper, we shall present partial safeguards against stopping factor "extractions" too soon*."

The most common alternative when carrying out Common Factor Analysis is to use 'Parallel Analysis' (PA). This randomly generates thousands of comparator datasets with the same sample size and number of variables as the real data and subjects them to EFA 'in parallel' with the real dataset. Since the randomly generated sets contain no true factors, comparison with the sample data indicates the number of factors to retain which explain more variance than could be expected by chance alone. (Preacher and MacCallum, 2003; Howard and Henderson, 2023). However, even Parallel Analysis has been shown to be less effective when the factors are highly correlated or when the underlying scale is based on non-continuous data, where it will tend to recommend slightly fewer meaningful factors than there are.

(Cho, Li and Bandalos, 2009), and when working with small scales with few items. (Braeken and Van Assen, 2017). [51]

Braeken and Van Assen, (2017) assert that the eigenvalue relationship does still have practical application outside of PCA, and proposed an 'Empirical Kaiser Function' (EKF), which is not offered by most software but can be calculated from the sample size, number of variables, and list of eigenvalues that all software provides. Building on this, Auerswald and Moshagen, (2019) provide a large-scale study with realistic datasets, and recommend the use of two separate criteria (for example, Parallel Analysis as well as the EKF); discrepancies between them will identify issues related to whether there is a single/uncorrelated factor or correlated factors, and whether larger samples would be needed. Bifactor structures, however, do not seem to have been explored.

Whatever method is used, the final number of factors extracted remains heavily influenced by the art, rather than the science of EFA: "*Conceptual interpretability is the definitive factor-retention criterion. In the end, researchers should retain a factor only if they can interpret it in a meaningful way, no matter how solid the evidence for its retention based on the empirical criteria earlier described*". (Worthington and Whittaker, 2006). As with so much of SEM guidance, slavishly following the rules of thumb is not recommended – more or fewer factors could be retained if it makes theoretical sense to do so.

1.6.2.6 Reliability measures – Cronbach's alpha, McDonald's omega, Coefficient H

Scale reliability (increasingly also termed scale replicability (Rodriguez *et al*, 2016b; Ferrando and Lorenzo-Seva, 2018), is a measure of how likely the scale is to produce consistent results with different samples, or with the same sample at different points in time.

[51] Software that offers Parallel Analysis options often also offers Minimum Average Partialling (MAP), and here again novice users may be unaware that this is not suitable for processes based on Thurstone's Common Factor Model. It should only be used for Principal Component Analysis, which is not what we are doing when we carry out an EFA for the purpose of revealing latent factors. (Bandalos and Boehm-Kaufman, 2009).

Widely misapplied (since it makes assumptions that are rarely met), Cronbach's coefficient alpha (α) is still the most commonly used test of scale reliability. Its underlying assumptions are normally distributed data, tau equivalence (that all items in a factor load equally onto it) and a unidimensional scale (one that is really measuring only a single construct). (Kalkbrenner, 2024). Use of Cronbach's α with inappropriate data types or distributions is likely in many cases to return reliability estimates lower than they really are. (McNeish, 2018).

McDonald's omega (ω) is considerably more robust to violations of normality and tau equivalence, but like α, assumes that the scale is unidimensional and that the error terms of the items are not correlated (the variance in each item that is unexplained by the factor). Both will over-estimate reliability where errors correlate (McNeish, 2018). In data that is normally distributed, unidimensional and tau equivalent, both coefficients will return similar results. Discrepancies between the two indicate that further investigation is needed.

Standard cutoffs applied in the literature (for both α and ω) are often considered to be 0.7 (acceptable), 0.8 (good) and (0.9) excellent. (Stensen and Lydersen, 2022). However, most software does not provide confidence intervals, so any measure that is near to a 0.7 point estimate ought to be treated with greater caution, since the real value could well be below this. (Kalkbrenner, 2024).

There are other alternatives that offer advantages over both α and ω, but these are not implemented in most software, and therefore do not get the use that they should. Coefficient H, developed by Hancock and Mueller, (2001) is robust to correlated error terms between items, correlated factors in multi-factor models. Crucially, it is weighted to account for differential loadings between items on the factor. It can be calculated separately using tools from the University of Kentucky, (Dueber, 2017). According to Rodriguez et al, (2016), *"high H values (>.80) suggest a well-defined latent variable, which is more likely to be stable across studies*".

It has been shown that alpha/omega can offer a *minimum* likely reliability, and Coefficient H will indicate the *maximum*. Reporting both measures is therefore

recommended by Kalkbrenner, 2024, perhaps representing something we might call a 'pseudo-confidence interval' for reliability.

1.6.3 Measures of fit specific to CFA for Scale Development

When an EFA is carried out for the purposes of scale development (scores from which can then be used in future studies), common practice is to follow up with a CFA which confirms the structure of the scale. This is either done by collecting new survey data or by carrying out an EFA then a CFA on a random split of the original data (as long as the sample is big enough to accommodate this, and tests are carried out to confirm the split sample approach has produced genuinely random subsamples). (Li *et al.*, 2014).

While EFA is useful for identifying individual factors, many EFA's will reveal some lower, but meaningful, loadings of items across all factors, suggesting that there may be correlations between factors, at the very least. In general, approaches to EFA are not sophisticated enough to reveal more complex multi-layered structures such as hierarchical or bifactor models, (described earlier in Section 1.4.4), which may provide a better fitted model from which to extract composite or factor scores to use in further analysis. These sorts of structures can better be examined via a CFA, where the theory-driven and non-saturated nature of the process leads to models that are 'over-identified', and fit can be tested.

Beyond measures of model fit though, there are additional measures that should be reported to give confidence that multi-dimensional scale scores can really be used. In common with scales produced in an EFA, a consideration of general scale reliability (via e.g. McDonald's omega) is a starting point. The more specialist tests are summarised below.

1.6.3.1 Explained Common Variance

ECV is the proportion of all common variance explained by a given factor. For the General Factor, this is for all items. For subscales, this computes the strength of the subscale relative to *all* explained variance of the items that load onto that factor (i.e.

including where those items also load onto the General Factor). A scale ECV above 0.9 indicates an essentially unidimensional scale, which in turn indicates that there is little utility in reporting sub-scale scores as well. ECV below 0.7 indicates that there is *always* value in reporting sub-scale scores as well. ECV between 0.7 and 0.9 requires a more case by case approach. (Quinn, 2014).

1.6.3.2 Omega Hierarchical (OmegaH and OmegaHS)

Omega Hierarchical is a measure that assesses the reliability of the General Factor and Specific Factors on a bifactor scale "*after partialling-out variance attributable to the specific or general factor(s), respectively*" (Funkhouser *et al.*, 2021). What this means is that, unlike standard McDonald's Omega measure that we encountered before in EFA, this measure helps us understand the percentage of systematic variance that can be attributed to the General Factor on its own, or any of the subscales on their own (in the case of their OmegaHS scores).

For simplicity in future studies, it is helpful to know that even if a bifactor structure exists, we can just use the General Factor score. (Dueber, 2017) suggests that, *"when OmegaH is high (> 0.80), total scores can be considered essentially unidimensional*". This is especially true when a large OmegaH estimate is found in conjunction with relatively small OmegaHS estimates. (Funkhouser *et al.*, 2021).

