EXPLORING THE ASSOCIATION BETWEEN ETHNICITY AND MENTAL HEALTH INEQUITIES: A STUDY OF ETHNIC MINORITIES IN THE UK

Facundo Herrera

BSc/MSc, Economics

MA, European Economic Studies

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy. The candidate has already achieved 180 credits for assessment of taught modules within the blended learning PhD programme.

April 2024

Faculty of Health and Medicine

Lancaster University

I declare that this thesis is my own work and has not been submitted for the award of a higher degree elsewhere.

ACKNOWLEDGEMENTS

I express my deepest gratitude to my supervisors, Professor Ceu Mateus and Professor Giuseppe Migali, for their unwavering support and encouragement throughout this academic journey. Special thanks to my wife Eleonora for her enduring encouragement from the outset. Lastly, I dedicate this PhD to my parents, Jose and Carmen, who instilled in me a profound commitment to social justice from an early age.

ABSTRACT

Background: Mental health inequities persist between ethnic minority and white majority groups in the UK. However, the pathways through which ethnicity interacts with socioeconomic determinants to shape mental health remain insufficiently understood. This limits the development of targeted policies to promote health equity.

Methods: This thesis adopted a mixed methods approach to elucidate ethnic mental health inequities in the UK context. First, a systematic literature review synthesised evidence on associations between ethnicity and mental health from 9 observational studies over the past decade. Next, a quasi-experimental analysis leveraged a regression discontinuity design using the 1972 Raising of the School Leaving Age (ROSLA) policy as an instrument to estimate the causal effect of education on mental health within ethnic minorities. Finally, an intersectional Oaxaca-Blinder decomposition examined the contributions of socioeconomic factors to the mental health gap between women from ethnic minorities and the overall UK population.

Results: The systematic review revealed that ethnicity effects are mediated by other determinants like housing and employment, with heterogeneity across ethnic minority groups. The quasi-experimental analysis found no significant effect of increased compulsory schooling on mental health for ethnic minorities. The decomposition showed that socioeconomic differences explain nearly 50% of the mental health gap for minority women, but over 50% remains unexplained, pointing to unobserved systemic biases.

Conclusions: The complex interplay between ethnicity, socioeconomics, and systemic factors shapes mental health inequities in the UK. Coordinated efforts addressing social determinants and structural biases are needed alongside further research on causal pathways using intersectional lenses. Tackling ethnic mental health disparities requires a multifaceted approach attentive to this inherent complexity.

Table of Content

Table of Tables

Tables of Figures

1 Chapter I: Overall introduction

1.1 Background

Despite being one of the wealthiest nations globally, the UK still faces considerable avoidable, remediable, and unjust health disparities, particularly regarding ethnic inequalities. In particular, ethnic minorities have shown worse outcomes than White British (Byrne et al., 2020). For example, Black women are four times more likely to die during childbirth than white women (Knight et al., 2017). Additionally, Black African and Black Caribbean individuals are more than eight times more likely to be placed under Community Treatment Orders than White individuals (Barkhuizen et al., 2020). South Asians have a 40% higher death rate from coronary heart disease (CDH) than the population (Gupta et al., 2006). These examples demonstrate the complex interplay of social determinants, such as ethnicity and gender, and their impact on health disparities.

The terms “health inequality”, “health disparity”, and “health inequity” are often used interchangeably. However, “health inequity” refers explicitly to inequalities/disparities that are “avoidable, remediable and unjust” (Whitehead, 1991; Whitehead, 2007). This study will frame disparities or inequalities as inequities.

1.1.1 Health inequity in the UK policy agenda

During the second half of the 20th century, the UK government implemented policies such as the National Health Service (NHS) and a generous welfare state to improve healthcare, among other outcomes. However, despite these efforts, health inequalities in the UK were still persistent and widening. The paradox of having a universal coverage system, a generous welfare system, and growing health inequities triggered public debate and called for further investigation. As a result, in 1980, the report of the Working Group on Inequalities in Health

("The Black Report") concluded that social inequalities in income, education, housing, diet, and employment conditions were behind health inequalities in the UK instead of shortcomings in the National Health Service (NHS) (Black, 1980). The report proposed four potential explanations for the observed health inequalities: measurement errors or other artefacts; social or natural selection, where individuals with poor health may be more likely to occupy lower socioeconomic positions; materialist, where health inequalities are the result of unequal distribution of resources and opportunities; and cultural or behavioural, where health disparities are due to differences in health behaviours or cultural norms between different groups.

The report favoured the materialist explanation. Some researchers deemed the explanations of artefact and selection not credible and unlikely to explain the overall gradient of health inequalities (Smith et al., 1990). A review of evidence on the "selection" explanation found it to be most likely at the start of one's career, least likely for children and senior citizens, and unlikely to explain much of the overall gradient of health inequalities (Bartley, 2017; Blane, 1985). Further research during the following decades supported the materialist hypothesis and evolved into the well-known "social determinants of health" (SDOH). The SDOH framework refers to living and working conditions throughout life, including income, wealth, and education (Braveman & Gottlieb, 2014; Welch et al., 2022). Figure 1.1 below illustrates the "rainbow model" for SDOH.

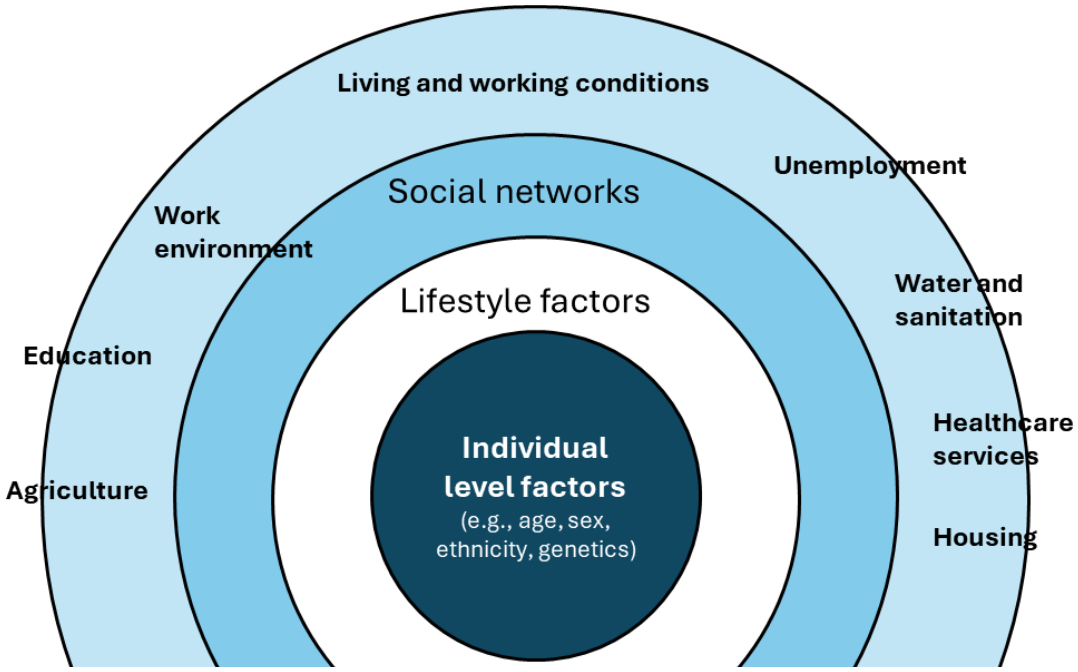


Figure 1.1 Social Determinants of Health (SDOH) – a socio-ecological model
Source: Adapted from Dahlgren and Whitehead (1993)

Much of the research on health inequalities in the UK adopted the SDOH. It was helpful to show that the patterns of health inequities highlighted in the Black Report did not decrease and widened during the 90s (Smith et al., 1990). Likewise, Marmot et al. (2010) revealed widening health inequities associated with income, education, employment and ethnicity in 2008, and more recently, Marmot (2020) showed that the trends have worsened since then. A recent 2024 report from the Health Foundation on the current and projected patterns of illness by deprivation in England depicts a grim present and future. In the most deprived areas, 14.6% of individuals aged 20–69 years experience major illness, more than double the rate in the least deprived areas (6.3%). Furthermore, those in the top 10% of deprivation are prone to develop significant illness a decade earlier than their counterparts in the least deprived areas, with a threefold increase in the likelihood of premature mortality before the age of 70. By 2040, over half of individuals in the most deprived areas are projected to either live with significant illness or have died by the age of 70, contrasting starkly with less than 30% in the least deprived areas, illustrating stagnation in efforts to narrow health disparities between 2019 and 2040 (Raymond et al., 2024).

1.1.2 Ethnic inequities in mental health

While health inequities have gained significant attention on policy agendas worldwide, it is imperative to delve deeper into specific areas where disparities persist. Among these, ethnic inequities in mental health stand out as a critical yet often overlooked aspect of the broader healthcare landscape. Understanding and addressing the unique challenges faced by different ethnic groups in accessing and receiving adequate mental health support is essential for promoting holistic well-being and achieving true health equity.

A critical aspect of ethnic inequities in mental health is the disparity in access to and utilization of mental healthcare services among BAME populations in the UK. Research has consistently shown that BAME individuals face significant barriers in accessing appropriate mental health support despite potentially higher prevalence of certain mental health conditions among some ethnic minority groups. These barriers are multifaceted and deeply rooted in both personal and environmental factors. Memon et al. (2016) identified stigma, cultural identity, financial constraints, and language barriers as significant obstacles to accessing mental health services for BAME populations in Southeast England. Furthermore, poor communication and perceived discrimination by healthcare providers exacerbate these challenges, fostering mistrust and fear within these communities.

The pathways through which BAME individuals enter mental health services also reflect stark disparities. Codjoe et al. (2019) noted that BAME populations are more likely to access mental health services through the criminal justice system rather than primary care, highlighting a troubling trend in service engagement. This underutilization of primary mental health services is further compounded by linguistic and cultural barriers, which contribute to poor engagement and outcomes. Vahdaninia et al. (2020) conducted a scoping review of mental health services designed for BAME communities in the UK and found that while tailored services can be beneficial, they remain underutilized due to cultural barriers and a lack of widespread availability. Additionally, (Simkhada et al., 2021) stressed the significance of gender roles and lack of cultural awareness among healthcare providers as significant obstacles to accessing mental health services, particularly within Nepali and Iranian communities in the UK. These findings underscore the urgent need for culturally sensitive healthcare approaches and targeted interventions to improve mental healthcare accessibility and cultural competence for BAME communities.

Moreover, research has demonstrated the negative impact of racism and discrimination on mental health (Becares et al., 2022; Nandi et al., 2020; Paccoud et al., 2022; Wallace et al., 2016). However, research on ethnic health inequalities in the UK remains sparse, as stressed by Nazroo (2022a), including mental health. While various studies have examined ethnic disparities over the past few decades (Erens et al., 2001; Harding & Maxwell, 1997; Marmot et al., 1984; Nazroo, 1999; Rudat, 1994; Sproston & Mindell, 2006; Wallace & Kulu, 2015; Wild et al., 2007), it was not until the COVID-19 pandemic that these differences were given significant attention by mainstream academic and policy research. For example, despite the 1997 Independent Inquiry into Inequalities in Health, chaired by Sir Donald Acheson, which focused on ethnicity, policy initiatives addressing health inequalities have not considered ethnicity since then. Moreover, the Department of Health's Strategic Review of Health Inequalities in England post-2010 significantly impacted the policy agenda. Nevertheless, despite its influence, policies disregarding ethnicity have been observed since then (Salway et al., 2016).

Therefore, this study aims to contribute to the empirical literature on ethnic inequities in mental health in the UK.

1.2 Theoretical framework

1.2.1 The social determinants of health inequities – The Diderichsen model

While the Social Determinants of Health (SDOH) framework has been widely embraced for analysing population health and disparities, Dahlgren and Whitehead (2021) claim that the Diderichsen model offers a more appropriate model to explore the fundamental causes of inequalities. The Diderichsen model of pathways to health inequities (see Figure 1.2) has the advantage of making the mechanisms and policy entry points more explicit than the Dahlgren rainbow model that explains the overall health population. Finn Diderichsen has proposed five primary mechanisms, each presenting a potential intervention point to address health inequities: i) social stratification, which refers to the unequal distribution of resources and opportunities that contribute to disparities in health outcomes; ii) differential exposure, which highlights the disproportionate exposure to some individuals' risk factors; iii) differential vulnerability, which refers to the varying susceptibility to illness and disease based on individual characteristics; iv) differential consequences of the disease, which focuses on the differing impact of illness and disease on different groups, and v) disease's broader consequences for individuals and society (Diderichsen et al., 2012).

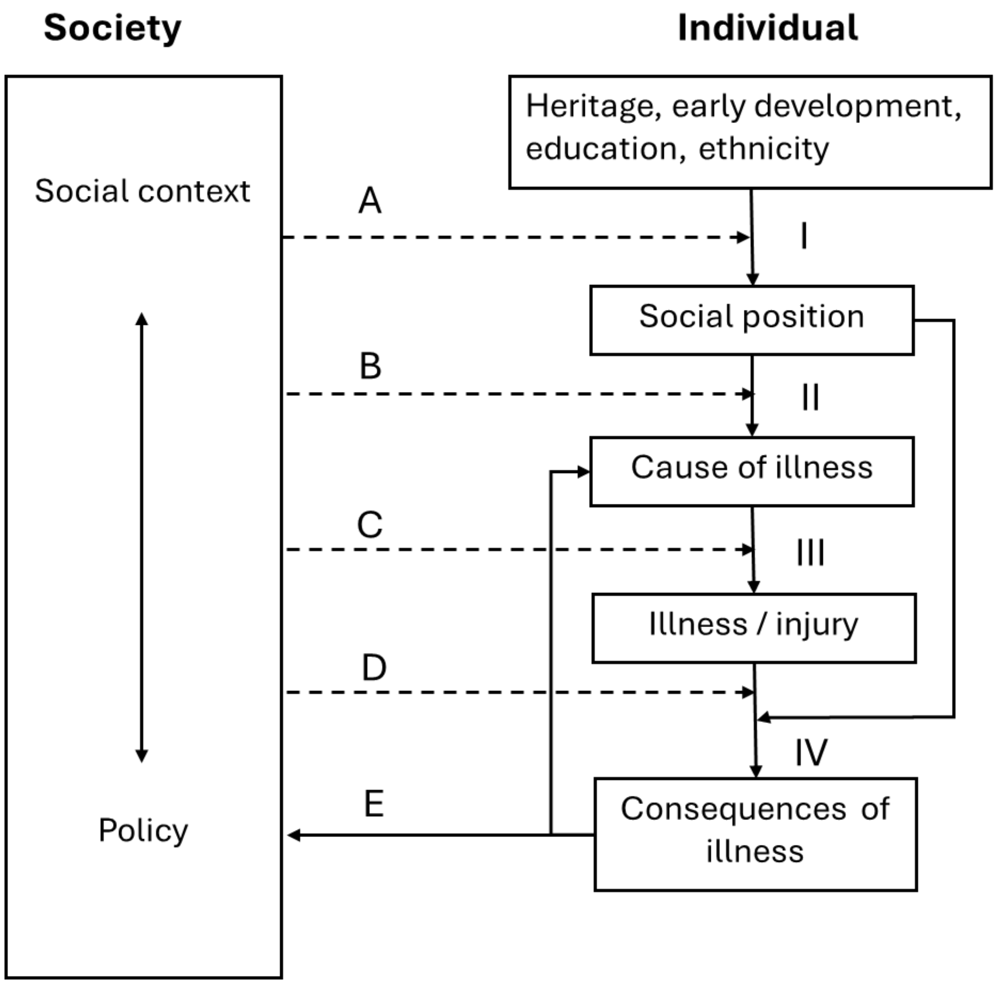


Figure 1.2 The Diderichsen model

Central mechanisms (I-V) and (A-D) policy entries

Source: Adapted from Diderichsen et al. (2001)

By elucidating the underlying mechanisms contributing to disparities, policymakers and researchers can craft more effective strategies to address the specific factors responsible for unequal health outcomes. This framework serves as the guiding principle for the present study.

1.2.2 An intersectional lens to ethnic health inequities

In the realm of mental health inequities, understanding the intricate interplay between ethnicity, power structures, and systemic oppression is paramount. While conventional frameworks like intersectionality have provided valuable insights, their application in addressing ethnic inequities in mental health remains underexplored (Richman & Zucker, 2019). Recognising this gap, recent scholarship within the 'decolonial turn' has emerged, offering nuanced perspectives that directly speak to the experiences of marginalised ethnic communities (Martinez Dy et al., 2015). By reinterpreting concepts like racism through a decolonial lens, scholars such as Grosfoguel et al. (2015) and Grosfoguel (2016) present a comprehensive framework. This framework not only acknowledges the intersecting nature of oppression but also elucidates the unique challenges faced by ethnic groups in accessing endowments that contribute to mental health.

From a decolonial perspective, racism is a global hierarchy of human superiority and inferiority shaped by centuries of political, cultural, and economic dominance within a modern/colonial world system that is capitalist, patriarchal, Western-centric, and Christian-centric (Grosfoguel, 2007). This conceptualisation recognises the fluidity and contextual nature of racism, which manifests differently across various social markers such as colour, ethnicity, religion, language, and culture.

The decolonial understanding of racism offers several advantages for intersectional research. Firstly, it inherently incorporates intersectionality by acknowledging oppression across multiple axes, including gender, religion, and culture. Secondly, it adopts a positional approach to intersectionality, recognising that social markers are constructed and context-dependent rather than fixed categories that essentialise individuals, as often observed in positivist intersectional studies. Thirdly, by framing oppression as the product of historically constructed institutions, the decolonial framework underscores the potential for political struggle to deconstruct oppressive systems. This perspective empowers individuals by emphasising agency while acknowledging the enduring institutional structures perpetuating racism.

1.2.3 Epistemological stance

The empirical stance in this research is grounded in critical realism rather than positivism, which often underpins quantitative analysis. Critical realism offers a more nuanced understanding of ethnic mental health inequities compared to positivism. Positivism reduces social reality to empirical regularities and facts that can be measured. This results in a flat ontology limited to the empirical level (Crotty & Crotty, 1998). In contrast, critical realism assumes reality is stratified into the empirical, actual and real (Bhaskar, 2013; Collier, 1994; van Ingen et al., 2020). The ‘real’ refers to underlying causal mechanisms that may not be directly observable but still exert influence.

Positivism struggles to examine the interplay between structure and agency. It either reduces analysis to methodological individualism or deterministic structural forces. Critical realism better incorporates how agency and structure shape one another through a dialectical relationship. Present structures result from past actions and constrain current agents (Collier, 1994; Gorski, 2013).

Additionally, positivism imposes fixed, deterministic categorisations of ethnicity. Critical realism avoids this by embracing positionality. Ethnic categories are viewed as starting points to understand hierarchies of power rather than definitive labels.

Therefore, this critical realist perspective shapes the empirical analysis and discussion of results and conclusions assuming complex reality strata and generative mechanisms, acknowledging data analysis as the starting point for retroductive reasoning to gain an in-depth understanding of the causes behind observable ethnic mental health inequities.

1.3 Outcomes: common mental health disorders

The decision to focus on common mental disorders, such as anxiety and depression, in this study is driven by both pragmatic and research-oriented considerations. Common Mental Disorders (CMDs), including conditions such as anxiety, depression, and stress, represent a significant public health concern in the United Kingdom. These disorders have a profound impact on individuals' quality of life and exert substantial pressure on healthcare systems and the broader economy. The prevalence of CMDs exhibits notable variations across different ethnic groups, with Black, Asian, and Minority Ethnic (BAME) populations often experiencing higher rates, a disparity further compounded by socioeconomic factors (Ahmad et al., 2022). This ethnic variation in CMD prevalence, coupled with documented disparities in access to and utilisation of mental health services among BAME groups, underscores the critical importance of examining ethnic mental health inequities in the UK context (Irving et al., 2021; Weich et al., 2004).