1.6.3.3 Coefficient H

This coefficient was popularised by Hancock and Mueller (2001), and is a quantitative measure of how well-defined by its items a factor is, and how likely it is to be replicable in future studies. It represents the correlation between a factor and an optimally-weighted item-composite. Each item is weighted by its loading on the factor, giving the maximum possible reliability. Coefficient H ranges from 0-1, with values under 0.7 suggesting the factor isn't especially well defined by its items. On the other hand, *"high H values (>.80) suggest a well-defined latent variable, which is more likely to be stable across studies.*" (Rodriguez et al, 2016).

1.6.3.4 Factor Determinacy Index

Factor Determinacy is the correlation between the factor scores estimated from a participant's responses to our items from survey, and their likely 'true' factor score on the latent variable itself (which cannot be measured directly). The Factor Determinacy Index, which ranges from 0-1, is another mechanism that can be used alongside Coefficient H to determine whether to use extracted (weighted) factor scores for each respondent in future analyses, instead of a unit-composite score that simply sums or averages the responses to the items. While Gorsuch, (1983, p 260) suggested that scores >0.8 suggest high Factor Determinacy, Ferrando and Lorenzo-Seva, (2018) suggest that Factor Determinacy should be >0.9 before an individual's factor score should be used in this way.

1.6.3.5 Item Estimated Common Variance – IECV

According to Stucky, Thissen, and Edelen (2013), IECV "*provides the extent to which an item's responses are accounted for by variation on the latent general dimension alone, and thus acts as an assessment of unidimensionality at the individual item level*." (p51). In addition, Stucky and Edelen (2015), suggest that selecting items with large loadings on the general factor and IECV "*greater than 0.8 or 0.85 will typically yield a fairly unidimensional item set that reflects the content of the general dimension*" (p. 202)

Here then, we calculate and examine the IECV for *each item*, and consider whether the scale as a whole has a mix of items with IECV greater than 0.85, and whether any lower loadings and IECVs are clustered onto individual subfactors. IECVs that are lower on a particular subfactor may suggest utility in reporting subscores from that subfactor in addition to the General Factor score.

1.6.3.6 Percentage of Uncontaminated Correlations – PUC.

The PUC represents the percentage of covariance items which only reflect variance from the General Factor. Along with ECV, the PUC influences whether the unidimensional solution will have excessive or acceptable parameter bias. (Deuber, 2017), who also reports that "*Rodriguez, Reise, and Haviland (2016a)*

indicate that "when ECV is > .70 and PUC > .70 relative bias will be slight and the common variance can be regarded as essentially unidimensional" (p. 232).

In addition, Reise et al (2013) report that "*When Percent of Uncontaminated Correlations (PUC) values are higher than .80, general ECV values are less important in predicting bias; when PUC values are lower than .80, general ECV values greater than .60 and OmegaH > .70 suggest that the presence of some multidimensionality is not severe enough to disqualify the interpretation of the instrument as primarily unidimensional.*"

Here then, interpretation is a little more complicated as it relies in the interplay between ECV, Omega H and PUC scores.

1.6.3.7 Average Relative Parameter Bias – ARPB

This test can be used to check if it is acceptable to use all items together as a single scale. "*Relative parameter bias [is] the difference between an item's loading in the unidimensional solution and its General Factor loading in the bifactor solution (i.e. the truer model), divided by the General Factor loading in the bifactor model.* (Rodriguez et al, 2016). For researchers who do not have access to software that can extract both General Factor and Specific Factor scores separately from a bifactor scale, knowing the ARPB is useful. Using scores from the full scale as if it were unidimensional poses no concern when ARPB can be shown to be less than 10%-15%. (Muthen et al, 1987).

Unfortunately, the tests outlined in this section (6.6.3.1 to 6.6.3.7) are not often incorporated into standard SEM software, which contributes to researchers using scales derived from CFA without fully understanding their unidimesionality or hierarchical reliability. Dueber, (2017) provides a Microsoft Excel based tool that can calculate all of these measures from sample data. Where a scale does not prove to be sufficiently unidimensional to rely on General Factor scores alone, (Dueber and Toland, 2023) suggest that interpreting the subscores alongside the total score will add value to interpretation, and provide advice on calculating when subscores should be used in this way.

1.6.4 Measures of Fit in CFA and full SEM

Earlier we noted that 'fit' in the context of a Linear Regression Model refers to the line of best fit that shows us how movement in the values of one or more predictor variables is associated with movement in the value of another. There, we were fitting a line to data. The data came first, and the line came second.

We then saw that 'Fit' in the context of EFA is more of a dark art, not as entirely 'exploratory' as the name would suggest, but is nonetheless still largely about exploring the story that the data tells us.

In Structural Equation Models (including Path Analysis and Confirmatory Factor Analysis), things are different. Here we are imposing causal assumptions. We are saying that the relationship predicting Y from X only works in one direction, and the equation cannot be reversed to predict X from Y. (Bollen and Pearl, 2013). We constrain some paths completely, and we force others to take on a certain value, or range of values. We are therefore designing the networks of relationships, describing the expected regression lines, and then seeing if our data fits them. In a sense then, the 'line' comes first and the data comes second.

Of course, in SEM there is not just a single regression line, or even a regression plane. Now we are working with a network of relationships where the "fit" is not to a surface in 3D data space, but to a set of equations that best explain how all the variables are connected.

1.6.4.1 The contrary nature of hypothesis testing in SEM environments

In all forms of SEM, we test our *a priori* causal assumptions through a measure of model-wide fit that shows that the model is consistent with the data we have collected.

Contrary to normal practice, where the researcher hopes to be able to reject the null hypothesis to show an effect, in SEM 'global fit' tests we hope to achieve whole-model goodness-of-fit measures that are *non*-significant. We use that non-significance as support for the hypothesised model. Structural models are

considered acceptable when we *fail to reject* the null hypothesis, which can be counter-intuitive to many researchers. Hayduk (2014) terms this the 'notable-null hypothesis', rather than a 'nil-null hypothesis'.

The non-significant result is saying that the *implied* variance-covariance matrix in the proposed model so closely mirrors the *actual* variance-covariance matrix of the sample dataset that we accept it as truly representing the sample (and, by extension, the population where the sample has been drawn in such a way that inference is possible). Crucially though, "*The causal assumptions perpetually remain only one study away from rejection"* although *"the longer they survive a variety of tests in different samples and under different circumstances, the more plausible they become."* (Bollen and Pearl, 2013).

1.6.4.2 Why so many measures of fit?

Segal's law states that "*A man with a watch knows what time it is. A man with two watches is never sure*". Nowhere is this adage more appropriate than in deciding on which measures of fit to use in SEM. A decades-long debate about the appropriate uses of the tests of fit rumbles on. To the uninitiated, the literature covering these debates is near impossible to navigate. Exactly which measures should be used, and in which combination? Do all measures need to be acceptable, or can a researcher accept a 'basket' of measures where one looks less convincing than the rest? Do certain types of measure fail for particular model structures? Is it acceptable to apply generalised rules of thumb for cut-off points? How do we deal with the fact that other, equivalent models may fit the data equally well? Is it ever appropriate to accept a model that does not quite fit, but which has practical application as an approximation of reality? A tiny fraction of the debate can be followed via Hu and Bentler, 1999; Tomarken and Waller, 2003; Barrett, 2007; Markland, 2007; Millsap, 2007; Bollen and Davis, 2009; Ropovik, 2015; Lance *et al.*, 2016; Marcoulides and Yuan, 2017; Xia and Yang, 2019; Peugh and Feldon, 2020; Ximénez *et al.*, 2022; McNeish and Wolf, 2023; McNeish and Manapat, 2024.