To comprehensively assess the impact of CMDs and related ethnic disparities, this thesis employs a combination of widely validated health-related quality of life (HRQoL) and mental health measures: the SF-12, SF-36, and General Health Questionnaire (GHQ). These instruments were chosen for their ability to capture the multifaceted nature of CMDs and consequences. The SF-12 and SF-36 provide broad assessments of mental and physical health status, allowing for the evaluation of CMD impacts on overall health and functioning. Meanwhile, the GHQ offers a more focused examination of psychological distress and minor psychiatric disorders, which is particularly relevant for identifying CMDs in community settings. Together, these measures enable a nuanced analysis of CMD prevalence, severity, and associated health outcomes across different ethnic groups, supporting a robust investigation of ethnic mental health inequities in the UK.

1.3.1 Validity of instruments for assessing CMDs among ethnic minorities

Several well-established measurement tools with robust psychometric properties are commonly adopted in research and clinical settings to assess health-related quality of life and psychological distress. Among these instruments, the SF-36, SF-12, and the General Health Questionnaire (GHQ) are extensively validated and widely adopted tools across diverse populations and settings, including ethnic minority groups in the UK. Notably, the SF-12 and

GHQ are included in the UKHLS dataset, further enhancing their accessibility and applicability in various research contexts.

SF-36

The SF-36 is a comprehensive questionnaire designed to measure health-related quality of life across various domains. It has been extensively studied and has demonstrated strong psychometric properties, including good internal consistency, test-retest reliability, and convergent and discriminant validity. The SF-36 has been validated across various populations and settings (Baschung Pfister et al., 2019; Zhang et al., 2012). Notably, the SF-36 Version II has shown improved reliability and construct validity over its predecessor in a large UK population sample, making it a robust tool for assessing health-related quality of life across diverse populations, including ethnic minorities (Jenkinson et al., 1999).

SF-12

The SF-12 is a shorter version of the SF-36 questionnaire designed to measure health-related quality of life. The SF-12 has been shown to have good internal consistency, test-retest reliability, and convergent validity with other health status measures (Huo et al., 2018). Significantly, research has assessed the construct validity of the SF-12 across different ethnic groups in the UK, indicating that it is generally valid for measuring health in ethnic minorities. However, this research also highlighted potential issues when the questionnaire is completed via informal translations by friends or family members, which may lead to systematic differences in scores (Jenkinson et al., 2001). This underscores the importance of considering linguistic and cultural factors in the administration and interpretation of the SF-12 among diverse populations.

Survey participants in the UKHLS study completed the SF-12 instrument, a concise questionnaire for assessing general health, which yields two distinct summary components: the Mental Component Summary (MCS) and the Physical Component Summary (PCS) (Ware et al., 1996). The MCS, regarded as a reliable and externally valid tool, verifies anxiety and depression across diverse populations (Bridger & Daly, 2019). The MCS scores are obtained from responses to six questions regarding the extent to which individuals experienced interference with social activities due to physical health or emotional problems, accomplished less than expected due to emotional issues, performed work or other activities less carefully than usual, and experienced feelings of calmness, peace, as well as downheartedness and depression. Participants rate their responses on a scale ranging from 1 (all the time) to 5 (none of the time). Subsequently, these responses are transformed into a single mental health functioning indicator, ranging from 0 (low) to 100 (high) (Curnock et al., 2016; Ware et al., 2002).

General Health Questionnaire (GHQ)

Another health outcome used in this thesis is the General Health Questionnaire (GHQ). The UKHLS study uses a specific measure to consolidate responses to 12 questions from the General Health Questionnaire (GHQ) into a unified scale. This process involves a recoding procedure to establish a standardised range for each variable, spanning from 0 to 3, as opposed to the original 1 to 4 range. Subsequently, the summation of these recalibrated values yields a comprehensive scale that varies between 0 (indicative of minimal distress) and 36 (reflective of heightened distress) (Cox et al., 1993).

The GHQ is a screening tool designed to assess psychological distress and mental health problems. The GHQ has been shown to have good internal consistency, test-retest reliability, and convergent and discriminant validity (Kashyap & Singh, 2017). Recent research using the GHQ-12 to assess mental health deterioration among ethnic groups in the UK during the COVID-19 pandemic found that Black, Asian, and Minority Ethnic (BAME) individuals, especially women and men from Bangladeshi, Indian, and Pakistani backgrounds, experienced a higher increase in mental distress compared to White British individuals. This suggests the

GHQ-12 is sensitive to detecting mental health changes in diverse ethnic groups (Proto & Quintana-Domeque, 2021), further validating its use in studies of ethnic mental health inequities.

Therefore, the three measures are well-established instruments with good psychometric properties, extensively validated and widely used in research and clinical settings to measure health-related quality of life and psychological distress across diverse populations, including ethnic minorities in the UK. While these instruments demonstrate good validity across ethnic groups, it is crucial to consider potential linguistic and cultural factors that may influence their administration and interpretation. The second chapter of this thesis covers all three measures, while the remaining two empirical chapters focus solely on the SF-12 and GHQ based on data available in the UKHLS.

1.4 Thesis structure

Figure 1.3 depicts the structure of this thesis, and Figure 1.5 delves into the research questions and methods used in the empirical chapters.

Chapter (section)	Content
Chapter I (section 1)	• Background and rationale for the study • Set out main operational definitions • Place the topic on the policy agenda • Introduce the theoretical framework • Establish the epistemological stance • Describe the dataset used in the study
Chapter II (section 2)	• Systematic literature review with narrative synthesis
Chapter III (section 3)	• A regression discontinuity design on the effect of ROSLA on mental health
Chapter IV (section 4)	• An intersectional Oaxaca-Blinder decomposition of the ethnic and sex mental health inequities in the UK
Chapter V (section 5)	• Sum up the discussion of all empirical chapters • Highlight major limitations • Discuss implications for policy • Propose future research

Figure 1.3 Structure of the thesis

Chapter (section)	Research questions	Methods
Chapter II (section 2)	• What is the relationship between ethnicity and mental health in the UK population? • How does mental health vary among people from different ethnic groups in the United Kingdom? • Is the potential relationship between ethnicity and mental health in the UK population mediated or moderated by other social determinants? • How, if any, are the effects of multiple social determinants incorporated into the analysis through an intersectional lens (i.e., additive versus multiplicative)?	Systematic literature review with narrative synthesis
Chapter III (section 3)	• What is the causal effect of an additional year of schooling on long-term mental health measured by SF12 and GHQ among ethnic minorities in the UK? • Does the effect of an additional year of schooling on long-term mental health among ethnic minorities in the UK vary by sex?	A regression discontinuity design on the effect of ROSLA on mental health
Chapter IV (section 4)	• How much of the mental health gap, measured by the SF12 and the GHQ-Likert scale, between ethnic minority and white majority groups in the UK can be attributed to differences in risk factors versus differences in the effects of those risk factors? • How much of the mental health gap, measured by the SF12 and the GHQ-Likert scale, between women and men in the UK can be attributed to differences in risk factors versus differences in the effects of those risk factors? • How much of the mental health gap, measured by the SF12 and the GHQ-Likert scale, between women from ethnic minorities and the rest of the UK population can be attributed to differences in risk factors versus differences in the effects of those risk factors?	An intersectional Oaxaca-Blinder decomposition of the ethnic and sex mental health inequities in the UK

Figure 1.4 Research questions and methods

2 Chapter II: A systematic review of the relationship between ethnicity and mental health inequities in the UK

2.1 Introduction

2.1.1 Background

Mental health issues are a growing public health concern worldwide, with depression, anxiety, and drug abuse being primary drivers of disability in young adults. Major depression is also a pivotal contributor to suicide and ischaemic heart disease, with close to 800,000 people dying due to suicide every year globally. Black, African, Caribbean, and Black British people in the UK have higher rates of mental illness and are more likely to access mental health services (Baker, 2021). Black women are the group most likely to experience common mental disorders such as anxiety or depression, while Black men are the group most likely to experience a psychotic disorder (Race Disparity Audit, 2017). Official statistics indicate that Black individuals are over four times more likely than white individuals to be held under the Mental Health Act. Black Caribbean individuals have the highest rate of detention among all ethnic groups, which significantly affects mental well-being (NHS Digital, 2022).

People from ethnic minorities are racialised in the assessment and treatment of mental illness, affecting their treatment outcomes. A report by the NHS Race and Health Observatory in 2022 found that ethnic inequalities in healthcare access, experiences, and outcomes are longstanding problems rooted in structural, institutional, and interpersonal racism (Kapadia et al., 2022).

There is a strong link between mental health and other health outcomes, with poor mental health associated with a range of physical health problems, such as chronic conditions (heart disease, diabetes, and obesity) and an increased risk of infectious diseases (Iqbal, 2021). Mental health also significantly impacts mortality rates, with those experiencing poor mental health being at increased risk of premature death, in addition to physical health outcomes and lower productivity (Bubonya et al., 2017; Kupferberg et al., 2016; Malik et al., 2022). Individuals with mental health problems may experience difficulties maintaining employment or productivity, leading to decreased income and financial insecurity. Thus, mental health problems can lead to social isolation, relationship difficulties, and decreased quality of life, contributing to adverse social and economic outcomes. On a broader scale, poor mental well-being is estimated to cost the global economy billions of dollars in lost productivity and healthcare costs (Campion et al., 2022).

That said, addressing ethnic inequities in mental health is not only advantageous from an economic standpoint but also an ethical obligation and a matter of promoting social justice and human rights (Borras, 2021). Ethnic minorities are disproportionately affected by mental health issues due to various factors, including social, economic, and environmental determinants. Therefore, understanding the underlying drivers of ethnic mental health inequities is essential for developing effective interventions and tackling such injustices.

The terms "health inequality," "health disparity," and "health inequity" are frequently used interchangeably. However, "health inequity" refers explicitly to inequalities or disparities that are considered "unjust, avoidable, and remediable" (Whitehead, 1991; Whitehead, 2007). Hence, this review will refer to disparities or inequalities as inequities.

2.1.2 The rationale for this review

As highlighted by Nazroo (2022a), race/ethnic disparities in health in the UK have been a topic of research for several decades, as shown by studies such as Marmot et al. (1984), Rudat

(1994), Harding and Maxwell (1997), Erens et al. (2001), Nazroo (1999), Sproston and Mindell (2006), Wild et al. (2007), and Wallace and Kulu (2015). However, ethnic disparities were not extensively and sufficiently discussed by mainstream academia and policy research before the COVID-19 pandemic. For example, despite the focus on ethnicity in the 1997 Independent Inquiry into Inequalities in Health –chaired by Sir Donald Acheson, no policy initiative aimed at addressing health inequalities since then has considered ethnicity. Likewise, the Department of Health's Strategic Review of Health Inequalities in England post-2010, which significantly impacted the agenda, entirely disregarded the issue of ethnicity (Salway et al., 2016). The COVID-19 pandemic has revealed such pre-existing ethnic inequities and the impact on mental health.

Therefore, this review will contribute to the evidence by focusing on results from three mental health instruments related to quality of life and well-being: the SF-12, SF-36 and the General Health Questionnaire (GHQ). These instruments have been discussed in section 1.3.1 above.

This systematic review is motivated by four research questions:

- *What is the relationship between ethnicity and mental health in the UK population?*
- *How does mental health vary among people from different ethnic groups in the United Kingdom?*
- *Is the potential relationship between ethnicity and mental health in the UK population mediated or moderated by other social determinants?*
- *How, if any, are the effects of multiple social determinants incorporated into the analysis through an intersectional lens (i.e., additive versus multiplicative)?*

While this review focuses specifically on the UK context, it is crucial to acknowledge relevant findings from studies conducted outside the UK, particularly in Europe and the Americas. Several studies adopting an intersectional lens in these regions have demonstrated the complex, multifaceted nature of ethnic and gender health inequities, including in mental health. For instance, research in the United States has highlighted how racial/ethnic disparities in health intersect with gender, socioeconomic status, and immigration status (Patterson et al., 2020; Perez et al., 2020; Scharron-del Rio & Aja, 2020; Shangani et al., 2020). Similarly, studies in several European countries have shown how factors such as discrimination, acculturation stress, and social support interact with ethnicity to influence health and mental health outcomes among immigrant and minority populations (Dreger et al., 2016; Hunt et al., 2020; Watson et al., 2019). These international findings underscore the importance of considering multiple, intersecting social determinants when examining ethnic mental health inequities in the UK context.

2.2 Methods

This review adopted a systematic review approach on quantitative observational studies on ethnic mental health inequities, following the recommendations from the 2020 Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021) (see Annex II for the PRISMA checklist). A review protocol has not been registered. Table 2.1 shows a modified PICO framework to establish the research questions, objectives, and inclusion/exclusion criteria.

Table 2.1 Parameters of the PECOS framework

Parameter	Description
Population	People from ethnic minorities of all ages residing in the UK
Exposure	Exposure to discrimination and inequities
Comparators	People from the ethnic majority (White British) of all ages residing in the UK
Outcome	Mental health and well-being measured by the SF-12, SF-36 and GHQ indicators
Study design	Observational and quantitative studies

2.2.1 Eligibility criteria

Table 2.2 describes the inclusion and exclusion criteria in line with the PECOS framework.

Table 2.2 Inclusion and exclusion criteria

Criteria	Inclusion	Exclusion
Study design	Observational and quantitative	Qualitative studies

		Studies focused on testing the validity of the questionnaires.
Geographic scope	United Kingdom only	Outside the United Kingdom
Health outcome	The SF-12, SF36 or GHQ measure mental health.	Any other mental health outcome or other health outcomes
Ethnicity	Ethnicity must be included at least as one of the predictors or mediators, and effects must be available by each of the ethnic sub-groups	Ethnicity is only a binary variable to adjust the estimation of other covariates. No effects are estimated by ethnic group.
Time	Only studies conducted in the last ten years, namely, from 2013 onwards	Studies older than 2013 are dropped

Mental health outcome

This review has focused on common mental disorders captured by the three instruments mentioned above: SF-12, SF-36 and the GHQ.

2.2.2 Information sources

A scoping search conducted in Web of Science helped test the search string's sensitivity and specificity and validate the search strategy. The suitability of the search string was achieved through an iterative process testing different queries in PubMed and Web of Science. The final query was conducted on nine databases: Web of Science, PubMed, and EBSCO (APA

PsycArticles, APA PsycInfo, CINAHL, EconLit, ERIC, MEDLINE Complete, SocINDEX with Full Text). The scoping search started on the 1st of November 2022, and all databases were queried for the last time on the 24th of January 2023.

2.2.3 Search strategy

The final search string was adapted to the dictionary of each database. No filters were used to avoid missing fundamental studies. Database searches were conducted in English. Table 2.3 shows only a few key terms, while Annex II provides the full search string for each concept and database. The search strategy was informed by the combination of four concepts: quantitative observational studies conducted in the UK, focused on mental health outcomes (SF-12, SF36, GHQ), and ethnicity as one of the predictors. The geographic scope was added to the search string to make the search more sensitive, that is, keywords for the United Kingdom or the four countries (England, Scotland, Northern Ireland, or Wales) had to be mentioned in either the title or the abstract.

Table 2.3 Search strings

Concept	Key words	Query
Study design	(quantitative OR "natural experiment" OR quasi-experimental OR difference-in-difference OR multi-level OR regression OR longitudinal OR time-series OR logistic OR linear OR Poisson OR …)	S1
Ethnicity	(Ethnic* OR race OR racial OR bame)	S2
Mental health outcome	("medical outcomes study SF-12" OR "medical outcomes study SF12" OR "medical outcomes study SF 12" OR … OR "SF 36" OR SF-36 OR … OR "General Health Questionnaire" OR GHQ OR …)	S3

Concept	Key words	Query
United Kingdom	(UK OR "United Kingdom" OR England OR …)	S4
Final query	S1 AND S2 AND S3 AND S4	S5

2.2.4 Selection process

All sources were retrieved from the respective databases and imported into EndNote software. Duplicates were removed automatically using EndNote. The title and abstracts were pre-screened using an MS Form© independently by two reviewers (FH and CM) following the inclusion/exclusion criteria. The selection process was conducted in two stages, first on abstract and titles and second by full-text screening. Each phase had two different data extraction forms, as discussed below.

2.2.5 Data collection process

Two data extraction tools were used at the title and abstract screening stage and the full-text screening stage. The first form focused on geographic location, mental health outcomes, integrating ethnicity in the analysis, study design and time of publication. In the full-text screening stage, the second tool extracted information on how ethnicity was incorporated into the analysis, sample sizes, and the health outcome indicator used. For example, studies that tested the instrument's validity were excluded from the final review. Likewise, studies that incorporated ethnicity only as an adjustment or binary variable were excluded. The inter-rater reliability rate of the two reviewers was over 95% at the abstract/title stage and 100% in the full-text screening.

A sample of both forms is included in Annex I. The stages of the data collection process are shown in Figure 2.1. More granular data was extracted for studies retained for final review.

2.2.6 Study risk of bias assessment

Following Simpson et al. (2021), the most appropriate quality appraisal tool given the study design under scope was the Validity Assessment Tool for Econometric Studies applied by Barr et al. (2010). This is a tool that was developed to assess the validity of econometric studies, which is more appropriate for quantitative and observational studies of this review than the standard RCT or epidemiologically oriented. The tool is made of nine items:

1. Unit of analysis
2. Comparison approach
3. Sample selection
4. Number of points of data
5. Response/follow-up bias
6. Exogeneity of policy exposure
7. Confounding
8. Sample size/power
9. Analysis

Each field is scored from 0 to 3, being 3 the highest quality. Hence, each study could score between 0 and 27. Annex I shows a full description of the tool.

2.2.7 Synthesis methods

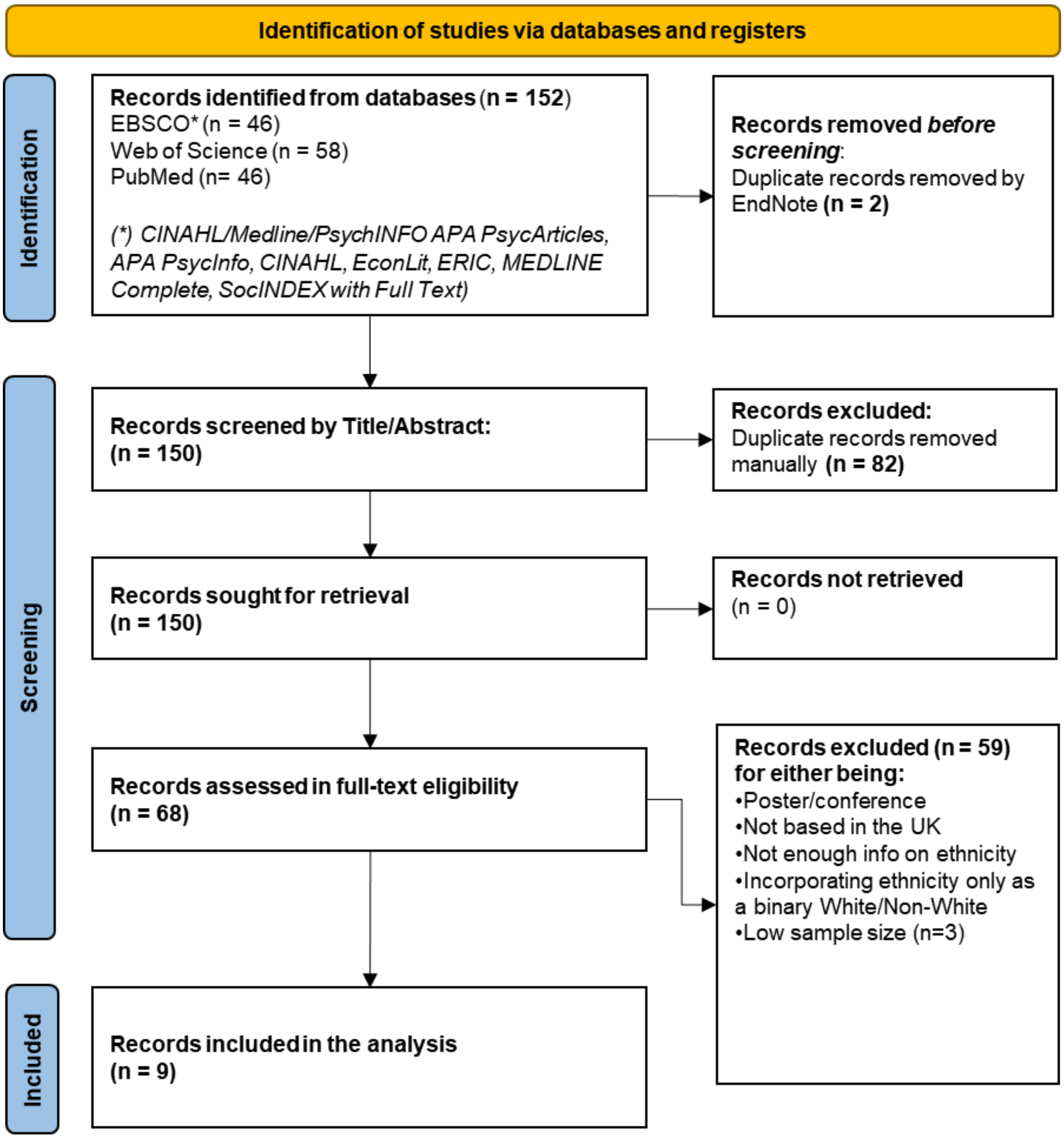
A meta-analysis of results was not feasible due to the heterogeneity of studies in terms of context, main exposure variable, modelling approach, categorisation of ethnic groups, and study design. Therefore, a **narrative synthesis** approach was the most appropriate method. Studies were quite heterogenous in methods and outcome to be grouped by that.

2.3 Results

This section discusses the screening and selection process results, the study characteristics, and the studies' findings.

2.3.1 Results of the screening and selection process

Figure 2.1 shows the screening process towards the final selection of studies. A total of 152 studies were retrieved as potential studies from nine sources: Web of Science, PubMed and EBSCO (APA PsycArticles, APA PsycInfo, CINAHL, EconLit, ERIC, MEDLINE Complete, SocINDEX with Full Text). After removing two duplicates with EndNote, 150 records were screened in title and abstract. Another 82 records were manually removed as duplicates, leaving 150 records for full-text screening. A total of 57 records were excluded for either not being based in the UK, not being quantitative/observational studies, or not focused on mental health. In particular, studies which did not incorporate ethnicity properly to allow estimation by each group were excluded. Also, studies that focused on purely methodological aspects of the validity of instruments, despite being on SF12, SF36, or GHQ, were not included in the final review. Therefore, only nine studies were retained for the final analysis.



From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71. For more information, visit: http://www.prisma-statement.org/

Figure 2.1 Summary of the literature search

2.3.2 Data summary

This section displays a summary of the studies retained for analysis in a tabular manner, organised according to six key: i) aims and research design, ii) participants and settings, iii) data sources and sample sizes, iv) selection of variables, v) approach to statistical modelling, vi) main empirical results, and vii) main limitations. Section 2.3.3 delves into more detail about each of the features.

Table 2.4 Studies characteristics

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
(Abed Al Ahad et al., 2022)	Longitudinal	To investigate the impact of air pollution on mental well-being in the UK using a longitudina	Adults (age: 16+)	United Kingdom	UKHLS: 10 waves (2009–2019)	60,146 adult individuals (age:16+) with 349,748 repeated responses across ten waves (2009–2019)	12-items "General Health Questionnaire (GHQ12)"	Air pollution (concentration of NO_2, SO_2, PM_{10} and $PM_{2.5}$)	Gender, age, country of birth, marital status, educational qualification, occupation, perceived financial situation, cigarette smoking	Four multi-level mixed effect logit models, one per each pollutant	The study found that individuals of Pakistani/Bangladeshi and other ethnicities and those not born in the UK had a higher likelihood of poor mental well-being as the levels of SO_2, PM_{10}, and $PM_{2.5}$ increased compared to British-white natives. However, this was not	First, the exposure bias was reduced, but further improvement could have been achieved by using more detailed data at the postcode level. Second, the frequency of follow-up varied among

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		l design that considers both spatial and temporal differences and assesses the mediator									observed in other ethnic groups. The results indicate that the influence of ethnicity on the relationship between air pollution and mental well-being is unclear.	individuals from wave 1 to wave 10. Third, the use of longitudinal weights was not possible because a balanced panel, which is necessary for their application, is not available in the UK Household Longitudinal Study (UKHLS).

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		effect of ethnicity										
(Bowe, 2017)	Cross-sectional	To compare the internalising mental health symptom levels between	Young people (age: 13-14) residing in England	England (2004-2010)	Longitudinal Study of Young People in England 2004-2010	13,134 young people, of which 753 were first-generation and 3,042 second plus generation	Internalising symptoms measured by GHQ-12	Dummy variable indicating generation (first versus second)	Ethnicity. Other covariates would have been added in a more sophisticated model (SEM) depending on the significance of the ANOVA test.	Independent sample t-test between 1st and 2nd generation	The results showed that first-generation immigrant adolescents had fewer internalizing symptoms compared to their second-generation or later counterparts. However, the difference was statistically significant but small (t(3910) =	The total sample size of the study is over 10,000. However, the sample size for each ethnic group is not large enough to provide adequate statistical power. The study did

Author, year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		first-generation and second-generation or later immigrant adolescents. Additionally, the									3.70, p < 0.001, CI95 = [-0.15, 0.04], Cohen's d = 0.12). Out of 11 immigrant groups, only 7 had a sufficient sample size (i.e. more than 30 individuals in both first and second-generation groups) for parametric comparison. The independent samples t-tests for these seven ethnic groups found no evidence of the	not use additional covariates to control for potential confounding factors.

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		study investigated the moderating effect of ethnicity on the differences in internalising									"immigrant paradox" between first and second-generation adolescents within their respective ethnic groups, except for the Black African group.	

Author, year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		symptoms between these two groups of immigrant adolescents										
(Chum et al., 2022)	Longitudinal	To examine how the effect of neighbourh	Adults (age: 16+)	United Kingdom	UKHLS: 4 waves (1,3,6,9) (2009-2018)	42,866 adult individuals (age:16+)	Mean GHQ score	Neighbourhood cohesion was measured through Buckner's neighbourh	The model includes dummies for fixed effects (individual, year, household,	A fixed-effect modelling approach was employed, which utilises	The results of the fully adjusted model showed that for most ethnic groups, an improvement in neighbourhood	The study's limitations include a small sample size for some ethnic sub-groups,

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		ood cohesion on mental health differs among ethnic groups. The research question						ood cohesion index	and regional), age, sex, marital status, education level, physical health (SF-12 physical component), net household income (£), generation of migration, residential relocation, and the natural logarithm	within-person estimators, allowing each individual to serve as their control.	cohesion was correlated with a corresponding improvement in mental health over time, as evidenced by a reduction in psychological distress, except for the White and Black African mixed group.	broad categorisation of some groups (such as "any other Black"), and reliance on self-reported data for the neighbourhood cohesion variable.

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		was: Does the relationship between neighbourhood cohesion and mental health over time vary							of age. It also controls for regional time-varying confounding factors such as regional ethnic density and regional deprivation measured by mean regional income using the 2009-2018			

Author, year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		by ethnicity?							National Survey for Living Costs and Food.			
(Gagne et al., 2021)	Longitudinal	Analyse psychological distress trends in 16- to 24-year-olds, considering the	Young adults (age: 16-24)	England	UKHLS: 10 waves (2009–2019) and six COVID-19 waves collected between April and November 2020	2009–2010 (n=4,587) 2018–2019 (n=2,333) April–November 2020 (n=2,382)	GHQ mean score	Exposure to covid-19 by exploring changes in the outcome variable across waves	Economic activity and cohabitation with parents as transition variables, and parental education, area deprivation, ethnic group, age and sex	Linear models analysed changes in psychological distress over time for England's 16-24-year-olds. A time dummy estimated changes	It was found that significant differences were present across three variables regarding the changes in psychological distress from 2009–2010 to 2018–2019. A more significant increase was observed in women compared to	COVID-19 waves had limitations that affected the analysis results. Low response rates and a small sample size for young adults made it impossible

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		pandemic's impact. Evaluate personal factors' (employment status, living arrangements, parental								across repeated cross-sectional waves. The models accounted for demographic differences and other variables, and tested interactions between time and variables. The	men, with an average marginal effect of 2.1 for women and 1.3 for men. Additionally, a more significant increase was noted in those aged 16–18 compared to older young adults, with an average marginal effect of 2.6 for the former and 1.2 and 0.9 for the latter two groups, respectively. Furthermore, a	to stratify by sex. Differences in sample composition across waves and missing parental data were potential biases. Exclusion of young adults living without parents resulted in removing more young adults, but

Author, year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		education, area deprivation, ethnicity, age, and gender) influence on these trends during the pandemic.								average marginal effect of time was calculated within variable categories to examine differences in the magnitude of change in GHQ scores across groups over time.	more significant increase was seen in the white UK, white other, and Indian groups, with average marginal effects of 2.0, 2.1, and 1.5, respectively, compared to other ethnic groups, where the average marginal effects ranged from -1.0 to 0.4.	findings were similar when parental education was omitted.

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		Investigate if economic shocks (e.g., job loss or decreased work hours) contribute to disparities										

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		in psychological distress changes in 2020 based on personal factors.										

Author, year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
(Lamb et al., 2021)	Cohort	The study's objectives are to investigate healthcare workers' socio-demographic, occupational, and	UK healthcare workers and ancillary staff (medical professionals, nurses, midwives, support staff, admin staff, management, and students who transitioned into clinical roles	Three South East London NHS Trusts covered both acute and mental health facilities.	The dataset consisted of pooled data from two online baseline surveys. The first online survey was shorter and gathered the GHQ-12-related questions and socio-demographic variables.	4,378 adults	GHQ, in addition to other secondary outcomes	Socio-demographic factors and other covariates	Socio-demographic and occupational factors (age, sex, ethnicity and role)	Binary logistic regression using survey weights	The results showed that black healthcare workers were less likely to exhibit signs of probable depression than their white colleagues. Furthermore, black, Asian, and other minority racial and ethnic groups were found to be less prone to engaging in alcohol misuse compared to white healthcare	Self-reported measures of occupation tend to overestimate the number of individuals who exhibit signs of a mental health disorder, also known as "caseness", and would therefore benefit from

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		mental health features, determine the factors linked to probable common mental disorders as assessed	during the COVID-19 pandemic); (age: the lowest threshold of age was not specified)		Participants were allowed to fill in a more extended version of the questionnaire with additional questions on secondary outcomes.						workers. The study also revealed that doctors were less likely to report symptoms of probable anxiety, depression, and post-traumatic stress disorder (PTSD) than other healthcare workers.	specific interventions.

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		by the General Health Questionnaire (GHQ-12), and explore the factors related to other adverse										

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		mental health outcomes										
(Pierce et al., 2021)	Longitudinal	To determine separate pathways for changes in mental health during the	Adults (age: 16+)	United Kingdom	UKHLS: 5 waves (8, 9, 10 and those from the COVID-19 survey)	19,763	GHQ-12 score	Time	Age, gender, partnered, previous health conditions, neighbour affluence	Latent class mixed models to identify discrete mental health trajectories and fixed-effects regression to identify predictor	The latent class analysis found five different mental health trajectories by October 2020. Most individuals (39.3% and 37.5%) had stable or very good mental health during the first six months of the pandemic. A recovering	Three possible limitations of the model are as follows: 1) the absence of consideration for prior experiences like violence, abuse or health behaviours

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		pandemic, characterise the individuals in each separate pathway, and determine difficulties that								s of change in mental health	group (12.0%) showed a decrease in mental health during the pandemic's initial shock but returned to pre-pandemic levels by October. The remaining two groups (4.1% and 7.0%) had consistently poor mental health, with one group showing an initial worsening that was sustained and the other reporting a steady decline	, 2) the possibility of missing other time-sensitive factors, and 3) no adjustment for seasonal mental health variations.

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		predict a decline in mental health									over time. These two groups were more likely to have pre-existing mental or physical illnesses, live in deprived areas, and be from Asian, Black or mixed ethnic backgrounds.	
(Prady et al., 2013)	Cross-sectional	To assess the association between	Women residing in Bradford (age: not specified)	Bradford, UK	Born in Bradford (BiB) study	12,453 women during 13,776 pregnancies (2007 – 2010)	GHQ-28 scores	Socio-demographic factors and other covariates	Age, employment status, parity, marital status, relation to baby's father,	The study implemented two models: univariate and multivariate logistic regressio	Financial worries were strongly tied to lower mental health for six of the eight groups.	Results suggest that other important factors may explain differences in mental

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		mental health and SES risk-factor by ethnic group and the overall population							country of birth and age at migration	n for each ethnic group and the other for the overall sample		health among ethnic minority groups. Limitations include missing information on mental health diagnoses, potential bias in questionnaire responses, and the cross-sectional design precluding

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
												drawing causal conclusions.
(Shankley & Laurence, 2022)	Longitudinal	To assess the effect of co-ethnic density on common mental health along with	Adults (age: 16+)	United Kingdom	UKHLS: 9 waves (1-9)	52,693	SF12 mental component	Co-ethnic density and segregation	The model considered individual-level factors such as age (with a quadratic component), gender, relationship status, country of residence, national identity, religion, economic	The study had three parts. Part one examined the connection between common mental disorders in ethnic minorities, co-ethnic density, and	The results indicate mixed support for the relationship between co-ethnic density and mental well-being. However, a consistent relationship was found between residential segregation and mental well-being, showing a non-linear effect where	The study found a correlation between segregation, co-ethnic density, and mental health but did not establish causation or investigate specific mechanisms. Mental

Author, year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		segregation							status, housing tenure, year of arrival in the UK, dummies for survey year, and education level. It also included community-level variables such as urban-rural classification and the percentage of	residential segregation at three geographical levels (LSOA, MSOA, and LA) using linear and quadratic associations. Part two explored these processes in nine ethnic minority subgroup	mental well-being was at its highest at medium levels of segregation, somewhat lower at low levels, and lowest at high levels. These findings were observed for the entire sample of ethnic minorities, with a stronger relationship for Black sub-groups than Asian sub-groups. The relationships	health was measured using SF12, but alternative measures could be explored.

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
									people aged 65 and over. Furthermore, the model took into account area density and socioeconomic disadvantage, measured by the percentage of economically active people over 16	s. Part three tested the robustness of observed associations using the survey's longitudinal panel component.	were most pronounced at the meso-local geographic scale of Middle Super Output Areas.	

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
									who were unemployed, the prevalence of female lone-parent households, and the percentage of households socially renting.			
(Wallace et al., 2016)	Longitudinal and cross-sectional	To examine the longitudinal	Adults (age: 16+)	United Kingdom	UKHLS: 4 waves (1,2, 3,4) (2009–2013)	2,902	SF12	Exposure to racial discrimination through a longitudinal variable that	Age, sex, income, education, residential history, employment	The authors implemented longitudinal and cross-sectional	People from ethnic minorities who reported being exposed only once to racial discrimination scored 1.93	First, there is no data on racial discrimination throughout the life course.

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		association between cumulative exposure to racial discriminat ion and changes in the mental health of ethnic						captures self-reported events of racial discriminati on		models through linear regressio n	points lower (95% confidence interval [CI] = -3.31, -0.56) than those without any exposure. In contrast, those who reported 2 or more domains of racial discrimination in 2 or more occasions, scored 8.26 points lower (95% CI = -13.33, -3.18) than those who reported no experiences of	Second, the domain of racial discriminat ion is not an exhaustive list. Third, wave 3 shows a higher level of racial discriminat ion than wave 1, which might indicate a measurem ent error.

Author , year	Research design	Aims, research questions, hypotheses	Participants	Setting	Data sources	Sample sizes	Mental health outcome	Main predictor(s)	Covariates	Statistical model	Main results	Limitations reported by authors
		minority people									racial discrimination. Controlling for racial discrimination and other socioeconomic factors reduced ethnic inequalities in mental health.	

2.3.3 Analysis of results

This section is structured into the six features of the studies retained for analysis: i) aims and research design, ii) participants and settings, iii) data sources and sample sizes, iv) selection of variables, v) approach to statistical modelling, vi) main empirical results, and vii) main limitations.

Aims and research design

As shown in Table 2.4, these studies explore the relationship between mental health and various societal and environmental factors, but their specific aims and populations of interest differ. Some studies focus on environmental stressors such as air pollution, while others examine the effects of personal characteristics and socioeconomic status. Some studies explore the role of ethnicity in mental health, while others investigate the mental health of healthcare workers or the impact of the pandemic on mental health.

Despite these differences, these studies all use some form of research design to analyse data from a specific population, whether longitudinal or cross-sectional. They highlight the importance of understanding the relationship between mental health and various societal and environmental factors, which can have important implications for public health and policy.

Participants and settings

Table 2.4 shows that eight out of nine studies focused on the adult population aged 16+, while other two studies focused on young people: Bowe (2017) focused on young people aged 13-14 residing in the UK while Gagne et al. (2021) on young adults aged 16-24 residing in England only. All studies were in the United Kingdom, as this was one of the inclusion criteria, but three were in specific locations. Bowe (2017) and Gagne et al. (2021) focused on England only, while Prady et al. (2013) focused on Bradford.

Data sources and sample sizes

Table 2.4 shows that most of the studies have used the UKHLS study as the primary source, except for Bowe (2017), who used the LSYPE (2004-2010), Lamb et al. (2021) who administered an online survey, and Prady et al. (2013) who used administrative data.

Selection of variables

Table 2.4 shows that the most prevalent indicator to measure mental well-being is the variants of the General Health Questionnaire (GHQ 12 or GHQ 28). Nevertheless, two studies have used the SF12 indicator (Shankley & Laurence, 2022; Wallace et al., 2016).

Studies aimed to explore the effect of a predictor, decomposing it further by ethnicity or exploring the effect of different social determinants of health by having a dummy for an ethnic group as one of the main covariates. Except for Bowe (2017), all studies have used the main socio-demographic variables (age, gender/sex, place of residence or country of birth). Of the nine studies, five included educational attainment; two included type of occupation, two added employment status, and two also had the parents' socioeconomic background.

Depending on the modelling approach, other dummy variables have been used. Chum et al. (2022) added dummy variables to capture individual, year, household and regional fixed effects in a multi-level analysis. Shankley and Laurence (2022) included individual and community-level variables such as ethnic density, area deprivation and socioeconomic proxies.