With regard to the only true statistical test (the Model Chi-Squared, [χ^2] Test), some introductory texts are quick to state that a disappointing result on this test can be

overlooked, so long as a basket of other approximate fit indices (AFIs) can be made acceptable. This (often over-hasty) dismissal results from the fact that the χ^2 test is well known to be sensitive to large sample sizes, which can cause even trivial misfit values to be multiplied into a significant χ^2 result (Shi *et al*, 2019; Curran and Bauer, 2023). However, disregarding a significant χ^2 on the unproven assumption that 'it must be because of the large sample' *may* mean incorrectly accepting a mis-specified model and *almost certainly* means that at least one of the parameter estimates is "*inaccurate at best, and at worst, squarely wrong*". (Ropovik, 2015).

Similarly, large numbers of published papers take a somewhat cavalier approach to the AFIs that are used to complement the χ^2 result. A common approach is the uncritical application of a set of fixed-cutoffs published in a landmark paper by Hu and Bentler, (1999), in which the authors proposed some broad guidelines that tightened the definitions of 'acceptable', 'good' and 'excellent' models. Hu and Bentler cautioned that the guidance should not be overgeneralised, but despite this, "*these cut- offs have achieved the status of ''Golden Rules'' in the minds of some researchers*" (Goffin, 2007).

A flurry of papers in the mid 2000's considered the appropriateness of Hu and Bentler's rules under different types of models and distributions of data, and critiqued editorial approaches to accepting models with a range of contradictory fit indices, and those where all the steps of model modification are not documented (Beauducel and Wittmann, 2005; Yuan, 2005; Barrett, 2007; Markland, 2007; Millsap, 2007). A general consensus emerged that, while religious adherence to the golden rules was not appropriate, abandoning AFIs altogether was not the solution either. Many researchers continue with Hu and Bentler's rules, (which were only ever tested in a limited range of model and data types), because they feed a natural craving for binary 'go/no-go' points.

Much more recently, detailed proposals for dynamic cut-off points have emerged, suggesting that Hu & Bentler's cutoffs would need to be much more stringent on some models, and may be too cautious in others. Model structure is a key driver of this variability. (McNeish and Wolf, 2023; McNeish and Manapat, 2024). This may

herald a new era of model-specific fit assessment, but the associated simulation tools are not yet widely known or incorporated into software, and are currently only suitable for confirmatory factor analysis with continuous indicators with multivariate normality. (Wolf and McNeish, 2023). Recent papers urge researchers to reject uncontextualized cutoff reporting, and instead provide a basket of measures, contextualised in relation to sample size, model type and structure, correlation strengths etc. (Rodriguez, Reise and Haviland, 2016a; van Laar and Braeken, 2021; Ximénez *et al.*, 2022; McNeish and Wolf, 2023; McNeish and Manapat, 2024).

This chapter (and the results chapters 6 and 7) take a conservative approach. Accepting fit indices that are too lenient (lower cutoff values) are more likely to lead to acceptance of an ill-fitting model. Setting more stringent values could result in the rejection of an acceptable model. In this work, I err on the side of caution, (contradicting the advice of Whittaker and Schumacker, 2022 who feel it is best to accept incorrect models rather than reject correct ones). Since this work aims to have some policy relevance, I feel that the risk of policy based on accepting a flawed model is the more damaging outcome. Stringent cut-off values are used, contextualised measures are provided, and the modification steps are clearly documented.

In addition to examinations of the combined explanatory power of the variables (R^2) and the strength of direct and indirect regression coefficients between variables (similar to inspecting these features in linear regression models), SEM and its subsidiaries Path Analysis and CFA use a common set of fit measures.

There are also some additional measures specific to CFA. In particular, there are tests to determine whether it is appropriate to use General Factor scores from bifactor models, and those that tell us whether scales are reliable and likely to be stable across studies (similar to the tests of reliability in EFA). The tests, and their weaknesses, are discussed below.

1.6.5 Tests of exact fit

1.6.5.1 The Model Chi-squared test (χ^2)

The χ^2 test is the first test of model fit in all forms of Structural Equation Model. It is often referred to as the 'exact-fit test'. (Barrett, 2007), and remains the *only* statistical test of significance available for testing SEMs (Whittaker and Schumaker, 2022).

To understand the importance of the test, it is first necessary to note the relationship between the model, the sample, and the population.

The principle of all χ^2 tests is that if our model structure is correct, and if we had data on the whole population, and we compared our model implied matrices to the actual population variance and covariance matrix, they would *exactly* match (Curran and Bauer, 2023). In reality, the complexity of social or psychological processes means that no SEM will ever be an exact match to the population, but this does not invalidate the test. (Curran *et al.*, 2002; MacCallum, 2003; Goffin, 2007).

We do not have data for a population; we will only ever have data for a sample. We accept that sample matrices can differ slightly from our model-implied matrices because we accept that there will always be a small amount of measurement error within a sample. Sampling theory shows us that if we repeatedly re-sampled the population, each sample would differ slightly as a result of this (Blaikie, 2003). Therefore, when we use the χ^2 test with sample data, we can accept a slight mismatch between the model-implied matrices and the sample matrices, so long as this mismatch falls within the bounds of ordinary sampling error. (Diamantopoulos et al, 2023).

The relationship between the sample data, and the population from which the sample is drawn is crucial for drawing inferences beyond the sample, that is, deciding whether the conclusions be extended to the population as a whole. The closer the sample selection is to true random sampling, and the larger the sample, the more we can make at least tentative inferences that the model structure would also generalise to the population, (Peugh and Feldon, 2020) though it is accepted

that true random sampling is almost impossible to achieve in applied behavioural science (Highhouse and Gillespie, 2009).

The χ^2 statistic represents the sum of squared differences between the observed sample covariances and those predicted by the model, weighted both by sample size and by how precisely each part of the data can be estimated. The first step in a χ^2 calculation is to produce a value called a fit function value (F)[52], which is a measure of the discrepancy between the model data structure and our sample. Smaller values are preferred; F=0 means a perfect match between model and sample. The F-value is then multiplied by the sample size minus 1 (N-1), giving the χ^2 statistic.

A small χ^2 value indicates minimal discrepancy between the model and the data, which is what we hope for, while a large value suggests poor fit. We interpret χ^2 in relation to its p-value. Recall that we are looking for the 'notable null hypothesis' that fails to reject the null hypothesis that 'there is no difference between the model implied data structure (the variance covariance matrix) and the structure of the data we have in our sample'.

The χ^2 test cannot be used with small samples; it leads to too ready an acceptance of models where many plausible alternatives exist. The converse problem also arises; in large samples (>200), it will often find trivial errors of misfit. (Bentler and Bonett, 1980; Whittaker and Schumaker, 2022). If the F-value is small, but the sample is large, even a trivial discrepancy reflected in a small F-value will be multiplied into a significant χ^2 value.

This known weakness of the χ^2 test has resulted in the common practice of reporting, and then conveniently ignoring, a significant χ^2 result, even though many researchers do not actually know whether their F-value was small or large, since most software does not report it. Assuming that the cause of a significant χ^2 is simply the result of a large sample, and not because the fit function value (F) was itself substantial, is unfortunately common practice.

[52] The fit function value (F) used in SEM assessment should not be confused with the F-statistic used in linear regression and ANOVA, as described earlier. They are not mathematically equivalent, they merely share a name.

A more significant concern is that it is assumed that the underlying test statistic (T) used to calculate the Model χ^2 value follows either a central χ^2 distribution (if our model implied matrices do match the sample), or a non-central χ^2 distribution (if they don't). In either case this involves an assumption that our sample is drawn from a multivariate normal population. Yuan (2005) and others have shown that in practice, real data rarely meet this assumption, which can affect the accuracy of the test statistic's distribution.

1.6.5.2 Degrees of Freedom: ratio with χ^2, and as a measure of falsifiability of the model

The Model χ^2/degrees of freedom ratio is a useful indicator of whether a significant χ^2 is actually a result of a large sample, rather than a genuine indicator of poor fit. Carmines and McIver (1983) propose that ratios <3 would diagnose a model with a significant χ^2 that is nonetheless probably a well fitted model. (A perfectly specified model would have a χ^2/df ratio of exactly 1).

Unfortunately, many papers fail to report full degrees of freedom information (Cortina *et al.*, 2017), without which this assessment cannot be made by the reader if the ratio itself is not provided. This failure to report adequate degrees of freedom information goes further than just the χ^2/df ratio test.

In Section 1.2.2 we encountered the idea of 'statistical currency' when looking at whether a model was identified (or over/under identified). We saw that when we build models, we start with a finite amount of statistical information (the variances and covariances between the variables in our sample). Some of this is 'spent' on estimating parameters in the model: what remains is the degrees of freedom of the model. This is the only information we now have to test how well our model fits the data and it is used in the χ^2 calculation. Mulaik (2001), describes degrees of freedom as the number of ways that a model could be disconfirmed – a model with very few degrees of freedom can only be tested in very few ways, making any confirmation relatively weak. A model that seems to fit well, but has only 1 or 2 degrees of freedom is 'near-saturated'. Caution should be applied to interpretation of the fit of such models, since any completely saturated model cannot be adequately tested.

Kenny *et al*, (2015) recommend at least 10df, particularly with smaller samples where N<200.

1.6.6 Approximate Fit Indices

Although the additional statistic derived from the χ^2/df ratio test can help guard against model rejection purely down to sample size (see section 1.6.5.2), reasonable concerns about sample sizes and the unrealistic distributional assumptions of the Model χ^2 test have led to the development of Approximate Fit Indices (AFIs) that could be used alongside it. The key AFIs are detailed below in Sections 6.6.6 and 6.6.7.

Barrett (2007) provides a definition for the difference between the Model χ^2 Test and AFIs: the former is a binary fit/no fit decision, whereas the AFIs merely "*indicate the degree to which a model might be 'discrepant'*". This of course begs the question 'how wrong is too wrong?'. Acceptable levels of 'wrong-ness' have gradually tightened (detailed in Hooper *et al*, 2008), culminating in Hu and Bentler's 1999 cutoffs which, as we have already seen, have achieved 'Golden Rules' status for many researchers.

A plethora of AFI tests are available in most SEM software, but "*to choose the most appropriate fit indexes, it is important to have some knowledge of the different sensitivity of the fit indexes to sample size, model misspecification, and model complexity*" (Beauducel and Wittmann, 2005). Information on this sensitivity is not as widely understood as it should be.

1.6.7 Relative AFIs

Relative fit indices (sometimes called goodness of fit (GOF) tests) are not statistical tests like the Model χ^2 test. They do not have an expected statistical distribution, nor do we use a p-value to draw conclusions. As we have seen, a large sample size can result in a significant Model χ^2 test when the sample size is large. GOF indexes are an additional measure that can help clarify whether a model is acceptable.

Relative GOFs take the model we have hypothesised and measure how closely it fits the structure of the sample data. The name is derived from the fact that they do this *relative* to the most restricted model possible, a baseline model which stipulates that there are absolutely no covariances between our variables (Curran and Bauer, 2023). A good fit = a higher score, hence the name 'goodness of fit'.

1.6.7.1 The Tucker-Lewis Index (TLI)

This is among the oldest of the relative fit indices. It expresses the model misfit *per degree of freedom*, meaning more complex models are penalised; it forces the question 'is the added complexity in this model worth it for the improvement in fit'? TLI uses the χ^2 derived from the T statistic, which we previously encountered, in its calculations. It is sensitive to violations of the distributional assumptions of that statistic, more so in fact than the Model χ^2 test itself, and choice of estimation technique is therefore important. (Yuan, 2005). The formula for calculating the TLI is given below:

$$TLI = \frac{(\chi^2_{baseline}/df_{baseline}) - (\chi^2_{hypothesised}/df_{hypothesised})}{(\chi^2_{baseline}/df_{baseline}) - 1}$$

The 'minus 1' in the denominator acts as a normalising constant which means results usually sit between zero (the worst possible fit), and 1 (a perfect fit). Because the formula uses ratios, results can exceed these boundaries, especially where there are very few degrees of freedom in a model, or χ^2 is smaller than df. Results that exceed the boundaries are normally truncated to the 0-1 range. (Kenny, 2024).

Since the baseline model assumes no variable in the model is related to another, its Model χ^2 test statistic will usually be very high, and it will have lots of spare degrees of freedom. There are lots of hypothetical ways to connect the variables in such a model, but most of those combinations would not capture the meaningful relationships between the variables. A good TLI score for our hypothesised model

shows that we have largely picked the correct paths, haven't included meaningless relationships, and haven't over-capitalised on small, spurious associations in the sample. The test works well at large sample sizes and where the baseline comparator has many degrees of freedom. However, results from models that do not have these characteristics should be treated with caution. (Muthen *et al.*, 2017).

1.6.7.2 The Comparative Fit Index (CFI)

The CFI is an alternative to the TLI which also takes into account sample size. As with the TLI, it results in values between 0 and 1, with 1 indicating a perfectly fitted model. CFI is calculated in such a way that its value cannot fall outside the 0-1 range, which makes it easier to interpret than the TLI. (Hooper *et al,* 2008).

$$CFI = \frac{(\chi^2_{baseline} - df_{baseline}) - (\chi^2_{hypothesised} - df_{hypothesised})}{(\chi^2_{baseline} - df_{baseline})}$$

Other, older relative fit indices exist, but have largely been superseded by a combination of the TLI and CFI. (Hooper *et al*, 2008).

Interpreting Goodness of Fit measures

Guidelines for TLI and CFI found in a wide range of textbooks, software and online guidance still recommend (often without any of Hu and Bentler's original qualifying statements), a standard cutoff of ≥ 0.95 indicating a good fit, despite ample evidence that this is heavily influenced by contextual factors such as sample size, model structure, number of variables, type of estimator and so on. (Shi *et al*, 2019; van Laar and Braeken, 2021). The '≥ 0.95 rule' has become so ingrained that it has turned what should be a thoughtful consideration of model fit into a binary 'fit/no-fit' decision, which risks continued model refinement being abandoned before time; "*A statement such as 'because the RMSEA, CFI, and TLI values suggest good fit, this model was chosen as the final model' is not sufficient"*. Xia and Yang (2019).