Approach to statistical modelling

Table 2.4 shows that all studies have used a regression analysis approach with varying specifications. Abed Al Ahad et al. (2022), Bowe (2017), Lamb et al. (2021), and Shankley and Laurence (2022) use regression analysis to explore the associations between mental health and various social, environmental, and demographic factors. Chum et al. (2022) adopt a fixed-effect modelling approach to estimate within-person effects, while Gagne et al. (2021) use linear models to analyse changes in psychological distress over time. Pierce et al. (2021) use latent class mixed models to identify mental health trajectories. Prady et al. (2013) use univariate and multivariate logistic regression to examine mental health inequalities across ethnic groups. Wallace et al. (2016) employ longitudinal and cross-sectional models to examine the effects of social support and other factors on mental health. Although none of the studies was able to identify a causal effect, some of them aimed to minimise bias from confounding factors.

Main empirical results

The studies present various findings on the factors influencing mental well-being across different ethnic groups, as shown in Table 2.4.

A common pattern that emerged is that mental well-being is affected by multiple factors, such as exposure to air pollution, neighbourhood cohesion, financial worries, exposure to racial discrimination, and the impact of the COVID-19 pandemic.

Regarding ethnicity, some studies found that individuals from certain ethnic groups, such as Pakistani/Bangladeshi and other non-UK-born individuals, are more likely to experience poor mental well-being in the presence of air pollution. Additionally, some studies suggest that there may be differences in mental well-being between first and second-generation immigrants in some ethnic groups but not in others.

Furthermore, the studies suggest that certain ethnic groups, such as Black sub-groups, may be more affected by residential segregation than Asian sub-groups. However, black healthcare workers were found to be less likely to exhibit signs of probable depression than their white colleagues, suggesting complex relationships between ethnicity and mental well-being.

Finally, the studies also highlight the impact of socioeconomic factors, such as financial worries, on mental well-being across different ethnic groups.

Studies' main limitations

Table 2.4 highlights the limitations discussed by the authors. A recurring limitation in several studies is the small sample size for specific sub-groups or ethnic groups. For example, Chum et al. (2022) reported that they had a small sample size for some ethnic sub-groups. Similarly, Gagne et al. (2021) noted that the sample size for young adults was small, and it was impossible to stratify the analysis by sex. Bowe (2017) also reported that the sample size for each ethnic group was not large enough to provide adequate statistical power. This limitation can impact the generalizability and reliability of the findings.

Another limitation is the reliance on self-reported data in some studies. For example, Chum et al. (2022) relied on self-reported data for the neighbourhood cohesion variable. Lamb et al. (2021) reported that self-reported occupation measures tend to overestimate the number of individuals who exhibit signs of a mental health disorder. Self-reported data can be subject to recall bias or social desirability bias, which can limit the validity of the findings.

On the other hand, the specific limitations reported in each study also vary. For instance, Abed Al Ahad et al. (2022) noted that using longitudinal weights was impossible because a balanced panel was unavailable in the UK Household Longitudinal Study. In contrast, Wallace et al. (2016) reported that no data on racial discrimination across the life course is available. These limitations are specific to the research question and type of data analysed. Overall, the common limitations reported in these studies highlight the challenges in conducting research with extensive and diverse datasets.

2.3.4 Risk of bias/quality

This section discusses the quality assessment of studies. Table 2.5 shows the scoring of each study by criteria. The maximum score for a study would be 27. However, none of the studies reached that score. Several studies reviewed here used longitudinal data, a valuable tool for tracking changes over time.

Additionally, most of the studies utilised nationally representative surveys that employed proper sampling methods and achieved high response rates, which helps ensure the validity and generalizability of their findings. However, none of the studies could incorporate an exogeneity of a policy, intervention, or exposure, nor could they exploit differences in outcomes between a target population and a valid comparison group or before and after a policy intervention. These limitations prevent researchers from making causal claims about the relationships they observe. While the overall sample sizes of these studies were generally satisfactory, they were not always sufficient for within-group analysis.

Table 2.5 Quality scores

Criteria	Scores	(Abed Al Ahad et al., 2022)	(Bowe, 2017)	(Chum et al., 2022)		(Lamb et al., 2021)	(Pierce et al., 2021)	(Prady et al., 2013)	(Shankley & Laurence, 2022)	
Unit of analysis	1-Ecological (aggregate data) / 2-Individual data / 3- Longitudinal (panel) data	3	2	3	3	2	3	2	3	3
Comparison approach	1-Cross-sectional / 2-Interrupted time series / 3-Difference in Differences	1	1	1	1	1	1	1	1	1
Sample selection	1- A non-random sample that is not representative / 2-Non random sample that is representative / 3- Nationally recognised survey, based on random sampling	3	3	3	3	2	3	2	3	3

Criteria	Scores	(Abed Al Ahad et al., 2022)	(Bowe, 2017)	(Chum et al., 2022)		(Lamb et al., 2021)	(Pierce et al., 2021)	(Prady et al., 2013)	(Shankley & Laurence, 2022)	
Number of points of data	1-One time point only after the policy start / 2- 3-5 with at least two after policy / 3- > 5-time points with at least two after the policy start	3	1	2	3	1	3	1	3	3
Response/follow-up bias	1- Response/follow-up rate <60% or non-reported, not weighted for non-response/loss of follow-up / 2- Response & follow-up rate 60-80%, data weighted for non-response/loss to follow-up / 3- Response & follow-up rate >80%	3	3	3	3	1	3	1	3	3

Criteria	Scores	(Abed Al Ahad et al., 2022)	(Bowe, 2017)	(Chum et al., 2022)		(Lamb et al., 2021)	(Pierce et al., 2021)	(Prady et al., 2013)	(Shankley & Laurence, 2022)	
Exogeneity of policy exposure	1- Policy variation relates to targeting/uptake/differential adoption of policy – likely to be associated with outcomes. E.g. targeting areas with poor initial outcomes / 2- Policy variation depends on administrative decisions unlikely to be associated with outcomes (e.g. different jurisdictions) / 3- Policy variation is as good as random, un-targeted roll-out/ arbitrary eligibility criteria	1	1	2	2	1	1	0	2	1

Criteria	Scores	(Abed Al Ahad et al., 2022)	(Bowe, 2017)	(Chum et al., 2022)		(Lamb et al., 2021)	(Pierce et al., 2021)	(Prady et al., 2013)	(Shankley & Laurence, 2022)	
Confounding	1-missing >2 confounders / 2-Missing 1-2 confounders / 3- All significant confounders included in the analysis	2	1	3	2	2	2	2	3	3
Sample size/power	1- No power calculations – sample size <100 / 2- No power calculations – sample size 100-500 / 3- Priori sample size calculations performed/large sample size, >500 observations	3	3	3	3	3	3	3	3	3
Analysis	1.-Both an inappropriate statistical technique was used, and the sample was small / 2-Either an inappropriate statistical technique was used or	3	1	3	3	3	3	3	3	3

Criteria	Scores	(Abed Al Ahad et al., 2022)	(Bowe, 2017)	(Chum et al., 2022)		(Lamb et al., 2021)	(Pierce et al., 2021)	(Prady et al., 2013)	(Shankley & Laurence, 2022)	
	the sample size was small. / 3- large sample size and an appropriate statistical technique was used									
Total score		**22**	**16**	**23**	**23**	**16**	**22**	**15**	**24**	**23**

2.4 Discussion

This systematic review explored the relationship between ethnicity and mental health in the UK, considering variation by ethnic group, moderation/mediation effects, and compound effects of ethnicity with other social determinants. This review's scope of mental health was limited to health-related quality-of-life measures such as SF12, SF36 and GHQ. The inclusion/exclusion criteria aimed to retain observational studies to explain mental health in the UK context published in the last ten years, including ethnicity as a main predictor, covariate or stratifying variable. In particular, studies that only included ethnicity as a binary variable (Black versus White) or adjustment were excluded. Nine observational studies were retained for final review. Methodologically, most studies adopted a longitudinal approach using the UKHLS data and cross-sectional analysis based on ad-hoc survey studies. None of them was able to identify causal effects. The results of this review provide important insights into ethnic mental health inequities.

2.4.1 Key findings

The nine studies reviewed show a complex relationship between ethnicity and mental health. The relationship is not straightforward and can be positive or negative depending on the setting, sample, and social determinants incorporated in the analysis. These findings are consistent with Mirza and Warwick (2022), who illustrate that socio-economic inequalities among ethnic groups seem clear and associated with economic participation, employment rates, income, academic achievements, housing, geographic location, deprivation levels, racial discrimination, citizenship, and the right to citizenship.

There are two prominent findings. First, the effect of ethnicity on mental health seems to be considerably mediated by other social determinants of health, such as housing, education, and employment. Second, the role of ethnicity varies across different ethnic minority subgroups.

Regarding social determinants mediating the effect of ethnicity and mental health, while some could be modifiable through policy interventions, others are cultural or behavioural aspects outside the scope of policy intervention. Some of these factors seem to protect, while others may worsen the ethnic gradient of mental health. For example, Abed Al Ahad et al. (2022) have shown that after controlling for the socio-economic position, the effect of air pollution on mental health was not moderated by ethnicity, though this varied by ethnic group. This result is in line with similar research, which found that, after adjusting for socioeconomic position, the impact of ethnicity on health may not be as strong. Minority groups often tend to reside in disadvantaged urban areas with higher exposure to factories, vehicles, and fossil fuel burning (Cézard et al., 2022; Egede, 2006; Su et al., 2011). Thus, unequal access to housing, education and the labour market, deprived neighbourhoods, and segregation of ethnic minorities could mediate –and worsen– the effect on mental health (Nazroo, 2022a).

In contrast, other social determinants could protect ethnic minority groups from adverse events. For example, Lamb et al. (2021) found that among NHS workers in London, ethnic minorities outperformed the White majority during COVID-19 regarding mental health. Black healthcare workers were less likely to suffer from depression than their White peers, and ethnic minorities were less likely to engage in alcohol misuse than the White majority. One possible explanation is the protective factor of religious identity and participation among ethnic minority groups. Not subject to policy intervention, this social determinant could probably enhance mental health, including associated behaviours such as avoiding alcohol (King et al., 2013). The protective effect of social cohesion and co-density discussed by Chum et al. (2022) and Shankley and Laurence (2022) align with other research too. Nazroo (2022a) stresses that while residing in deprived areas can negatively impact health, the concentration of ethnic minority individuals in areas with others of similar ethnicity can have a positive effect, as evidenced by Bécares et al. (2009). Feelings of security, including lower exposure to racial harassment and discrimination and greater social support, can contribute to enhanced mental health. Indeed, some studies indicate that ethnic minority individuals rate their neighbourhoods more positively than official measures of deprivation would suggest, primarily because these areas foster a sense of inclusive community for individuals like them, as indicated by research conducted by Bajekal et al. (2004) and Becares and Nazroo (2015).

The impact of social determinants on mental health may differ among ethnic groups based on pre-existing conditions. If an ethnic group is already disadvantaged regarding social status, they may encounter additional obstacles when adverse events affect the entire population. In such scenarios, the disadvantaged group already lagging may suffer even more significant disparities. In a longitudinal analysis, Pierce et al. (2021) showed that Asian, Black and Mixed groups, who tended to live in deprived areas and struggled financially before COVID-19, underperformed in mental health during and after the pandemic than the White majority. Such inequities widen during challenging contexts, contributing to pervasive and persistent disparities.

Regarding the compound and multiplicative effect of social determinants, none of the studies has explicitly aimed to assess the compound effect of ethnicity and other social determinants such as sex, gender, religious identity and practice. There was no explicit or implicit intersectional gaze in the empirical strategy. Intersectionality is a theoretical framework that claims that multiple factors, such as race, gender, sexuality, class, and ability, shape people's identities and experiences, and these factors interact in complex ways. Intersectionality recognises that no single factor determines people's experiences of discrimination and privilege but a combination of many. This approach emphasises the unique and overlapping forms of oppression and discrimination that communities may face and recognises human experiences' diversity and complexity. Despite lacking an intersectional approach, some studies stratified the analysis by demographic variables, evidencing potential interlocking effects. For example, Bowe (2017)analysed the effect of migrant generation on mental health by ethnicity and found that the Black and second-generation group was particularly affected. Likewise, the latent class analysis by Pierce et al. (2021) showed that ethnic minority and social deprivation compounded to impact mental health trajectories.

The role of racism in understanding ethnic mental health inequities

The findings from the reviewed studies suggest a complex interplay between ethnicity, social determinants of health, and mental health outcomes. While the research does not directly attribute these disparities to racism, it raises crucial questions about the underlying structures and systems that contribute to these inequities. The consistent differences observed across various social determinants such as housing, education, and employment among ethnic minority groups may point to broader systemic issues. These disparities, which in turn influence mental health outcomes, could potentially be indicative of long-standing structural imbalances in society. However, it is essential to note that the relationship between these factors and racism is not definitively established in the reviewed literature. Further research is needed to explore the extent to which historical and contemporary forms of systemic racism may contribute to the observed inequities in social determinants and, consequently, to ethnic mental health disparities. This cautious interpretation acknowledges the potential role of systemic factors while recognizing the need for more targeted studies to establish direct causal links.

From a decolonial perspective, racism is a global hierarchy that enforces human superiority and inferiority, rooted in centuries of political, cultural, and economic dominance by a capitalist, patriarchal, Western, and Christian-centric world system (Grosfoguel, 2007). Moreover, racism is rooted in historical systems of domination that marginalize groups based on physical, cultural, or symbolic characteristics, creating a racialized social hierarchy. Racism operates through three interlinked processes: structural racism, interpersonal racism, and institutional racism (Nazroo et al., 2020). Firstly, structural racism appears in the unequal access to economic, physical, and social resources. This inequality is material and has cultural and ideological implications; the devaluation of racial or ethnic minority identities justifies this disparity. Secondly, interpersonal racism takes many forms, from subtle insults to discrimination and physical aggression. This kind of racism causes harm and emphasises the low status of the targeted individual and others with similar racial identities, causing significant psychological and social stress. Finally, institutional racism is evident in standard policies and procedures that result in negative experiences for members of racialized groups within these institutions. These cumulative disadvantages over a lifetime could contribute to ethnic health disparities (Nazroo, 2022a).

The findings on the role of different manifestations of racism in shaping ethnic mental health inequities suggest that some social determinants of health are within the scope of policy intervention that could be used as levers for change. Also, the interaction of these determinants is far from simple and requires further research to disentangle the pathways.

2.4.2 Limitations

A limitation of this review is the lack of causal identification of ethnicity on mental health across all studies. Despite the observational nature of these studies, none of them attempted or were able to apply a quasi-experimental approach. More in-depth research would have been needed to understand whether such approaches were entirely feasible, but this was out of the scope of this review. Another limitation of the study might be the exclusion of studies earlier than 2013. However, even if a relevant study had been conducted back then, the external validity of findings might be less, considering the evolving context.

2.4.3 Implications for practice, policy, and future research

The impact of COVID-19 has revealed pre-existing ethnic inequities in the UK, which might have worsened, and if they remained unaddressed, these could become pervasive and persistent (Becares et al., 2022). More research is needed on the pathways of ethnicity to inequity in mental health and focused on those social determinants within the policy intervention scope.

3 Chapter III: The effect of education on mental health among ethnic minorities in the UK – a Regression Discontinuity Design

3.1 Introduction

The relationship between education and health has long been intensely scrutinised in public health and health economics. While numerous studies have demonstrated a strong correlation between educational attainment and various health outcomes, the causal nature of this relationship remains a topic of ongoing debate and investigation. This is particularly true when considering mental health outcomes and specific population subgroups, such as ethnic minorities.

The question at stake

This study seeks to answer the central question: *Does increased educational attainment causally improve long-term mental health outcomes among ethnic minorities in the UK?* This question is compelling and significant for several reasons:

1. Addressing a Critical Knowledge Gap: While the education-health relationship has been extensively studied in general populations, there is a striking lack of evidence regarding its causal effects on mental health within ethnic minority communities in the UK. This gap is particularly concerning given the well-documented health inequites these populations face.
2. Policy Relevance: Understanding the causal impact of education on mental health in minority communities can inform targeted educational and public health interventions. If a positive causal relationship is established, it could provide a strong

rationale for investing in educational programs to improve long-term mental health outcomes in these populations.

3. Methodological Innovation: By applying advanced Regression Discontinuity Design (RDD) techniques to a natural experiment (the 1972 Raising of the School Leaving Age), this study offers a methodologically robust approach to estimating causal effects, even with limited sample sizes. This approach can serve as a model for future research in similar contexts.
4. Intersectionality of Education, Mental Health, and Ethnicity: Exploring how the education-mental health relationship may vary by ethnicity and sex within minority communities provides insight into the complex interplay of these factors, contributing to a more nuanced understanding of health disparities.

Research context and contribution

Numerous studies have shown a strong correlation between education and health. The relationship between the two is multifaceted, with different pathways at play. Despite its complexity, common predictive factors influence education and health, making it difficult to establish a clear cause-and-effect relationship. Researchers have been dedicated to unravelling this connection for many years, aiming to comprehend better how education and health influence each other.

Research examining the potential causal connection between education and health in the UK and other countries has centred mainly on leveraging changes in compulsory schooling regulations to discern the impact of higher educational attainment on health outcomes, including mortality rates (Clark & Royer, 2010; Clark & Royer, 2013), body size, lung functioning and blood pressure (Barcellos et al., 2018, 2023), and cognitive abilities (Banks & Mazzonna, 2012). Studies like those conducted in the UK context by Davies et al. (2018), Janke et al. (2020), Avendano et al. (2020) and Amin et al. (2023) showed mixed results, potentially influenced by factors such as the specific health metrics employed and differing directions of effect observed. While physical health implications have received more attention, the influence of education on mental health, especially among those with limited educational backgrounds, has been relatively underexplored. In the UK context, Avendano et al. (2020) is the only study examining the impact of ROSLA on mental health (SF-12 and GHQ) in the overall population using three datasets –UKHLS, Annual Population Survey, and the Biobank.

Considering the limited extent of evidence that investigates the causal connection between education and mental health in the UK, this gap becomes even more pronounced when examining this effect within ethnic minorities. No study has been conducted to explore such a link within this sub-population in the UK, as confirmed by the systematic literature review results in Chapter 2 (section 2).

Therefore, this study makes two valuable contributions:

1. It focuses on the effects of the 1972 Raising of the School Leaving Age (ROSLA) on mental health among ethnic minorities.
2. It leverages contemporary theoretical advancements in implementing and interpreting Regression Discontinuity Design (RDD) as a local randomised experiment (Cattaneo et al., 2015; Sekhon & Titiunik, 2017), offering a methodologically robust approach even with limited sample sizes.

3.2 Literature review

3.2.1 Evidence of the causal link between education in general and mental health

The positive correlation between education and health status across all age groups is well-documented in health economics. Various potential explanations exist for the role of education in promoting better health. Numerous models suggest a positive association between education and health due to shared factors—observed and unobserved—influencing educational attainment and health outcomes, such as parental socio-economic position, genetic abilities, time preferences, and risk preferences (Gehrsitza & Williams Jr, 2022). Grossman's (1972) canonical demand for a health model is renowned for its successful prediction regarding the education-health gradient. According to this model, education plays a significant role in determining people's health by influencing the effectiveness of health investments. People with higher education levels tend to achieve a higher health stock for each unit of health investment. This investment may encompass factors that enhance optimal health, such as adopting a better diet or accessing more advanced medical care (Grossman, 1972). Hence, the model identifies two ways education can directly impact health. Firstly, education can enhance individuals' knowledge of the relationship between health behaviours and outcomes, enabling them to make better choices regarding health inputs. Secondly, schooling can increase the productivity of health inputs, resulting in improved health outcomes. Education's influence on health can also be mediated by its impact on labour market outcomes, as higher income levels can make healthy goods more accessible. Additionally, individuals with higher education may benefit from a safer work environment (Cutler & Lleras-Muney, 2010) and have healthier and more educated peers (Gaviria & Raphael, 2001).

The Grossman model has spurred the emergence of extensive empirical literature to test its hypotheses (Cutler & Lleras-Muney, 2012; Grossman, 2006; Kaestner & Grossman, 2009). However, this research has brought numerous challenges in estimating the causal link between education and health. These challenges include endogenous time preferences (Fuchs, 1980), reverse causality (Case et al., 2005; Cornaglia et al., 2015; Currie & Stabile, 2006), simultaneity (Behrman et al., 2011), and omitted variable bias (Grossman, 2015). Researchers have grappled with the intricate nature of these issues, recognising their potential to confound the relationship between education and health outcomes. Consequently, careful consideration and innovative methodologies are necessary to address these challenges and advance our understanding of the complex interplay between education and health.

To overcome identification challenges, researchers have increasingly turned to compulsory schooling reforms to obtain causal evidence on the effects of education on health outcomes (Adams, 2002; Albouy & Lequien, 2009; Barcellos et al., 2018; Black et al., 2008; Chou et al., 2010; Clark & Royer, 2010; Clark & Royer, 2013; Davies et al., 2018; Lleras-Muney, 2005; Mazumder, 2008; McCrary & Royer, 2011; Meghir et al., 2018; Oreopoulos, 2006; Van Kippersluis et al., 2011; Wilson, 2017). Nevertheless, even studies employing similar identification strategies and research settings show divergent conclusions regarding the effects of education on health. For instance, when examining the raising of the school leaving age (ROSLA) reforms in the United Kingdom, which resulted in nearly half of the population receiving an additional year of education, some studies find no significant impact on self-reported health. In contrast, other research reveals improvements in specific lifestyle outcomes, such as diabetes and obesity (Barcellos et al., 2018, 2023; Davies et al., 2018). These discrepancies highlight the complexity of the relationship between education and health and the need for further investigation.

Prior research has presented conflicting outcomes regarding the relationship between education and mental health, specifically focusing on compulsory schooling adjustments. European-based investigations by Crespo et al. (2014) and Mazzonna (2014) report the beneficial impacts of extended schooling years on mental health. In contrast, Lager et al. (2017) observe detrimental effects on emotional control during military conscription in Sweden following an increased minimum school leaving age, attributing this to potential negative school environment alterations. Similarly, findings from Dursun and Cesur (2016) concerning Turkey reveal that a three-year compulsory schooling extension leads to reduced life satisfaction in men despite elevated earnings. Furthermore, the study conducted by

Courtin et al. (2019) examines a 1959 two-year prolongation of mandatory schooling in France. It establishes a link between extended education and heightened depressive symptoms among women. Discrepancies in these findings may arise from variations in mental health measures, diverse effects across countries and reforms, and the lack of exploration of underlying mechanisms linking compulsory schooling and mental health.

Consequently, given the mixed evidence, establishing causality in the education-health relationship remains a focal point of research.

3.2.1.1 The 1972 ROSLA

This chapter employs a regression discontinuity (RD) design to assess the enduring impact of the 1972 ROSLA on mental health. This legislation, implemented in Great Britain, extended the mandatory schooling period by one year. The choice of RD design is well-suited for examining the consequences of this policy shift, which led to a sudden and significant increase in the proportion of students taking secondary school exams (Clark & Royer, 2013).

The 1972 ROSLA has a lengthy background, originating from the 1944 Education Act. This act raised the minimum age for leaving school from 14 to 15 and made provisions for a further increase to 16 at the discretion of the Minister of Education. In 1964, the government announced its intention to raise the school leaving age to 16, scheduled for September 1970. However, there was a delay of two years, and the school leaving age was ultimately raised to 16 in 1972 through Statutory Instrument 444 in England and Wales, taking effect on the 1st of September, 1972. According to the new regulation, individuals born on or after the 1st of September, 1957, were required to remain in school until the end of the academic year in which they turned 16. In Great Britain, adherence to the minimum school leaving age was nearly universal, with a strong correspondence between age and grade, resulting in very few students being placed in a grade different from the one suggested by their birth month and year. The first cohort affected by this change was born between the 1st of September, 1957, and the 31st of August, 1958.

The 1972 ROSLA offers a compelling context for examining the influence of mandatory schooling on mental health. It extended the duration of compulsory education beyond what most European reforms in the 1950s and 1960s achieved. Additionally, it impacted a significant proportion of the cohort since approximately a quarter of the school cohort left school at age 15 during that time. In the early 1970s, young individuals faced no difficulties entering the labour market, leading many to decide against continuing their education beyond the minimum leaving age. Consequently, the opportunity cost of an additional year of schooling may have been high for some affected students.

3.2.2 Aims and research questions

This study aims to estimate the causal effect of an additional year of schooling on long-term mental health within ethnic minorities in the UK, exploiting the ROSLA policy as a natural experiment by focusing on two key research questions:

1. **What is the causal effect of an additional year of schooling on long-term mental health measured by SF12 and GHQ among ethnic minorities in the UK?**
2. **Does the effect of an additional year of schooling on long-term mental health among ethnic minorities in the UK vary by sex?**

3.3 Methods

This study applies a quasi-experimental design approach to estimate the causal effect of schooling on long-term mental health among ethnic minorities in the UK by exploiting a policy as an exogenous event, mimicking a natural experiment. This policy is the raising of the school living age (ROSLA) of 1972.

3.3.1 The UK Household Longitudinal Study (UKHLS)

All the empirical chapters of this research use data from the latest twelve waves of the UKHLS, using the ethnicity booster in the survey. The UK Household Longitudinal Study (UKHLS), or Understanding Society, is a household panel study managed by the Institute for Social and Economic Research (ISER) at the University of Essex. This study gathers longitudinal data by conducting interviews with all household members aged over ten over an extended period. It encompasses all four UK countries and diverse economic, social, and behavioural variables. Understanding society builds upon the British Household Panel (BHPS), conducted from 1991 to 2009 and consisted of 10,000 households. Since its inception in 2009, Understanding Society has expanded to include 40,000 households, incorporating 8,000 previous BHPS households. This integration of the BHPS sample enables researchers to access data dating back to 1991.

The samples in UKHLS

The UK Household Longitudinal Study (UKHLS), also known as Understanding Society, comprises several distinct sample groups: the General Population Sample (GP), the former BHPS sample, **the Ethnic Minority Boost Sample (EMBS)**, and the Immigrant and Ethnic Minority Boost Sample (IEMBS). The General Population Sample (GPS) is further divided into two subsets, one for Great Britain and the other for Northern Ireland. The sampling methods differ for these subsets, with the Great Britain sample being proportionately stratified and clustered. In contrast, the Northern Ireland sample is unclustered and selected using a systematic random approach. The fieldwork duration for the Great Britain sample is 24 months, while for Northern Ireland, it spans 12 months. The initial wave of the GPS involved approximately 26,000 households. The former BHPS sample was integrated into the UKHLS during Wave 2 in 2010 (McFall et al., 2021). The **Ethnic Minority Boost Sample** (EMBS) starts in Wave 1 (2009-2010) of the UKHLS with approximately 4,000 households. The **Immigrant**

and Ethnic Minority Boost Sample (IEMBS) sample was incorporated in the second year of Wave 6 (2015), comprising approximately 2,500 households (McFall et al., 2021). Figure 3.1 depicts the timeline of the UKHLS and the former BHPS.

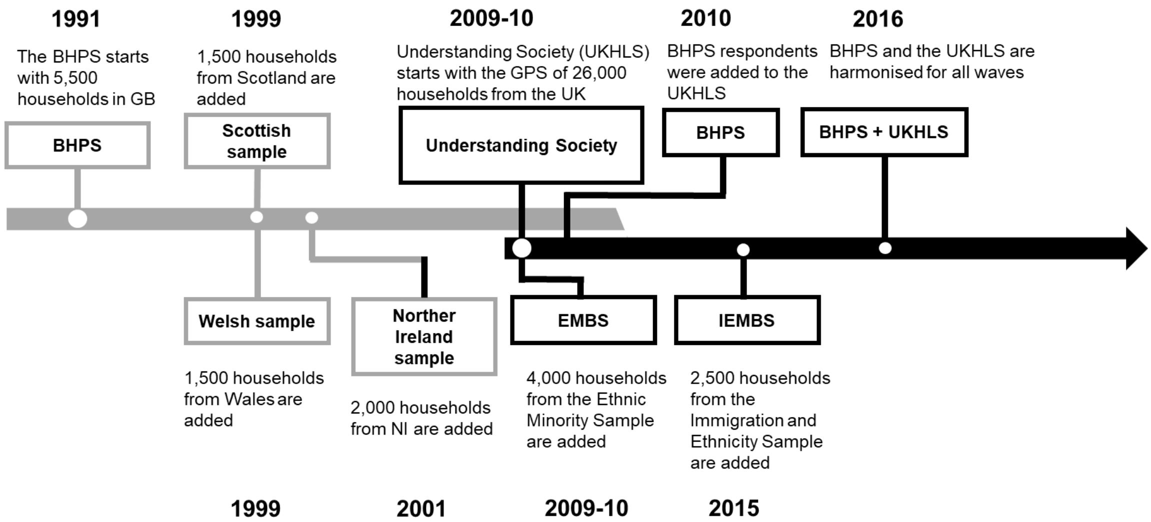


Figure 3.1 Timeline of BHPS and UKHLS
Source: Adapted (Lynn, 2009; McFall et al., 2021)

In addition, UKHLS is very important for this RDD analysis and identification strategy to have data on month and year of birth. These variables enable us to identify individuals exposed to the ROSLA accurately. The survey also features variables related to schooling, such as "school leaving age" and "age left further education." By using these variables, it is possible to construct an education leaving age that corresponds to the total years of education completed (Clark & Royer, 2013).

3.3.2 Concepts and measures

This section explains how all measures were operationalised in this study.

Mental health outcomes (SF-12 and GHQ-Likert)

This chapter used the SF-12 and GHQ-Likert indicators to capture the common mental disorders and quality of life. Their properties and the corresponding literature are discussed in detail in section 1.3.1 above. The unweighted sample average of SF-12 is 49.06, and weighted is 48.26. The second health outcome used in this chapter is the General Health Questionnaire (GHQ). The unweighted sample average of the GHQ-Likert is 11.18, and the weighted is 11.35.

Age and date of birth. Age is a variable derived from birth and measured in completed years at the interview. This variable is also used to derive five and 10-year intervals. The youngest individual in the sample is 16, and the oldest is 103. Month and year of birth were combined to create a variable month-year of birth, which was used as the running variable for the RD design.

Sex. This is a derived variable and is checked across waves. It takes 1 for males if all the information in the survey suggests so and 2 for females. The variable would take 0 if there were any inconsistencies in the available information and the forename in the administration database did not suggest a specific gender. The number of inconsistencies is relatively low. In waves 1 to 12, there are at most two individuals with a value equal to 0. These were coded as missing in the analytical sample.

Ethnicity. Ethnicity is available in the UKHLS through two different variables[1]. One is self-reported, while the other is derived from different sources. This study has adopted the derived version for validation. In the UKHLS, ethnicity is recorded for 17 distinct groups, but this study has regrouped them into five larger groups following the ONS classification used in the literature on health inequities in the UK, such as in the 2020 Marmot Review (Marmot, 2020).

Table 3.1 Categorisation of ethnicity groups in the survey sample

Ethnicity groups according to ONS classification	Ethnicity groups in the UKHLS
White	• British / English / Scottish / Welsh / Northern Irish • Irish

[1] racel_dv (self-reported) and ethn_dv (derived)

Ethnicity groups according to ONS classification	Ethnicity groups in the UKHLS
	• Any other white background
Mixed	• White and Black Caribbean • White and Black African • White and Asian • Any other mixed background
Asian	• Indian • Pakistani • Bangladeshi • Chinese • Any other Asian background
Black	• Caribbean • African • Any other Black background
Other minority	• Arab • Gypsy or Irish traveller • Any other ethnic group

Born in the UK and immigration status. This binary variable takes 1 if a respondent was born in the UK, and 0 otherwise. This study uses the variable derived from multiple sources rather than the self-reported.

Age of leaving full-time education. There is a variable that captures the age respondents left full-time education. Some outliers were identified and recoded as missing following the literature (Avendano et al., 2020).

Identification of ethnic minorities affected by the policy. The existing research examining the impact of ROSLA in the UK has largely overlooked the effects on ethnic minorities. This omission may be attributed to a lack of interest in health inequalities among ethnic minorities, as discussed in the previous chapter, as well as the issue of small sample sizes. Notably, the proportion of the non-white population tends to increase in younger age groups, potentially partly due to significant migration from former colonies during the 1970s (Myers, 2009). However, it is important to emphasise that ethnic minorities were already a part of the UK community at the time of the 1972 reform.

Consequently, one crucial step in the empirical estimation process was identifying the specific ethnic minority groups impacted by the policy. This group would correspond to ethnic minorities enrolled in the UK education system when the reform occurred. Working with this dataset posed a challenge due to the absence of an appropriate variable to identify this group. Thus, it became necessary to combine different variables for analysis.

The strategy consisted of identifying ethnic minority participants who were either born in England or arrived in England at the age of 14 or younger. To provide context and illustrate the identification process, we present data for both white and non-white populations in Table 3.2 and Table 3.3. This comparison allows us to:

1. Demonstrate the relative sizes of white and non-white populations in the dataset.
2. Highlight the specific subgroup of non-white individuals who were likely affected by the ROSLA policy.
3. Provide transparency in our sample selection process.

Table 3.2 shows 1,592 observations for people born outside the UK arriving in England at the age of 14 or younger, and Table 3.3 shows 7,905 observations for ethnic minorities who were born in England. Therefore, the sample for this chapter comprises 9,497 observations, representing responses collected from 8,304 unique respondents throughout the study.

Table 3.2 Breakdown of ethnicity by the age of arrival in England

Age of arrival in England	**Ethnicity**		**Total**
	White	**Non-white**	
Arrived at 15 or older	1,904	4,947	6,851
Arrived younger than 15	925	**1,592**	2,517
Total	2,829	6,539	9,368

Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

Table 3.3 Country of birth by ethnicity

Country of birth	Ethnicity		Total
	White	Non-white	
England	45,543	**7,905**	53,448
Scotland	5,460	90	5,550
Wales	3,528	89	3,617
Northern Ireland	3,280	13	3,293
Outside the UK	4,640	13,103	17,743
Total	62,451	21,200	83,651

Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

By presenting data for both white and non-white populations, we can clearly illustrate how we derived our study sample of ethnic minorities affected by the ROSLA policy.

3.3.3 Analytical sample

The present study's dataset comprised 431,803 and 432,201 valid responses for the SF-12 and GHQ questionnaires, respectively (University of Essex & Institute for Social and Economic Research, 2023). The analytical sample was derived from the final 12 waves of the UK Household Longitudinal Study (UKHLS) to leverage the ethnicity booster. Subsequently, earlier waves from the British Household Panel Survey (BHPS) were omitted from the empirical strategy due to the limited representation of ethnic minority groups in those samples.

Table 3.4 and. shows the valid answers for the outcome variables across waves within the restricted sample of ethnic minorities affected by the ROSLA policy. **This restricted sample, as discussed above, is made of non-white respondents born in England and non-white respondents who arrived in the UK at the age of 14 or younger**.

Table 3.4 Number of non-missing observations with valid answers for SF-12

Years	Wave	Restricted sample	Overall sample

2009-10	1	2,992	47,400
2010-11	2	235	39,888
2011-12	3	243	40,586
2012-13	4	239	39,236
2013-14	5	187	37,130
2014-15	6	169	35,197
2015-16	7	886	36,996
2016-17	8	260	35,295
2017-18	9	649	32,218
2018-19	10	156	30,926
2020-21	11	152	29,379
2021-22	12	115	27,552
Total		**6,283**	**431,803**

Note: the restricted sample size for this variable is smaller than 8,304 because there are 2,021 missing answers. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

Table 3.5 Number of non-missing observations with valid answers for GHQ

Years	Wave	Restricted sample	Overall sample
2009-10	1	2,293	39,700
2010-11	2	256	43,414
2011-12	3	242	40,576
2012-13	4	222	38,781
2013-14	5	188	37,133
2014-15	6	1,436	38,865
2015-16	7	893	37,175
2016-17	8	262	35,472
2017-18	9	658	32,440
2018-19	10	159	31,222
2020-21	11	154	29,688
2021-22	12	115	27,735
Total		**6,878**	**432,201**

Note: the sample size of the restricted sample for this variable is smaller than 8,304 because there are 1,426 missing answers. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

Table 3.6 Descriptive statistics for the restricted sample born within 100 months of the ROSLA cut-off date (1949-1965)

Variable	Pre-ROSLA	Post-ROSLA	All
SF-12	48.43	47.95	48.08
GHQ	11.89	11.9	11.9

Age	59.84	50.32	52.87
Female	0.49	0.51	0.5
Age left FT education	14.01	16.07	15.52
Born in England	0.33	0.67	0.58
Have a degree	0.23	0.24	0.23
Have other HE degree	0.12	0.15	0.14
Have A level	0.13	0.19	0.17
Have GCSE	0.18	0.21	0.2
Have other qualification	0.17	0.11	0.13
Does not have any qualification	0.17	0.11	0.12
N	273	748	1,021

Note: the cut-off date of birth of the ROSLA is September 1957. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

Table 3.7 Descriptive statistics for the restricted sample born within 40 months of the ROSLA cut-off date (1954-1960)

Variable	**Pre-ROSLA**	**Post-ROSLA**	**Restricted sample**
SF-12	47.74	49.04	48.56
GHQ	13.1	11.47	12.08
Age	58.09	54.06	55.63
Female	0.53	0.54	0.54
Age left FT education	14.06	16.03	15.26
Born in England	0.36	0.5	0.44
Have a degree	0.22	0.19	0.20
Have other HE degree	0.07	0.16	0.12
Have A level	0.16	0.25	0.21
Have GCSE	0.24	0.2	0.22
Have other qualification	0.16	0.1	0.12
Does not have any qualification	0.15	0.1	0.12
N	150	235	385

Note: the cut-off date of birth of the ROSLA is September 1957. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

3.3.4 Empirical strategy

The introduction of this section commences with a presentation of a causal diagram illustrating the policy under examination. Subsequently, it delves into a comprehensive exploration of the fundamental aspects of an RD design, encompassing the local randomisation approach and the distinction between fuzzy and sharp designs.

3.3.4.1 The causal diagram of ROSLA

Figure 3.2 presents this study's dynamic acyclic graph (DAG) following a fuzzy RD design. The aim is to estimate the causal impact of education – defined as years of schooling in the current study – on mental health, as attempted in the literature (Avendano et al., 2020; Davies et al., 2018; Janke et al., 2020; Mazzonna, 2014). The issue is that education is an endogenous variable because other confounding factors affect both education and mental health. However, the introduction of ROSLA has provided an opportunity of a natural experiment.

This policy affected those who were born in September 1957 or after while left those born earlier as a potential valid counterfactual, provided we use those subjects around the cut-off. This is depicted in Figure 3.2 where the cut-off date of birth acts as an instrument (Z) for the endogenous variable staying in full-time education until 16 or later (D). This method is able to control for observable and unobservable confounding factors (Huntington-Klein, 2021).