In addition, for the CFI specifically, it is only recently understood that the baseline model sets the 'metric space' within which the comparison is made. This concept of 'metric space' is defined by van Laar and Braeken (2021), and is derived from the noncentrality parameter (λ) which represents the absolute misspecification of any model. Though it is easily calculated by subtracting the degrees of freedom of a model from its χ^2 value, it is not directly produced in most SEM software.

The metric space in which the assessment of model fit is being made needs to allow for a fine-grained enough calculation, of where the absolute misspecification of any model sits on the scale of baseline model to saturated model, in order for CFI to estimate the relative improvement of the hypothesised model. The visualisation below (based on a written example from van Laar and Braeken) illustrates how the λ of the baseline model absolutely drives the usefulness of the CFI result.

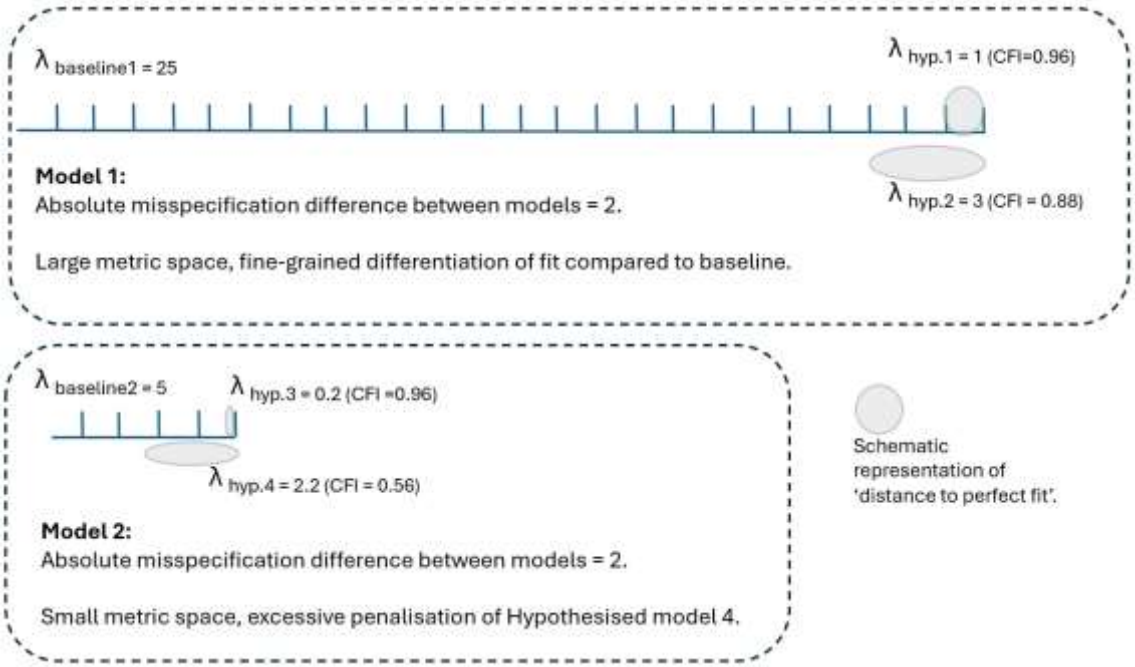


Figure 39: Visualising the importance of 'metric space' in interpreting CFI results

Unpacking what we already know about degrees of freedom and the χ^2 statistic tells us that λ will also be sensitive to sample size, the number of variables (and therefore possible relationships in the model), and the strength of correlations between them. Overall, van Laar and Braeken demonstrate that a large metric space leads to more

stable CFI estimates, and that the interpretation of the CFI result is almost meaningless without an understanding of it. This is especially true in smaller samples and where correlations between the variables are weak. If the observed variables in the sample have relatively weak correlations with each other, then a baseline model assuming no correlations is already a reasonable fit. In such a case, a *correctly* hypothesised model may not look to be a great improvement on the baseline, resulting in misleadingly small CFI scores that would fail the ≥ 0.95 cutoff and lead to rejection.

Large samples will automatically increase the metric space (because of the relationship between sample size, χ^2 and λ). Large samples combined with high correlation strengths result in CFI results which correctly identify a good model most of the time, regardless of the number of variables. Small samples and/or small correlations are likely to lead to rejection of correct models, and a high number of variables exacerbates that problem.

Van Laar and Braeken recommend that the non-centrality parameter (λ_0) of the baseline model (the bottom line of the CFI calculation, sample size, and model complexity) are reported to contextualise CFI results, especially those that fall below the standard cutoff of ≥ 0.95. They recommend that metric space in the model should be >1400 for reliable CFI interpretation.

1.6.8 Absolute AFIs

Alongside the indices of relative fit are those which assess the absolute fit of a model, the most widely reported of which is the RMSEA, followed by the SRMR. These measures are called 'absolute' because they do not rely on comparison to a baseline 'no correlations' model. Instead, they measure the size of the discrepancies between the observed data and what the model predicts. Where CFI and TLI measure how much improvement over a baseline model has been achieved, RMSEA and SRMR focus on measuring the magnitude of the error that remains. They are assessed on how close to zero the results are (rather than how close to 1, as with the CFI and TLI), and as such, are sometimes called 'badness of fit' measures.

1.6.8.1 The Root Mean Square Error of Approximation (RMSEA)

RMSEA's popularity as a fit index is bolstered because confidence intervals can be constructed for the point estimate, and most SEM software provides these. These set boundaries for the likely maximum and minimum values that *could* be true for a given model, which the point estimate sits within. A wide confidence interval indicates caution is required in interpreting the point estimate, and the upper and lower bounds provide the most pessimistic and optimistic values for our real RMSEA, respectively (Kenny *et al*, 2015).

The RMSEA is calculated thus:

$$\text{RMSEA} = \sqrt{\frac{\chi^2_{\text{hypothesised}} - df_{\text{hypothesised}}}{df_{\text{hypothesised}} \text{ x } (N-1)}}$$

We see immediately that it again relies on the χ^2 statistic, which we know incorporates sample size, and which Yuan, (2005), shows us is sensitive to violations of the distributional assumptions associated with that. It uses this to calculate the non-centrality parameter for the hypothesised model (the measure of absolute misspecification). This is standardised by degrees of freedom, and the square root of the whole thing effectively gives a measure of overall misspecification of the model. The result can range from zero to infinity, with results near to zero preferred.

Once again, standard cutoffs are often invoked, based largely on the work of Browne and Cudeck, (1993), with textbooks and guidance recommending, <0.05 excellent fit, <0.08 (moderate fit), and ≥ 0.10 (unacceptable fit). Lai, (2020), among others, are critical of this approach and these cutoffs as representing a form of circular argument; we state that <0.05 is a well fitted model, and when asked what a well-fitted model is, we state that it is one with an RMSEA of <0.05 (or a CFI of ≥ 0.95, etc etc).

For RMSEA, further caution about using standardised cutoffs relate to it being an unstandardised, or 'unit-less', measure and therefore <0.05 for one model does not mean the same as it would for another. The structure and complexity of the model, and the strength of correlations (or factor loadings in CFA) can have some counter-intuitive effects. Ximénez *et al.*, (2022) show that higher correlations/loadings create a 'reliability paradox', where factors where items that load most strongly onto their factors (normally a welcome characteristic) actually cause RMSEA values to worsen. McNeish and Wolf, (2022) also show that the complexity of the model is crucial; "*Whereas 0.06 might be a great RMSEA cutoff for detecting misspecified models for the three-factor model with 15 items (as studied by Hu & Bentler, 1999), it could be completely inadequate for detecting misspecification in a one-factor model with eight items*".