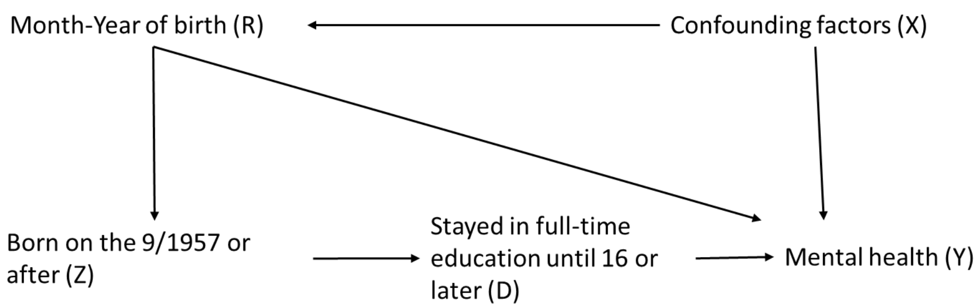


Figure 3.2 A causal diagram of a Fuzzy RD design

Note: Following the RDD terminology, R is the running variable, Z is the instrument, D is the endogenous regressor or treatment variable, X is(are) the confounding factor(s), and Y is the outcome of interest. Note that the arrow connecting R and Y exists solely within a fuzzy RD design, whereas it is absent in a sharp RD design. Source: Adapted from Huntington-Klein (2021)

3.3.4.2 The Regression Discontinuity Design (RDD): An Increasingly Popular Research Approach for Estimating Causal Effects

The regression discontinuity design (RDD) is a research approach that has gained significant popularity recently due to its robust framework for causal inference. In RDD, treatment assignment is based on a known rule, where units with a score above a cut-off receive treatment, while those below do not (Figure 3.2). This design is particularly valuable when randomised treatment assignment is not feasible.

Initially introduced by Thistlethwaite and Campbell (1960), RDD's recent surge in popularity can be attributed to the seminal work of Hahn et al. (2001), who established conditions for nonparametric identification of average treatment effects. Interpretating RDD as a local experiment, as proposed by Lee (2008), has further enhanced its appeal, allowing treatment status to be considered as good as randomised in a local neighbourhood of the cut-off. The increasing popularity of RDD has led to the development of sophisticated methodological tools for estimating and interpreting RDD effects. These advancements have provided researchers with a more intuitive interpretation of the RDD parameter, enabling them to think about treatment and control groups rather than a single point where no observations exist (Sekhon & Titiunik, 2017).

Thus, RDD offers several critical advantages over other quasi-experimental approaches, such as matching methods:

1. **Strong Causal Inference**: RDD exploits exogenous variation created by the treatment assignment rule, enabling causal estimates even in the presence of unobserved confounders. This is in contrast to matching methods, which rely on the assumption of selection on observables (Cattaneo et al., 2015; Cattaneo et al., 2016; Cattaneo et al., 2017; Vazquez-Bare et al., 2016).
2. **Local Randomisation**: Near the cut-off, the treatment assignment can be considered as good as random, mimicking a randomised controlled trial and providing strong internal validity (Cattaneo et al., 2019, 2023; Titiunik, 2021).
3. **Minimal Assumptions**: RDD primarily relies on the continuity of potential outcomes at the cut-off, a more plausible assumption than the strong ignorability required for matching methods (Cattaneo et al., 2023).
4. **Robustness to Small Sample Sizes**: Recent methodological advancements in bandwidth selection and local randomisation inference have made RDD more robust when working with smaller sample sizes, which is crucial for studying specific subpopulations(Cattaneo et al., 2015; Cattaneo et al., 2017; Titiunik, 2021).

Unlike other quasi-experimental designs, RDD is the closest to experimental design in the hierarchy of causal inference robustness (Cattaneo et al., 2017; Kim & Steiner, 2016).

3.3.4.3 Fuzzy RD design (FRDD) versus sharp RD design (SRDD)

In all Regression Discontinuity (RD) designs, treatment assignment adheres to the rule $T_i = 1(X_i \geq c)$. This rule determines that units scoring below a specified threshold 'c' are placed in the control group, while those with scores above 'c' are allocated to the treatment group. In the case of the Sharp RD design, all units placed in the treatment group effectively received the treatment, and none of the units assigned to the control group received treatment. In this context, $T_i = 1(X_i \geq c)$ not only determines treatment allocation but also the actual treatment received by the units. However, sometimes, there are RD designs where deviations occur from this ideal scenario. Some units with scores Xi ≥ c might not receive treatment, or conversely, some units with scores Xi < c might unexpectedly receive treatment, or both cases. This situation, where units receive a treatment condition divergent from their initial assignment, is termed imperfect compliance or non-compliance. The RD design characterised by imperfect compliance is called the Fuzzy RD design, distinguishing it from the Sharp RD design characterised by perfect compliance (Cattaneo et al., 2023; Cunningham, 2018; Huntington-Klein, 2021). This chapter employs a fuzzy RD design due to the possibility that certain students born after the cut-off date might still have left school even if the mandatory schooling age were extended to 16 years.

3.3.4.4 RDD under a local randomisation assumption

This study is the first to adopt this approach to explore the effect of ROSLA on mental health among ethnic minorities. This approach is particularly pertinent considering the relatively small sample sizes.

When Thistlethwaite and Campbell (1960) introduced their RDD, they argued that the abrupt change in treatment status at the cut-off resembles random assignment near the cut-off point. This idea has also been commonly used in the continuity-based framework, but the formal derivation of identification and estimation results relies on the continuity and differentiability of regression functions. In contrast, the local randomisation approach formalises that the RD design behaves like a randomised experiment near the cut-off by imposing explicit randomisation-type assumptions stronger than continuity-based conditions. It assumes that units within a small window around the cut-off are comparable, allowing for analysis as if they were randomly assigned to treatment or control. This approach builds statistical tools based on this assumption and focuses on units near the cut-off window (Cattaneo et al., 2023).

In this framework, we are considering an RDD where the continuous score is X_i, the treatment assignment is $T_i = 1(X_i \geq c)$, and Y_i is the observed outcome with the corresponding potential outcomes $Y_i(0)$ and $Y_i(1)$ for the respective control and treatment groups. When employing the RD design with a local randomisation assumption, instead of assuming the continuity of the unknown regression functions $\mu_1(x) = E[Y_i(1) = x]$ and $\mu_0(x) = E[Y_i(0) = x]$ at the cut-off, the researcher assumes the existence of a narrow window around the cut-off. This window, denoted as $W = [c - w, c + w]$, is defined such that for all units whose scores fall within this window, their assignment above or below the cut-off is treated as if it had been determined randomly, similar to a randomised experiment. This assumption is sometimes referred to as "as if" random assignment (Cattaneo et al., 2023). Nevertheless, Titiunik (2021) stresses that an RDD should not be regarded as a canonical randomised experiment but rather as a natural experiment belonging to the broader category of observational studies.

The local randomisation approach has two assumptions:

- **(LR1) There is a known joint probability distribution of scores within W**
- **(LR2) The score within W does not affect the potential outcomes**

LR1 means that the assignment mechanism of the score must be known within the window, as is the case in a randomised experiment. In the local randomisation framework, the probability $P_W[.]$ is defined conditionally for units with $X_i \in W$. All probability and moment calculations and parameter definitions are typically performed within the window W. In this framework, LR1 states that $P_W[X_W \leq x] = F(x)$, where $F(x)$ is a known joint cumulative distribution function. For instance, this condition is satisfied when all units have an equal probability of receiving any score value within W, resulting in an equal probability of being assigned to the control $(X_i < c)$ or treatment $(X_i < c)$ when the window W is symmetrically centred around the cut-off c. LR2, known as the exclusion restriction, ensures that the potential outcomes do not depend on the score for units within window W, as would be the case in a true double-blind, randomised experiment. In formal terms, let $Y_i(0,x)$ and $Y_i(1,x)$ represent the potential outcomes without explicit dependence on the score variable except through their second argument, such that $Y_i(0) = Y_i(0,x_i)$ and $Y_i(1) = Y_i(1,x_i)$. In the case of non-random potential outcomes, the second condition implies that $Y_i(0,x') = Y_i(0,x)$ and $Y_i(1,x') = Y_i(1,x)$, for all $x, x' \in W$ and all units with $x_i \in W$. If the potential outcomes are random, the condition signifies that $PW[Y_i(0,x') = Y_i(0,x) = 1$ and $PW[Y_i(1,x') = Y_i(1,x) = 1$ for all $x, x' \in W$ (Cattaneo et al., 2023).

Under these assumptions, the estimation approach is described by the model:

$$\boldsymbol{y_i = \beta_0 + \beta_1\, 1(Born_i > c) + f(Born_i) + \varepsilon_i} \;(\mathbf{1})$$

Where y_i is the outcome, and $1(Born_i > c)$ is an indicator that assumes 1 for people born on or after the 1st of September 1957 and 0 otherwise. In equation 1, $f(Born_i)$ is a continuous function in the month-year of birth around the cut-off. The validity of this approach relies on satisfying the two assumptions (LR1 and LR2), which in this context means, first, that increasing the minimum school leaving age (treatment) should be assigned randomly to subjects. Second, no factor other than schooling should have experienced a discontinuous change around the cut-off dates. Given that the assignment is only determined by the individual's date of birth, LR1 can be considered fulfilled. LR2 is also satisfied, as confirmed by the literature (Avendano et al., 2020; Clark & Royer, 2010; Clark & Royer, 2013; Davies et al., 2018; Janke et al., 2020).

3.4 Results

This section starts from the association between education and mental health within the analytical sample of this chapter (section 3.4.1), namely, ethnic minorities affected by the ROSLA policy. Next, section 3.4.2 presents a set of estimations assuming a sharp RD design with compliance with the policy. These estimations include an RD design estimated through OLS, some rdplots, continuity-based RD estimation using a least-squared methods, and also a local randomisation approach. Finally, section 3.4.3, implements a fuzzy RD design using a local randomisation approach, reporting the first stage, reduced effect and the local average treatment effect (LATE). The result section concludes with falsification tests.

3.4.1 The association between education and mental health among ethnic minorities

This section explores the relationship between an extra year of education and the mental well-being of ethnic minorities in the UK. As stressed by the existing literature, education often exhibits endogeneity, which means that the impact of an additional year of education on mental health could be intertwined with other variables. The remainder of this chapter will employ a regression discontinuity design to tackle this endogeneity issue.

Table 3.8 and Table 3.9 describe the results of the OLS estimation on SF-12 and GHQ for three model specifications that incorporate different educational variables. The first model explores the association between the highest level of education attained and mental health, and the second model looks at the association between age left FT education, while the third model explores the impact of a dummy variable indicating whether the person stayed in FT education until 16 or older.

Table 3.8 shows a positive association between education the SF12 instrument, thus, education seem to contribute to mental health.

Table 3.8 OLS estimation of education on mental health (SF12)

	Model 1 b/se	Model 2 b/se	Model 3 b/se
Have a degree	4.820***		
	(1.482)		

Have other Higher Education degree	5.024***		
	(1.653)		
Have an A-level	6.236***		
	(1.579)		
Have a GCSE level	4.627***		
	(1.534)		
Have other qualification	2.356		
	(1.699)		
Age left FT education		1.493***	
		(0.569)	
Left FT education at 16 or older			1.755
			(1.339)
Age dummy	Yes	Yes	Yes
Age^2 dummy	Yes	Yes	Yes
Month of birth dummy	Yes	Yes	Yes
Sex dummy	Yes	Yes	Yes
Wave dummy	Yes	Yes	Yes
N	714	711	715
R-squared	0.0636	0.0409	0.0401

*Note: All models include a dummy variable for month of birth, survey year, sex, and second-order polynomial of age. The dummy variables for education attainment adopt 'No qualification' as the base. Age left FT education is a continuous variable between 11 and 18. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931. *** p<0.001, ** p<0.05, * p<0.1.*

Table 3.9 shows similar results to Table 3.8 above. As the GHQ instrument measures distress, the negative sign in this case indicates that more education contribute to lowering distress.

Table 3.9 OLS estimation of education on mental health (GHQ)

	Model 1	**Model 2**	**Model 3**
	b/se	**b/se**	**b/se**
Have a degree	-0.856		
	(0.821)		
Have other Higher Education degree	-1.458		
	(0.895)		
Have an A-level	-1.075		

	(0.861)		
Have a GCSE level	-0.676		
	(0.847)		
Have other qualification	0.026		
	(0.906)		
Age left FT education		-0.303	
		(0.190)	
Left FT education at 16 or older			-1.061
			(0.703)
Age dummy	Yes	Yes	Yes
Age^2 dummy	Yes	Yes	Yes
Month of birth dummy	Yes	Yes	Yes
Sex dummy	Yes	Yes	Yes
Wave dummy	Yes	Yes	Yes
N	778	783	786
R-squared	0.0577	0.0573	0.0558

*Note: All models include a dummy variable for month of birth, survey year, sex, and second-order polynomial of age. The dummy variables for education attainment adopt 'No qualification' as the base. Age left FT education is a continuous variable between 11 and 18. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931. *** p<0.001, ** p<0.05, * p<0.1.*

3.4.2 A sharp RDD of ROSLA on mental health among ethnic minorities

This section displays the estimation of ROSLA on mental health among ethnic minorities adopting a sharp RD design using both continuity-based and local randomisation approaches. Both estimations assume there are no significant issues of compliance, that is, those who were affected by ROSLA continued full-time education after 16 years of age. This is a strong assumption, as shown by Table 3.10, which points to 191 respondents out of 742 affected by ROSLA who did not comply with the policy. This is consistent with the literature, which suggests a fuzzy RDD is the most appropriate design in the overall sample. However, this section presents results from different estimations assuming sharp design to test how the lack of compliance may affect the estimates.

Table 3.10 Age left full-time education across intervention groups

Age left FT education	Pre-ROSLA	Post-ROSLA	Total
11	2		2
12	14	2	16
13	69	4	73
14	107	41	148
15	60	144	204
16	18	303	321
17	3	195	198
18		53	53
Total	273	742	1,015

Note: grey cells show the non-compliers, that is, those who did not finish FT education at 16 or older after the policy was implemented. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

3.4.2.1 RD Plots of ROSLA on education attainment

The effects of this reform are visually depicted in the rdplots in this section. The effect of ROSLA on the age left full-time education presents the average educational attainment according to the month and year of birth. Consistent with expectations and other literature, introducing the policy significantly increased the average age at which individuals completed their full-time education. Additionally, there was a notable rise in the proportion of individuals who continued their education until at least 16. This pattern for this sub-population is similar to the one observed in the overall UK population.

In the rdplots below, the x-axis represents months born before or after the reform, with 0 marking the cutoff point. In Figure 3.3, the y-axis shows the proportion of individuals who remained in full-time education at different ages, while Figure 3.4, Figure 3.5, and Figure 3.6 shows the proportion of people how left FT education at 16 or older, 17 or older and 18 or older, respectively.

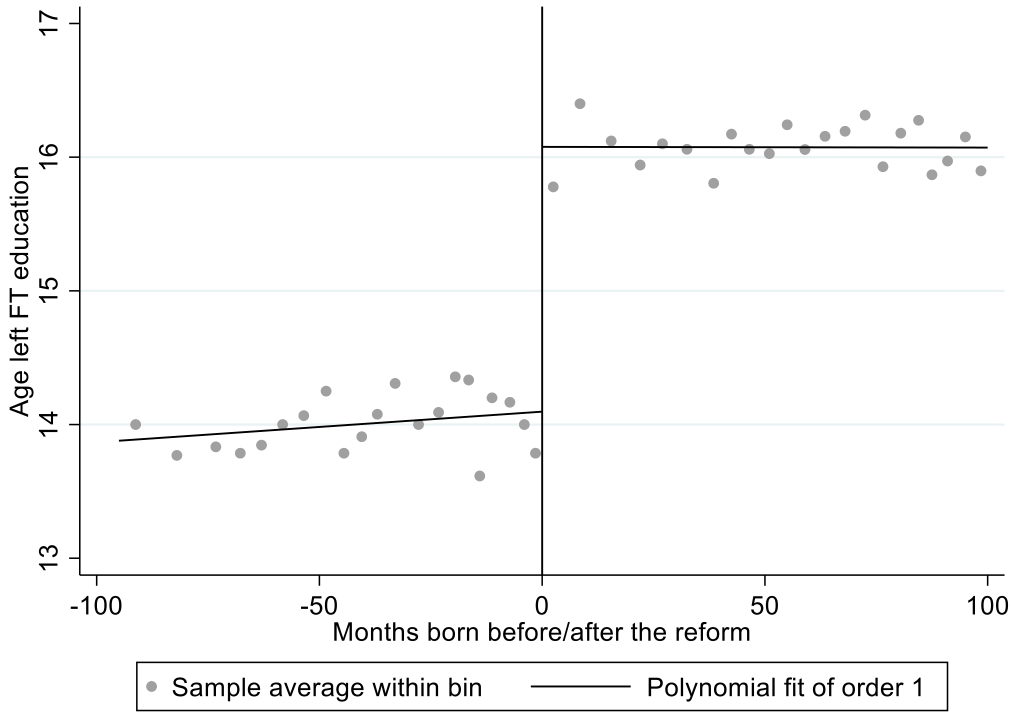


Figure 3.3 The effect of ROSLA on the age left full-time education

Note: Rdplot with optimal bin selection, quantile-spaced bins with mimicking variance method (qsmv), and polynomial of order 1. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

Figure 3.4 shows a consistent rise and a discontinuity after the introduction of ROSLA.

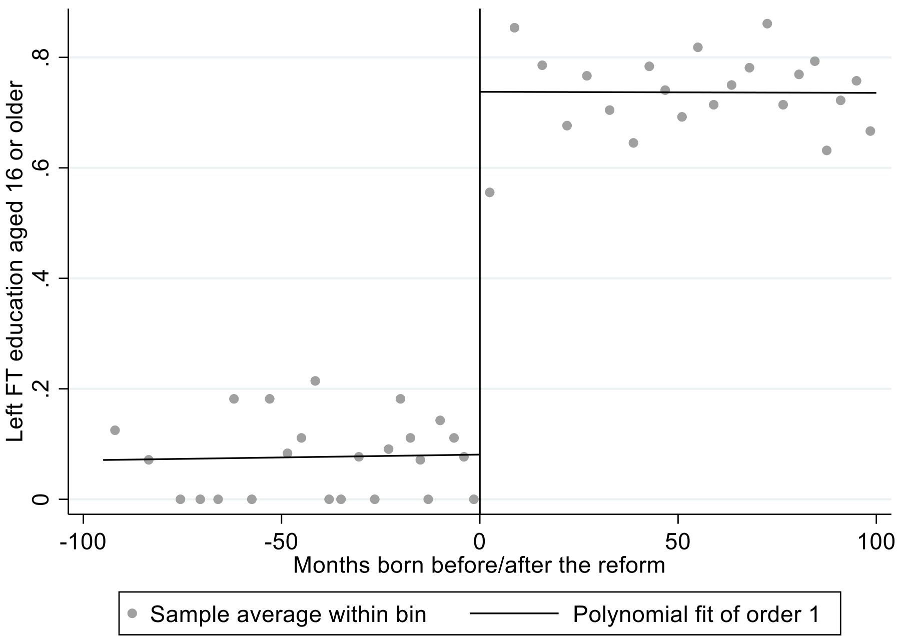


Figure 3.4 The effect of ROSLA on the proportion of students leaving full-time education at 16 or later

Note: Rdplot with optimal bin selection, quantile-spaced bins with mimicking variance method (qsmv), and polynomial of order 1. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

Figure 3.5 and Figure 3.6 shows the effect of ROSLA on leaving FT education at 17 or older and 18 or older, respectively. Both figures show a clear discontinuity at the threshold.

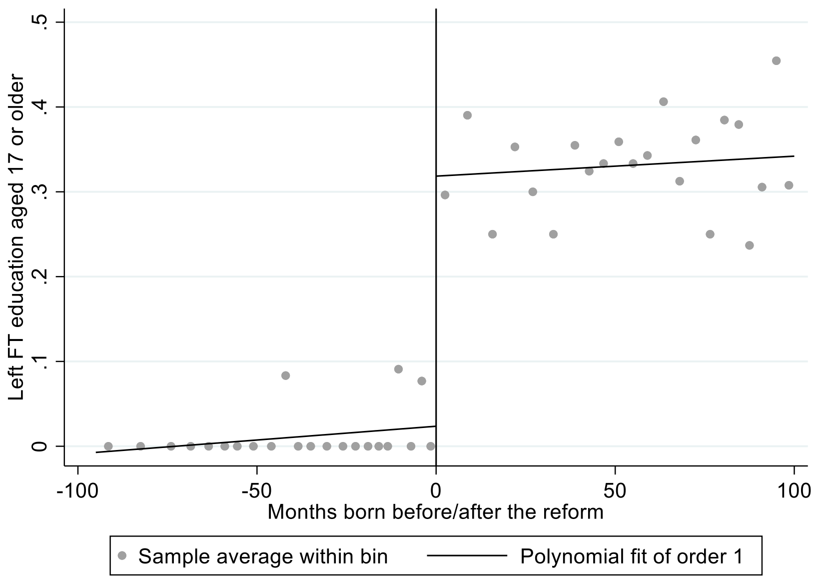


Figure 3.5 The effect of ROSLA on the proportion of students leaving full-time education at 17 or later

Note: Rdplot with optimal bin selection, quantile-spaced bins with mimicking variance method (qsmv), and polynomial of order 1. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

The striking feature of Figure 3.6 is the stark contrast between the left and right sides of the cutoff. On the left side (representing those born before the reform and thus not affected by it), we see only one data point, which is near zero. This single dot indicates that no individuals born before the reform stayed in full-time education until age 18 or later. The absence of other data points on the left suggests a very low or non-existent rate of extended education among this group. In contrast, the right side of the graph (representing those born after the reform and affected by it) shows multiple data points scattered above zero, with a slight downward slope. This pattern indicates that a significant proportion of individuals affected by the reform stayed in education until 18 or older. However, this proportion decreases slightly for those born further after the reform date.

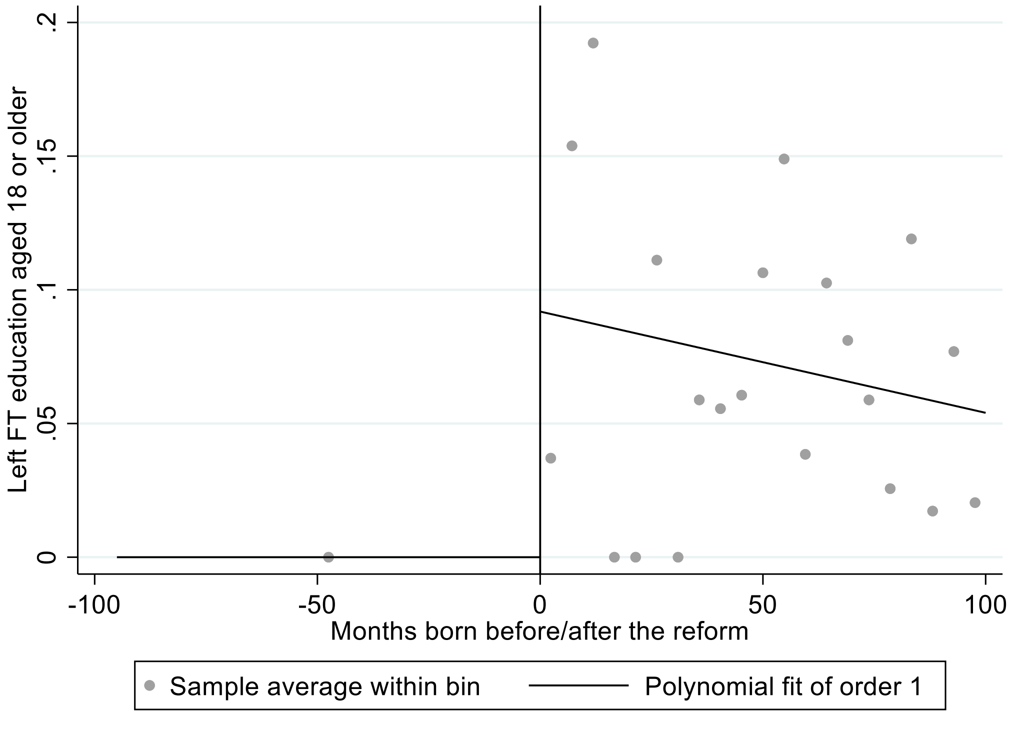


Figure 3.6 The effect of ROSLA on the proportion of students leaving full-time education at 18 or later

Note: Rdplot with optimal bin selection, evenly-spaced bins with mimicking variance method(es), and polynomial of order 1. The lack of variability at the left of cut-off did not allow for a quantile-spaced bin. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

3.4.2.2 RD Plots of ROSLA on mental health

Figure 3.7 and Figure 3.8 visually illustrate the impact of this reform by showcasing the average mental health outcomes based on the month and year of birth. In contrast to results in the overall population (Avendano et al., 2020; Davies et al., 2018), the effect appears positive.

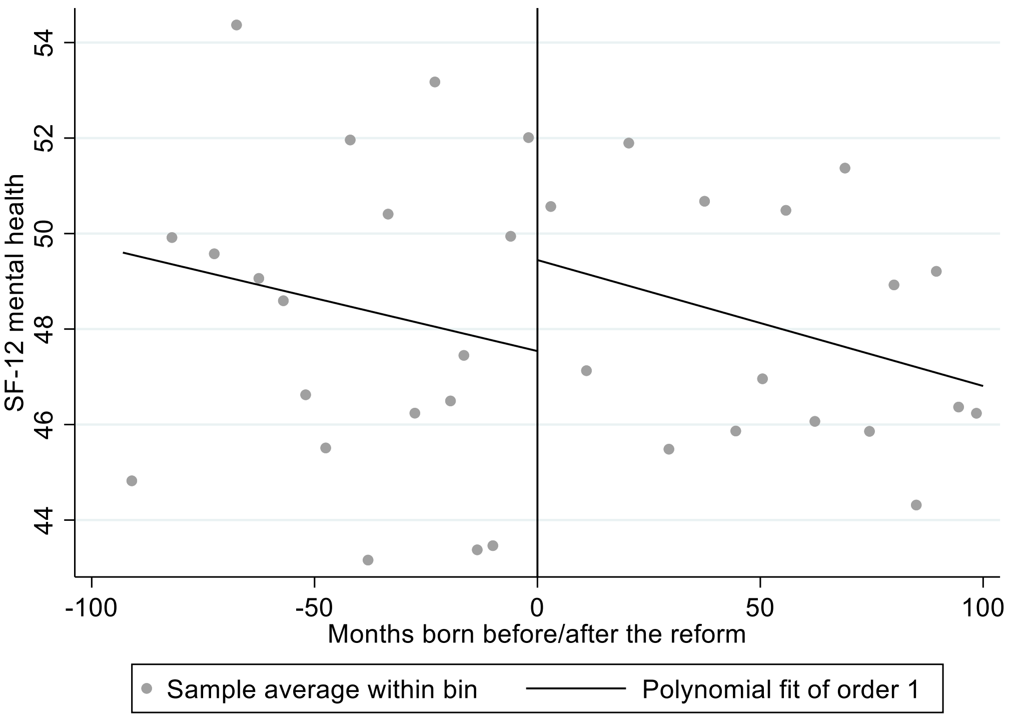


Figure 3.7 The effect of ROSLA on SF12

Note: Rdplot with optimal bin selection, quantile-spaced bins with mimicking variance method (qsmv), and polynomial of order 1. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

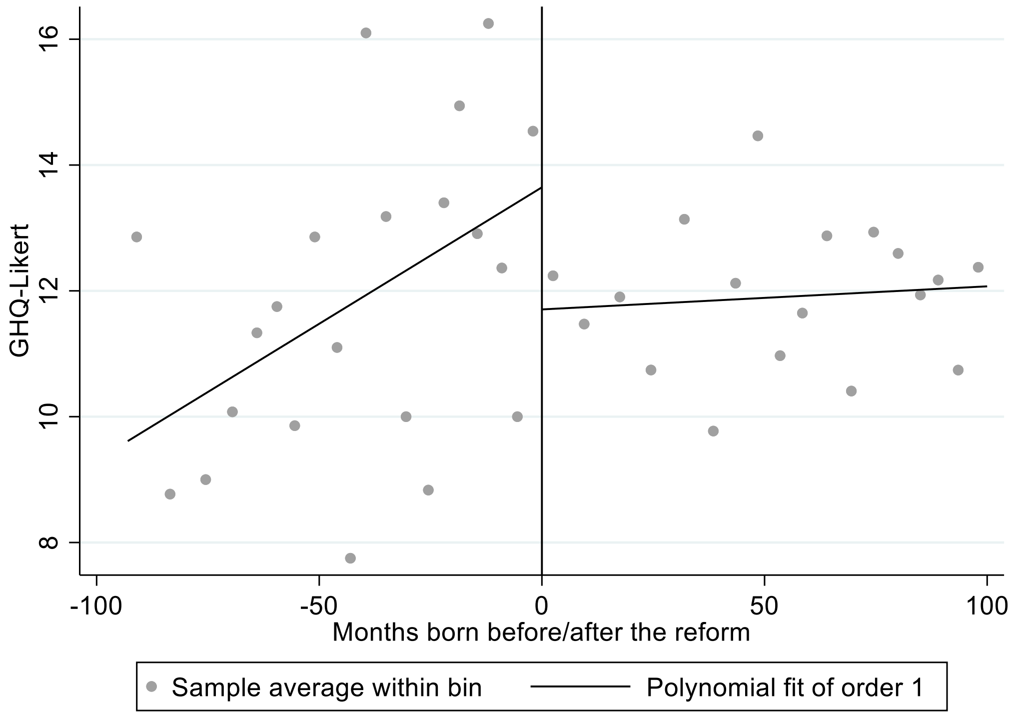


Figure 3.8 The effect of ROSLA on GHQ

Note: Rdplot with optimal bin selection, quantile-spaced bins with mimicking variance method (qsmv), and polynomial of order 1. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

3.4.2.3 OLS and continuity-based RD estimation assuming sharp design

Table 3.11 Effects of ROSLA on SF-12 through OLS shows results for an OLS estimation of the effect of ROSLA on mental health, while Table 3.12 Effects of ROSLA on GHQ through OLS and Table 3.13 Effects of ROSLA on mental health among ethnic minorities (sharp design) – continuity assumption display results for the same estimation using the continuity-based and least-square with optimal bandwidth selection developed by Calonico et al. (2014) through the -rdrobust- command in Stata©.

The OLS estimates for the ROSLA policy suggest a positive impact on mental health measured by the SF-12 but are not statistically significant. The sign of this effect on mental health measured by the GHQ-Likert scale is also positive and statistically significant. However, these estimations must be taken with caution as the assumption of perfect compliance is quite strong.

Table 3.11 Effects of ROSLA on SF-12 through OLS (reduced form)

Variables		**SF-12**	
	Model 1	**Model 2**	**Model 3**
	b/se	**b/se**	**b/se**
1975 ROSLA	1.906	2.036	2.263
	(1.861)	(1.881)	(1.919)
Age		-1.703	-1.191
		(1.307)	(1.411)
Age^2		0.017	0.011
		(0.012)	(0.014)
			(1.728)
Month of birth dummy			Yes
Survey year dummy			Yes
N	715	715	715
R-squared	0.00481	0.00737	0.0361

*Note: The outcome variable SF-12 captures mental health functioning, ranging from 0 (low) to 100 (high). All models are estimated through OLS using a dummy variable for the effect of ROSLA and controlling for heteroskedasticity-robust standard errors. These models correspond to a reduced form that shows the independent variable's effect on outcome in the context of a sharp RDD. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931 *** p<0.001, ** p<0.05, * p<0.1*

Table 3.12 Effects of ROSLA on GHQ through OLS (reduced form)

		GHQ-Likert scale	
	Model 1	**Model 2**	**Model 3**
	b/se	**b/se**	**b/se**
1975 ROSLA	-1.941**	-1.993**	-1.974**
	(0.987)	(0.989)	(0.980)
Age		0.765	0.875
		(0.712)	(0.814)
Age^2		-0.007	-0.008
		(0.007)	(0.007)
Month of birth dummy			Yes
Survey year dummy			Yes

N	786	786	786
R-squared	0.0102	0.0115	0.0537

*Note: The outcome variable GHQ-Likert scale ranges between 0 (indicative of minimal distress) and 36 (reflective of heightened distress). All models are estimated through OLS using a dummy variable for the effect of ROSLA and controlling for heteroskedasticity-robust standard errors. These models correspond to a reduced form that shows the independent variable's effect on outcome in the context of a sharp RDD. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931 *** p<0.001, ** p<0.05, * p<0.1*

Table 3.13 Effects of ROSLA on mental health among ethnic minorities (sharp design) – continuity assumption shows that the impact of ROSLA on metal health is negative if measured by SF-12 and positive by the GHQ-Likert scale. However, neither estimate is statistically significant. Similar to the OLS estimates in Table 3.11, the lack of compliance might be affecting the estimation.

Table 3.13 Effects of ROSLA on mental health among ethnic minorities (sharp design) – continuity assumption

	SF-12	**GHQ-Likert scale**
1975 ROSLA	-1.168	-2.059
	(6.621)	(1.870)
N	715	786

*Note: This estimation was conducted using the rdrobust command, which assumes a continuity-based approach. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931 *** p<0.001, ** p<0.05, * p<0.1*

In the next section (3.4.3), a sharp RD design assumption is abandoned, and a fuzzy RDD assumption is adopted. As a fuzzy RDD fits under an instrumental variable approach, section 3.4.3 will report the first stage (ROSLA -> education), reduced form (ROSLA -> mental health), and the LATE effect (education -> mental health instrumented through ROSLA). Since the reduced effect is the same as a sharp design, the effect of ROSLA on mental health through local randomisation was omitted in the current section to avoid duplication.

3.4.3 A fuzzy RDD of ROSLA on mental health among ethnic minorities

This section implements a fuzzy RD design through a local randomisation approach. In addition, estimations are broken down by sex. The estimations were implemented through the -rdrdrandinf- user command in Stata© (Cattaneo et al., 2015; Cattaneo et al., 2016; Cattaneo et al., 2017; Vazquez-Bare et al., 2016). The optimal bandwidth is estimated through the -rdwinselect- companion command to rdrdrandinf in Stata©, developed by the same authors.

3.4.3.1 The effect of ROSLA on the education leaving age among ethnic minorities

This section examines the effect of the 1972 Raise of School Leaving Age (ROSLA) policy on educational attainment within ethnic minorities in England who were enrolled in the education system. A fuzzy RDD follows an instrumental variable approach, and, in the language of the instrumental variable, this estimation corresponds to **the first stage effect**.

Table 3.14 shows the estimates of the impact of the policy on the decision to stay in full-time education. The first column corresponds to the age left full-time education, and the other columns to whether they stayed until 16 or after, 17 or after, and 18 or after. The last three estimations are modelled as dummy variables in outcomes. Estimations are done for the ethnic minority sample and broken down by sex.

The results suggest that the ROSLA policy effectively encouraged students to stay in full-time education beyond 16 years of age. This effect becomes weaker with age. This is consistent with findings in the literature (Avendano et al., 2020; Davies et al., 2018; Janke et al., 2020). Interestingly, results in terms of sign and significance do not vary by sex.

Table 3.14 Effects of ROSLA on education among ethnic minorities – local random approach with optimal window selection

	Age left school			>= 16 Leaving age			>= 17 Leaving age			>= 18 Leaving age		
	Pooled	**Female**	**Male**	**Pooled**	**Female**	**Male**	**Pooled**	**Female**	**Male**	**Pooled**	**Female**	**Male**
1975 ROSLA	2.049***	2.093***	2.000***	0.685***	0.704***	0.667***	0.322***	0.352**	0.285*	0.104	0.074	0.143
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.014	0.076	0.160	0.690	0.476
Mean<c	14.097	14.167	14.000	0.065	0.323	0.000	0.032	0.236	0.000	0.000	0.000	0.000
Mean>c	16.146	16.259	16.000	0.750	0.396	0.667	0.354	0.501	0.286	0.104	0.267	0.359
N	711	377	334	715	378	337	715	378	337	715	378	337

*Note: These estimations were conducted using the local randomisation approach with optimal bandwith (-12,10) using the Stata© command -rdrandinf. Mean><c is the mean value of the outcome variable to the left and right of the cut-off, respectively. The p-values correspond to the finite sample estimation. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931. *** p<0.001, ** p<0.05, * p<0.1*

3.4.3.2 The effect of ROSLA on mental health among ethnic minorities

This section examines the effect of the 1972 Raise of School Leaving Age (ROSLA) policy on mental health within ethnic minorities in England who were enrolled in the education system then. Following the instrumental variable setting, **this corresponds to the reduced form estimation**. Table 3.15 shows that none of the effects are statistically significant.

Table 3.15 Effects of ROSLA on education among ethnic minorities

(ITT)	**SF-12**			**GHQ-Likert scale**		
	Pooled	**Female**	**Male**	**Pooled**	**Female**	**Male**
1975 ROSLA	0.753	0.814	0.818	-0.760	-1.729	0.316
p-value	0.784	0.764	0.828	0.556	0.376	0.880
Mean<c	48.511	49.972	46.488	12.684	13.800	11.444
Mean>c	49.263	50.786	47.306	11.925	12.071	11.760
N	715	378	337	786	417	369

*Note: These estimations were conducted using the local randomisation approach with optimal bandwith (-12,10) using the Stata© command -rdrandinf. Mean>< is the mean value of the outcome variable to the left and right of the cut-off, respectively. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931. *** p<0.001, ** p<0.05, * p<0.1*

3.4.3.3 The causal effects (LATE) of education on mental health among ethnic minorities

This section focuses on the **causal effect of education – induced by the ROSLA policy – on mental health**. The estimated effect in a FRDD approach is the LATE (local average treatment effect), which is the ratio of the reduced-form to the first-stage estimate. The reduced-form corresponds to the ITT (intention-to-treat) effect.

Table 3.16 shows the results of estimations using an optimal bandwidth of -12 to 10 in the running variable from the cut-off date, which reduces significantly the number of observations. The results suggest a positive impact of education on mental health being instrumented by the ROSLA policy. However, none of the estimates are statistically significant either for the pooled sample or by sex. Table 3.17 shows the same estimation only for the pooled sample, this time on the maximum sample, that is, without restricting it to the optimal bandwidth. Despite the higher number of observations, the statistical significance does not change and the sign of effect changes.