RMSEA is also sensitive to the number of variables and the degrees of freedom in the model. Simpler models, and/or those with few degrees of freedom can be wrongly assessed as poorly fitting (or at least exceeding the somewhat arbitrary cutoffs off 0.05, 0.08 or 0.1) when model structure changes. Shi *et al*, (2019) show that for a correctly specified latent model with 10 indicators and high loadings of 0.8 on the factor, even small misspecifications led to an 'unacceptable' RMSEA, whereas increasing the number of variables at the same loadings returned an 'excellent' result. Furthermore, Kenny *et al*, (2015) find that while rates of incorrect rejection of correctly specified models under the RMSEA fit measure are near zero percent for a model with 10df and a sample size of 200, rejection rates for correct models rose to 25% for models with only 1df at the same sample size. The authors conclude that their work extends to all forms of CFA, Path Analysis and full SEM. Taasoobshirazi and Wang, (2016) draw similar conclusions, advising that researchers should *"avoid reporting the RMSEA when sample sizes are smaller than 200, particularly when combined with small degrees of freedom*".

Reporting of the RMSEA therefore needs to be highly contextualised. Lai, (2020) proposes that its utility is actually as a comparator of models, rather than a measure of the absolute fit of a single model. "*If it is difficult to define "good" fit, it will also be difficult to show a model has a "good" fit. However, it is much easier to show one*

model's fit is better than another model's fit. No matter what RMSEA and CFI values correspond to "good" fit, it is always true that smaller RMSEA values and larger CFI values correspond to better fit…Therefore, model evaluation and selection will be more meaningful if the researcher not only reports the RMSEA or CFI of the final model but also reports the final model's improvement in RMSEA or CFI over other competing models. Doing so helps to reduce the reliance on cutoffs and thus avoid the problems with cutoffs".

1.6.8.2 Standardised Root Mean Square Residuals (SRMR)

Our remaining 'badness of fit' measure is the SRMR, which complements RSMEA, since it is able to diagnose localised misfit in the model, where RMSEA is better suited to spotting global discrepancy. For this reason, it is recommended that they are reported together. (Whittaker and Schumacker, 2022). As with the RMSEA, it is possible to derive confidence intervals for SRMR, which is useful for additional statistical tests of 'close fit' (Maydeu-Olivares, 2017). Unfortunately, this is not commonly implemented in most SEM software.

Reporting the SRMR helps overcome the interpretation problems that come from the RMSEA's unstandardised result, as the SRMR is more intuitive and "*can be approximately interpreted as the average residual correlation*" in the model. (Ximénez *et al.*, 2022 p.369).

SRMR does not rely on the χ^2 statistic or non-centrality parameter we have seen before. It is therefore somewhat more robust to violations of distributional normality, though its performance is notably worse in large models with severe non-normality. (Pavlov *et al*, 2021). Neither does SRMR directly consider degrees of freedom in the model, meaning it does not penalise complex models over simpler models in the way that RMSEA or TLI do (which could be a strength or a weakness, depending on the model context).

The SRMR test works by examining the observed covariances in the sample and comparing them to the predicted covariances from the model structure. For each pair of covariances, it calculates and standardises the residual (unexplained)

variance, to make the residuals comparable regardless of the original scales of measurement of the variables. These values are then squared, in a similar way to the 'squared errors' approach we saw earlier in linear regression, which results in all values becoming positive. Squaring also inflates the values of the biggest residuals. Summing the squares and deriving the average gives the average squared discrepancy in fit per pair of variables. The square root of this (effectively reversing the earlier squaring operation) is the SRMR value.

Similar standard cutoffs for excellent, acceptable and unacceptable fit are used as for RMSEA (<0.05 excellent fit, <0.08 (moderate fit), and ≥ 0.10 (unacceptable fit)), and should be treated with caution for all the reasons similar to those previously covered for other fit indices. In addition, Maydeu-Olivares, (2017) demonstrates that SRMR is systematically biased upwards, particularly in *well-fitting* models. This occurs because sampling error (those small variations that are sample-specific and would vary with each experiment) contributes a relatively constant amount to each residual, but when *true* model misfit is small, the sampling error will be the dominant component, inflating SRMR values and potentially leading to incorrect model rejection.

Since the RMSEA is an assessment of global misfit, the SRMR makes a useful companion measure to it, because it can better identify local misfit. A good RMSEA result may mask local misfit in the model, because its calculation does not examine individual covariance relationships. The SRMR, by calculating and then squaring each residual, would inflate the value of a particular highly problematic path, and in consequence, the overall SRMR result will be larger. An inflated SRMR coupled with a good RMSEA warrants investigation into specific structural misfit.

1.6.9 Comparing model fit

1.6.9.1 Balancing parsimony and theoretical richness in social science SEMs

We have seen how the test of exact fit, and a collection of fit indices can be used to provide an 'all around' assessment of an individual model's fit. We have also seen

that they are commonly abused, with standardised cutoffs used as a rationale for abandoning further model improvement. According to Xia and Yang, (2019), "*Achieving a set of desired values of RMSEA, CFI, and TLI (e.g., according to the conventional cutoffs) is only one marker showing that the model improvement may be successful. Thereafter, one still needs to explain whether other options exist to improve the model, why the options are or are not adopted and, as was suggested by Barrett (2007), what are the substantive scientific consequences of considering this model to be the final one?*"

Researchers should want to find the best model, rather than one that merely meets a set of (somewhat arbitrary) cutoffs. This will almost inevitably require comparing models. In general, there exists a rule of thumb that the most parsimonious model is best: researchers should select the model which uses the fewest explanatory variables to explain the maximum variation in the outcome variable. (Raykov and Marcoulides, 1999). There are obvious and sensible reasons for this philosophy; if effective policy or practice can be built on gathering data on the most limited set of variables, efficiency should be maximised. But, as with so much else in SEM, the parsimony rule has become almost an article of faith.

There are strong arguments that, while this may be the best approach in maths or physical science applications, assuming that the most parsimonious theory or model is more plausible than a simpler one is not as easily supported in other fields. (Coelho, 2019). In fields such as evolutionary biology, ecology, and especially in the social sciences, highly complex webs of interactions exist where multiple variables can each play a *small* part in influencing a final outcome, or a minor mediating relationship can have substantive importance in the practical application of the theory. A 'maximum parsimony' (fewest predictors) model that explains the vast majority of variation in an outcome of interest, but loses some of that nuance, may not necessarily be the best model. In addition, not only do we want a model that we can say 'closely fits' the data, we aim for a model that allows us to extract valid sample estimates for the parameters. If we constrain paths that really do have a small but meaningful effect, those real effects will simply find an outlet elsewhere and will manifest as biased parameters on other paths. (Curran and Bauer, 2023).

There are several tests of model comparison which allow researchers to consider whether additional complexity is 'worth it' for the gain in explanatory value, which are particularly valuable when complex CFA structures such as bifactor models are under consideration (Gignac, 2016).

1.6.9.2 Understanding nested models

Tests that can compare the fit of one model to another depend on whether the two models are 'nested' or not. Models are 'nested' if the simpler (more parsimonious) model can be derived by imposing constraints on the more complex model. Models are not nested if, to get from one structure to another requires simultaneous addition *and* subtraction of parameters. (Curran and Bauer, 2023).

For nested models, it is possible to compare them statistically. Adding new paths between variables (which is equivalent to removing some constraints that were imposed on the simplest, starter model) may explain a significant amount of the previously unexplained variance in the data. If so, we can judge the model to be a significant improvement and opt to keep the additional paths (the less constrained version of the model). For this test, we use the Likelihood Ratio Test, which compares the χ^2 statistic of both models.

If a more complex (less constrained) model is constructed by simultaneously adding *and* removing constraints, from a base model, then the models are not nested and cannot be subjected to the same tests of statistical comparison. We may inadvertently take out one of the more powerful explanatory paths, while at the same time adding some weaker paths. In non-nested models, because both additions and removals of parameters occur, it becomes difficult to attribute changes in model fit to specific modifications, and standard statistical tests for nested models are not valid. "*A complex model may even explain less variance than a simple one, if the complex one doesn't include the "right stuff" that the simple one does have*." (van Bergen, 2016).

We can compare nested models using Likelihood Ratio Test, and non-nested models using other 'information criteria' tests known as the AIC and BIC. These are explained briefly below.

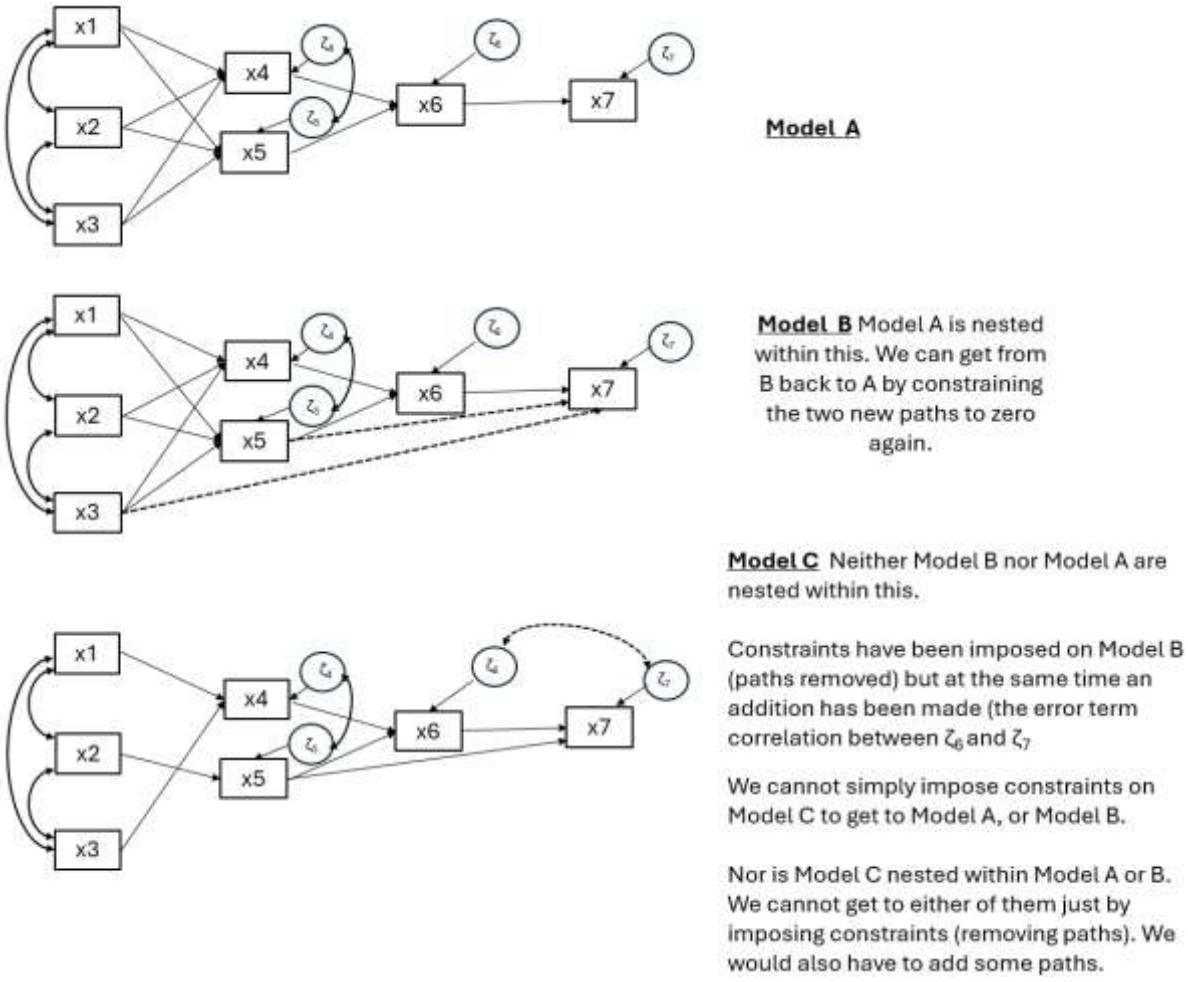


Figure 40: Nested and Non-Nested Models

1.6.9.3 The Likelihood Ratio Test (χ^2 Difference Test).

The LRT test for nested models answers the question 'does adding this path to my model improve the fit *to a significant enough degree* to make it worth retaining'? It is a statistical test, where the null hypothesis is that both models fit equally well. The alternative hypothesis is that the more complex model fits significantly better, by explaining significantly more of the variance.

If the LRT test returns a non-significant result, then we therefore fail to reject the null hypothesis that the two models are the same, and conclude that the new parameter(s) we have added to our base model are not worth retaining.

By contrast, a significant LRT result leads to rejection of the null hypothesis. We conclude that the inclusion of the extra parameter(s) *does* improve the model's fit, and we retain the more complex model.

As with all inferential tests, the result is affected by sample size, and with small samples (under 200), the test may not have the power to discern differences. But because it is based on the χ^2 statistic, we already know that it is also sensitive to large samples, which might identify a difference that is trivial in practice.

The test is conducted by taking the χ^2 and degrees of freedom for each model. The degrees of freedom of our more complex model will of course be smaller, because more parameters need to be estimated. We first determine the χ^2 difference, by subtracting the χ^2 of Model B from the χ^2 of Model A. We then subtract the degrees of freedom of Model B from those of Model A – this gives us the degrees of freedom *for the χ^2 Difference Test itself*.

We consult critical value tables for a χ^2 distribution at that given df value, which returns the p-value, telling us whether the difference between the two models is significant. In practice, most software will now provide this without recourse to printed tables.

To identify whether the 'better' model is actually a 'good' model, we must still assess its individual fit indices, as we saw in Sections 1.6.5, to 1.6.8. While LRT can tell us whether one model is better than another, it does not indicate that a given model is good, in and of itself. (Curran and Bauer, 2023)

1.6.9.4 AIC and BIC for non-nested models

The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are commonly reported in the fit outputs of SEM software but are meaningless when interpreted for a single model. Their indices are not normed to within a standard

scale (e.g. 0-100), so interpretation is difficult. Their utility lies in comparing models, and the consensus is that lower scores on either are better. (Hooper *et al*, 2008). They must be comparing models using the same sample data and outcome variables, (i.e. you cannot compare the AIC score from two separate projects). Comparing AIC/BIC scores for two models built from the same sample and leading to the same outcome variable will tell us which is 'least bad'. As with the LRT test of nested models, this is not the same as telling us if a model is 'good'. (Peraillon, 2019).

What is meant by 'least bad' out of two models is specific to the way these indices work. Akaike, who was from an Information Theory background, describes the AIC as measure of 'information loss'. A model is a representation of what we believe to be true in the population, but can never be an absolutely perfect representation of that, and the AIC helps us choose between models so that we can keep the one that, in all likelihood, based on our sample structure, has lost the least information in explaining the relationships. (Peraillon, 2019). Or, to put it another way "*AIC is a numerical value by which to rank competing models in terms of information loss in approximating the unknowable truth*." (Symonds and Moussalli, 2011).

AIC (and BIC which is a modification) both function similarly, need samples in excess of 200 (Hooper et al, 2008) and have penalties for model complexity built in, though the penalty for complexity is stiffer in BIC.

Whether one model is objectively less good than another is usually decided on the rules laid out in Burham and Anderson's 2002 work. A difference of ≥2 suggests they are comparable and does not give grounds for rejection. A difference of up to 6 means that not discounting a given model can probably be defended. A difference >10 indicates that the model is objectively less good than another. (Symonds and Moussalli, 2011). Similar guidelines are used for BIC, which are slightly more generous to reflect the fact that it more heavily penalises model complexity.

1.7 Modification/Re-Specification(5).

In the steps of SEM, 'Modification' is represented as following 'Evaluation', but the two stages are really iterative. Whittaker and Schumacker, (2022) discuss the

debated positions on modification. At one extreme are those who believe that if the theoretical model is shown to be empirically wrong, any modification is effectively abandoning theory, and is therefore inadvisable. Much more common is the position that poor model fit can often be addressed by tweaking connections in the model without substantively altering the theoretical picture, and modification is both useful and necessary.

SEMs can be enormously complex, and the risk of researchers 'wandering away' from theory in search of incremental gains in fit indices is a recognised risk, exacerbated by the easy availability of Modification Indices (MI) in most software. These are 'theory-blind' measures of model improvement, which use elegant maths to make short work of seeing where the fit of a model can be enhanced. (Curran and Bauer, 2023). Each MI suggests where parameter restrictions could be removed (for example if we allow two things to covary that we have not specified in the model), improving the fit. (Goffin, 2007).

The temptation to apply those changes in search of publishable results is high, but unless the researcher can truthfully say that the suggested modification (a) reveals something in the data that they should have known all along and/or (b) can be justified from the theory, their use should be avoided. The method is "*inherently susceptible to capitalisation on chance characteristics of the data, thus raising the question of whether model modifications generalise to other samples or to the population*"(MacCallum *et al*, 1992).

Modifications can also be driven through examination of individual model parameters, pruning of insignificant paths, and consideration (with extreme caution) of whether error terms between variables should be allowed to correlate.

Whatever modification steps are taken, they should be done one-by-one, amply justified by theory, and documented, with the model re-evaluated between steps.

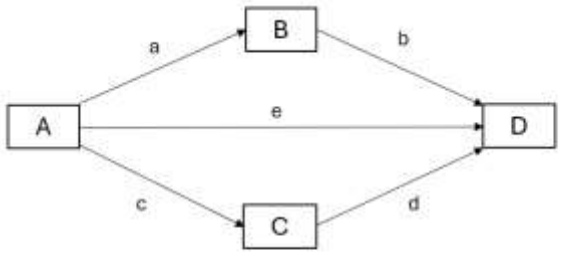
1.8 Interpretation(6): What does the model tell us?

We have moved through Specification, Identification, Estimation, Evaluation and Modification. We have arrived at a model that we believe is an empirically good fit to the sample data, providing proof that our theory (or a substantial part of it) is plausible.

This is where the distinction between the test of exact fit, versus reliance on indices that only tell us about approximate fit, are important. Pavlov *et al*, (2021), neatly sum up the two philosophies of SEM – those who believe that there can never be a model that is a precise reflection of complex social phenomena, and therefore proving exact fit (via the Model χ^2 Test) is not necessary, so long as a collection of other fit indices indicate a close enough approximation. On the other hand, there are those who maintain that assessing the test of exact fit *is* important because it is *only* that which should allow us to draw statistical inference from the parameter estimates. There are few other areas of scientific endeavour that do not rely on tests of statistical significance being 'passed' before conclusions are drawn about what this may mean about relationships in the population that the sample is drawn from.

Assuming we have reached the point where we feel confident in drawing such inferences, a substantial part of interpretation of the structural element of a full SEM or Path Analysis is in assessing whether any mediating relationships we have hypothesised are supported. A variable is a mediator if it can be shown to account for the relations between a predictor and an [outcome] variable, (Curran and Bauer, 2023).

Significant individual paths in a chain do not allow us to infer significant mediation. Indeed, every path in a chain may be individually significant, but it does not follow that the entire chain relationship is also significant, since its overall significance is a function of the products of some of those individual relationships. This is illustrated in Figure 41, below (adapted from (Curran and Bauer, 2023).



TOTAL EFFECT: Sum of the values on **all possible paths** from predictor to outcome
TOTAL INDIRECT EFFECT: Sum of **all possible indirect** paths from predictor to outcome
TOTAL SPECIFIC EFFECT: Product of any **single indirect** path leading from predictor to outcome

e	direct effect of A on D
a x b	Specific Indirect Effect (A on D, via B)
c x d	Specific Indirect Effect (A on D, via C)
(a x b) + (c x d)	Total indirect Effect (sum of products)
(a x b) + (c x d) + e	TOTAL EFFECT of A on D

Figure 41: Interpreting significant mediating relationships

SEM software will provide us with point estimates for every parameter, and it is recommended to bootstrap the standard errors for those estimates to be confident of any significant paths[53].

Interpreting the model therefore incorporates discussion of all significant direst paths, and then further interpretation of the mediating effects we have proposed. Our research hypotheses *are* those paths. We may have hypothesised by our model that some relationships are entirely direct, e.g. that A causes D. In others, we may have hypothesised that the effect of A on D is mediated by (can partly be accounted for by) an increase or decrease in other variable(s).

We evaluate, interpret, modify and re-interpret the model in relation to our initial theorised hypotheses, and aim to account for or accommodate any non-significant paths in ways that are theoretically supportable and in line with our wider theoretical framework. Where this is not possible, we accept that the causal theory itself may be fundamentally flawed.

[53] Bootstrapping in this context means software randomly selects a large subset of the sample over and over again (usually 1000 times). It runs model fit tests against each sample, and creates an empirically derived distribution of the 1000 versions of estimates obtained. It then constructs confidence intervals around these from which we can assess whether point estimates for each parameter are reliable.

With this background, the Part II of the thesis should now be accessible even to readers with no background in statistical models. Chapter 6 begins with the development, testing, exploration and confirmation of the structure of a new scale to measure resistance to landscape change, via EFA and CFA. Chapter 7 takes the factor scores for a large sample of respondents on that scale, and uses it as the outcome variable in a linear regression model, and a Path Analysis Model, to test and propose a plausible structure for the influence of a range of core values and political affiliations on resistance to rural change from climate policy. For any unfamiliar SEM terminology or process used in those chapters, the reader will be able to refer to explanatory background in this one.

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