Table 3.16 Effects of education on mental health among ethnic minorities - optimal bandwidth

(2SLS)	SF-12			GHQ-Likert scale		
	Pooled	**Female**	**Male**	**Pooled**	**Female**	**Male**
Left FT education at 16 or older	1.098	1.157	1.228	-1.094	-2.396	0.475
p-value	0.784	0.764	0.828	0.556	0.376	0.880
Mean<c	48.511	49.972	46.488	12.684	13.800	11.444
Mean>c	49.263	50.786	47.306	11.925	12.071	11.760
N	715	378	337	786	417	369

*Note: These estimations were conducted using the local randomisation approach with optimal bandwidth (-12,10) using the Stata© command -rdrandinf. Mean>< is the outcome variable's mean value to the cut-off's left and right, respectively. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931. *** p<0.001, ** p<0.05, * p<0.1*

Table 3.17 Effects of education on mental health among ethnic minorities – maximum bandwidth

	SF-12	GHQ-Likert scale
1975 ROSLA	-0.686	0.049
p-value	0.622	0.916
Mean<c	48.43	11.89
Mean>c	47.953	11.93
N	715	786

*Note: These estimations were conducted using the local randomisation approach without optimal bandwidth using the Stata© command -rdrandinf. Mean>< is the outcome variable's mean value to the cut-off's left and right, respectively. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931. *** p<0.001, ** p<0.05, * p<0.1*

3.4.4 Falsification tests for the local randomisation approach

The robustness check in the context of the local randomisation approach consists of running falsification tests. As highlighted by Cattaneo et al. (2023), in an FRDD, the falsification analysis is done on the treatment assignment rather than the treatment received. Hence, this is the same as in a sharp RDD.

Density test

This test – also known as the McCrary test – aims to assess whether there is sorting on the running variable (Cunningham, 2018). In this context, it means testing whether students have managed to self-select into one of the treatment groups. Using the -rddensity- command in Stata© developed by Cattaneo et al. (2018), the test gives a T statistic of 0.3502 with a p-value of 0.76262, failing to reject the null hypothesis. The null hypothesis is that there is no sorting.

Intention to treat (ITT) on pre-treatment covariates

An additional way to conduct a falsification test within the local randomization approach involves calculating the Intent-to-Treat (ITT) effect on predetermined covariates known in advance to remain unaffected by the running variable, such as age or sex. Table 3.18 shows that none of the estimations are statistically significant.

Table 3.18 ITT effect on predetermined covariates

(ITT)	**Sex**	**Age**	**Born in the UK**
Born before/after September 1957	-0.043	-1.040	-0.183
p-value	0.800	0.194	0.918
Eff. Obs <c	50	50	30
Eff. Obs >c	60	60	32
Tot.Obs<c	271	273	133
Tot.Obs>c	748	748	565
Mean<c	0.501	56.64	1.933
Mean>c	0.504	55.60	1.750
N	1,019	1,021	698

3.5 Discussions

3.5.1 Key findings

The effects of extending the duration of compulsory schooling on mental health have received limited attention, especially in the UK, and no study has looked into this within ethnic minorities. Hence, this chapter aimed to contribute to the existing knowledge by investigating how an extra year of schooling, prompted by the ROSLA policy, could causally influence long-term mental health among ethnic minorities. The research utilised the ROSLA policy as a natural experiment. It assessed its impact on mental well-being using the SF-12 and GHQ instruments through a fuzzy RDD within a local randomisation assumption following Cattaneo et al. (2015) and Titiunik (2021). The findings showed that the effect of additional years of education on long-term mental health among ethnic minorities is not statistically significantly different from zero. These findings are robust even after widening the bandwidth to include the maximum sample size.

The estimation began with examining the relationship between education and mental health using Ordinary Least Squares (OLS), which consistently showed a positive and statistically significant association with the SF-12 across various specifications. However, this association was not statistically significant for the GHQ-Likert scale. It is worth stressing that these correlations suffer from endogeneity in education, as extensively discussed by the literature (Avendano et al., 2020; Barcellos et al., 2018; Clark & Royer, 2013; Davies et al., 2018). The strategy continued with exploring the effect of ROSLA on mental health, assuming almost perfect compliance with the policy. This is a strong assumption as the data shows some non-compliers. Although the rdplots showed discontinuity and breaks in the cut-off, the estimations assuming a sharp RD design through a continuity-based approach and least-squared were not statistically significant. Only the effect on the GHQ-Likert scale through OLS showed statistically significant coefficients.

These findings closely align with the outcomes observed in earlier research that utilised comparable shifts in school leaving age within different nations and the general population. Four studies utilised the 1972 increase in the School Leaving Age (ROSLA) from 15 to 16 as a natural experiment to investigate the relationship between education and mental health. In examining health effects within the UK Biobank dataset, Davies et al. (2018) did not identify a discernible connection between education and self-reported depression. Similarly, combined survey data, Janke et al. (2020) failed to establish a causal link between education and chronic mental conditions such as depression and anxiety.

Avendano et al. (2020) examined the correlation between an additional year of education and mental health outcomes. They discovered that an extra year of education was associated with a 30% higher likelihood of depression or anxiety based on the Annual Population Survey. However, their UKHLS data analysis yielded no significant results when assessing mental health with SF-12 and GHQ. Consequently, there were variations in results across different datasets, with education potentially detrimental to mental health in Understanding Society but possibly beneficial in the UK Biobank.

Furthermore, Avendano et al. (2020) proposed that forcing students who are uninterested in prolonged schooling into a potentially stressful academic environment could compromise their mental well-being compared to their peers.

Regarding two distinct educational reforms, Janke et al. (2020) found the absence of a statistically significant impact stemming from an additional year of education on any of three summary measures: the likelihood of experiencing chronic health conditions, the presence of constraining chronic health conditions, and the count of chronic health conditions.

In a more recent study, Amin et al. (2023) identified a positive effect on adult mental health in the overall population resulting from ROSLA. They employed sibling fixed effects with controls for polygenic scores in their analysis.

One of the possible explanations for the lack of effect is the decreasing returns of the effect of education on mental health. As suggested by Kamhöfer and Schmitz (2016) and Pischke and Von Wachter (2008), the Grossman model points out that education's influence on mental health, seen through the lens of human capital, operates with diminishing returns, implying that the impact of each extra unit of education on mental health lessens, raising the possibility that after a certain point, like around age 14, further schooling might have only a minimal long-term effect on mental health.

More education within a school system that is not particularly empowering for vulnerable and marginalised communities could offset the positive effect of education. The adverse effect of forcing students to stay in education for an additional year, found by Avendano et al. (2020), might be even more significant for ethnic minorities. For example, Crozier (2023) conducted research revealing that even though certain BAME children display commendable academic accomplishments, a persistent gap in achievement remains apparent, particularly evident within Black Caribbean, Pakistani, and 'Gypsy', Roma, and Traveller communities. Furthermore, BAME children encounter higher school exclusions and unfavourable educational experiences, notably observed among those with Black Caribbean and South Asian backgrounds. This pattern fosters a cycle of reduced performance, criticism, conflict, and marginalisation, primarily explored within educational institutions. As emphasised by Nazroo (2022a), institutional racism significantly contributes to the impact on the mental well-being of ethnic minority groups. Educational establishments, including schools, operate with policies and procedures that perpetuate discrimination against marginalised groups.

Evidence suggests that schools in England may be a source of stress for ethnic minorities. The enquiry into racism in secondary schools in England conducted by Joseph-Salisbury (2020) concluded that the teaching workforce remains predominantly white, and many educators, including those from BME backgrounds, admit to lacking preparation for promoting anti-racism in their teaching. The inadequacy extends to school curricula, which often overlook the diversity of today's society and neglect to address the colonial and racist aspects of modern Britain. Moreover, the presence of police in schools, though detrimental for all students, disproportionately affects ethnic minorities and working-class students due to the issue of over-policing. Likewise, Alexander and Shankley (2020) claim that the recent Prevent policies have generated racialised surveillance of Muslim and South Asian pupils, demonstrating the prevalence of institutional racism. Therefore, it is likely that the negative effect of institutional racism in education systems offsets any positive effects of education on mental health.

3.5.2 Limitations

The research in this chapter is not free of limitations in common with the vast literature adopting an RD design and exploring the causal effect of schooling on health, including mental health. To begin with, additional years of education do not necessarily translate into human capital accumulation. As highlighted by Kamhöfer and Schmitz (2016) and Pischke and Von Wachter (2008), if returns to education decrease after 14 years old, then an extra year does not bear the expected benefits.

Secondly, unobserved variables that influence mental health may still exist across the life course, yet these variables remain unaccounted for. While a Regression Discontinuity Design (RDD) aids in managing this concern, its efficacy may not be flawless. Given that the sample consists of individuals born within 12 months, a significant portion of unobserved variables has probably been considered. RDD designs are deemed to be close to random assignment when individuals near the threshold lack the means to manipulate the assignment variable — in this instance, the month-year of birth. Existing literature maintains that a result of this is the randomisation of treatment variation near the threshold, similar to a randomised experiment (Cattaneo et al., 2015; Cattaneo et al., 2019, 2023; Cattaneo et al., 2017; Titiunik, 2021). However, chance could lead to imbalances even in Randomised Controlled Trials (RCTs).

Thirdly, the quality of education after the initial period might have undergone a decline or impact negatively on other aspects of physical health. For example, Plotnikov et al. (2020) found that additional compulsory schooling triggered by ROSLA 1972 reform was associated with a heightened negative refractive error (myopia) using an RD design. Moreover, Cowan et al. (2012) reported that all the necessary buildings to accommodate additional cohorts were not ready by 1970, so new shifts had to be made to arrange temporary classes in playgrounds, suffer from overcrowded classrooms and lack of equipment for older children. All of this might have impacted the quality and experience of education.

Furthermore, the observed effect represents an average without delving into potential distributional repercussions, as exemplified in the research conducted by Amin et al. (2023). For example, the analysis by sex was useful to see similar results across female and male sub-populations. Moreover, individuals with heightened levels of educational attainment often tend to render lower self-assessments of their health, as evidenced by Bago d'Uva et al. (2008).

Lastly, there could be additional factors situated between education and mental health that function as mediators; if these mediators remain unaffected by increased educational exposure, the resultant influence on mental health might not be as substantial. Testing these effects requires a causal mediation analysis approach.

3.5.3 Implications for practice, policy, and future research

The findings from this study have several important implications. In terms of practice, the results highlight the need for greater focus on promoting mental health and wellbeing within educational settings, especially for marginalised groups like ethnic minorities. Schools should implement evidence-based programs and policies to foster a positive school climate and sense of belonging and provide mental health services and support. Additionally, educators require better preparation and ongoing professional development around culturally responsive teaching practices and building an inclusive learning environment free from discrimination.

Regarding policy, the research underscores the importance of addressing systemic and institutional racism in education. Policymakers need to reform school policies and practices that disproportionately impact students from ethnic minority backgrounds, such as disciplinary actions, ability grouping, and partnerships with law enforcement. There is also a need for more significant investment in mental health services tailored to the unique needs of minority youth. Policies should promote culturally competent care and work to reduce mental health disparities.

In future research, more work is needed to elucidate the mechanisms linking education and mental health among ethnic minorities. Researchers should explore potential moderators like school climate and experiences of discrimination. Future studies could also employ methods like mediation analysis to identify factors mediating the relationship between education and mental health. More research is also needed on distributional effects and whether compulsory education has differential impacts across subgroups. Finally, additional research should assess the longer-term impacts of educational reforms on mental health trajectories over the life course.

In summary, this study highlights critical areas for improvement in educational practice, policy reform, and future research to promote the mental well-being of minority youth. A continued focus on equity and inclusion within education systems is critical for supporting the mental health of ethnic minorities.

4 Chapter IV: An intersectional Oaxaca-Blinder decomposition of the ethnic and sex mental health inequities in the UK

4.1 Introduction

Mental health inequites between ethnic minorities and between women and men in the United Kingdom represent a critical public health challenge. Recent evidence suggests that women from ethnic minorities are at higher risk of common mental disorders (Alghamdi et al., 2023; Devonport et al., 2023; Nazroo, 2022a). These disparities reflect systemic inequalities and pose significant obstacles to achieving health equity. The critical question that emerges is: What drives these mental health gaps, and how can we effectively address them?

This study aims to answer this overarching question by decomposing the mental health gap between ethnic groups, sexes, and their intersections in the UK. By using the Oaxaca-Blinder decomposition method, we seek to explore the contributions of various social determinants of health (SDOH) to these existing gaps. This approach allows us to address three critical questions:

1. To what extent do differences in risk factors versus differences in the effects of those risk factors contribute to the mental health gap between ethnic minority and white majority groups?
2. How much of the mental health gap between women and men can be attributed to differences in risk factors versus differences in their effects?
3. What factors drive the mental health gap between women from ethnic minorities and the rest of the UK population, and how do these factors interact?

The significance of these questions lies in their potential to inform targeted interventions and policies. By understanding the relative importance of each determinant, we can develop more effective strategies to reduce inequities and promote mental health equity.

Our study is grounded in intersectionality, a framework introduced by Kimberlé Crenshaw in 1989. This approach allows us to analyse how the compounding effects of various social disadvantages impact mental health, particularly for women from ethnic minorities. The intersectional perspective is crucial for understanding how different forms of oppression, including racial and gender biases, can simultaneously create compounded and intensified disadvantages (Crenshaw, 1990).

Furthermore, we draw on Diderichsen's framework on the social determinants of health inequities, which suggests that these inequities arise from five fundamental mechanisms: social stratification, differential exposures, differential vulnerabilities, and varied consequences of diseases (Diderichsen et al., 2012). This conceptual framework guides the empirical research through the Oaxaca-Blinder decomposition as we can examine the extent to which different socio-determinants of health contribute to the observed mental health gaps.

The answers to our research questions have far-reaching implications. They can guide policymakers in allocating resources more effectively, help healthcare providers tailor interventions, and inform public health strategies to reduce mental health disparities. Moreover, by adopting an intersectional approach, we can shed light on the unique challenges that subgroups often overlook in broader population studies.

4.2 Literature review

Empirical evidence suggests that ethnic minorities exhibit worse mental health compared to the white majority in the UK. The prevalence of mental health conditions is twice as high among Black Caribbean men compared to White men, with Black Caribbean and Black African individuals facing a significantly elevated risk of being diagnosed with severe, psychosis-related mental illnesses compared to the white majority population (Nazroo, 2022a).

Ethnic disparities in multimorbidity were observed among 20,800 service users with psychosis, with higher odds identified for individuals of Black African, Black Caribbean, and Black British ethnicity. In contrast, individuals of Chinese and Other ethnicities exhibited reduced odds compared to White British individuals (Fonseca de Freitas et al., 2022). A recent report by the UK Government to investigate racial disparities in the UK highlighted that ethnic minority communities exhibit a higher fear of hate crimes than their actual incidence, as highlighted by the Crime Survey for England and Wales (CSEW) from March 2018 to March 2020, with 16% of Asians and 13% of Blacks expressing significant concern about being targeted due to their race or ethnicity (UK Government, 2021). It is well established that experiences of ethnic and racial harassment are linked to adverse health outcomes, particularly in mental health, in the UK (Becares et al., 2009; Karlsen & Nazroo, 2002; Karlsen et al., 2005; Wallace et al., 2016), as well as in other regions (Becares et al., 2012; Paradies et al., 2015). According to the 2017 Race Disparity Audit, Black women are identified as the demographic with the highest likelihood of having encountered a common mental disorder, such as anxiety or depression (Audit, 2017). In sum, the findings point to the intersectional effect of ethnic and sex harassment on mental health.

Other socioeconomic and contextual factors combined with discrimination may contribute to the gap, too. The literature suggests that institutional racism within mental healthcare, coupled with intertwined structural, interpersonal, and institutional racism, collectively contribute to these disparities in both the risk of mental health issues and the quality of care received (Mirza & Warwick, 2022; Nazroo, 2022a).

The observed disparities in mental health outcomes among ethnic groups point to a complex phenomenon influenced by various factors, some of which may be detrimental or protective. The correlation between disparities and ethnicity and other socio-determinants of health means that these inequalities are not merely statistical differences but are deemed inequities for being "avoidable, remediable and unjust" (Whitehead, 1991; Whitehead, 2007). Socioeconomic determinants, such as income, education, and housing, to name a few, contribute significantly to this gap, as they stratify social and ethnic groups differently. The interlinkage of these socioeconomic factors with ethnicity and sex suggests a structural or systemic dimension to the disparities, implying the existence of institutional barriers and systemic racism within the broader societal framework. Understanding the intricate relationship between mental health disparities and these stratifying factors is essential for developing targeted interventions that address the root causes and promote equity within diverse communities (Mirza & Warwick, 2022; Nazroo, 2022a, 2022b).

Regarding conceptual frameworks, acknowledging "fundamental causes" as critical drivers of persistent health inequities in underserved communities has increased attention to the Social Determinants of Health (SDOH) in research, programs, and policies. This shift represents a departure from previous frameworks centred on individual agency and stresses the structural nature of SDOH as a fundamental cause of health disparities (Thimm-Kaiser et al., 2023).

Applying the health inequity model developed by Diderichsen et al. (2022) to ethnic health inequity means that ethnic minorities are on lower strata across those SDOH — educational attainment, income, housing ownership, social/cultural capital — (mechanism I), are at heightened risk of adverse health outcomes (mechanism II), show differential vulnerability to same health risks (mechanism III), suffer from different consequences of diseases. The uneven impact of COVID-19 on ethnic minorities in the UK is a clear example of those mechanisms in place (Katikireddi et al., 2021).

From a methodological standpoint, the Oaxaca-Blinder decomposition emerges as a promising tool for examining the influence of these mechanisms – specifically, the effects of the level of endowments and the differential impact of social stratification. Notably, its application in the UK context for studying health inequities, particularly in the realm of mental health and across ethnic groups and sex, remains limited. Beyond the UK, researchers have applied an Oaxaca-Blinder approach to decompose mental health inequities. These studies include a decomposition of the mental health gap between natives and foreign-born in Sweden (Brydsten et al., 2019b), self-reported health gap between the Baltic and rest of Europe induced by the economic crisis (Brzezinski, 2019), mental health gap between high and low economic groups (Harouni et al., 2018), mental health gap across education and migration status in Sweden (Linder et al., 2020), and mental health gap across urban/rural group in China (Sun & Lyu, 2020). This study aims to fill such a gap by exploring the differences in sex and ethnicity and the intersections of both.

4.2.1 Aims and research questions

By adopting the Oaxaca-Blinder decomposition methods, this study aims to disentangle the complex interplay of these socio-determinants of health and their contributions to the mental health inequity between sex and ethnic minorities and the white majority in the UK. Therefore, this study has three main research questions:

- How much of the mental health gap, measured by the SF12 and the GHQ-Likert scale, between **ethnic minority and white majority groups** in the UK can be attributed to differences in risk factors versus differences in the effects of those risk factors?
- How much of the mental health gap, measured by the SF12 and the GHQ-Likert scale, between **women and men** in the UK can be attributed to differences in risk factors versus differences in the effects of those risk factors?
- How much of the mental health gap, measured by the SF12 and the GHQ-Likert scale, between **women from ethnic minorities and the rest of the UK population** can be attributed to differences in risk factors versus differences in the effects of those risk factors?

The selection of these specific research questions and comparisons is deliberate and builds upon the findings from Chapter 3. While Chapter 3 focused exclusively on ethnic minorities to isolate the causal effect of education within this group, Chapter 4 broadened the scope to explore mental health disparities across multiple dimensions. This expansion allows to:

- Examine the overall ethnic minority-white majority gap, providing a comprehensive view of racial/ethnic mental health disparities in the UK.
- Investigate the gender gap in mental health across the entire population, acknowledging that gender disparities may manifest differently within and across ethnic groups.

- Specifically focus on women from ethnic minorities compared to the rest of the population, addressing the intersectionality of gender and ethnicity highlighted in our theoretical framework.

This approach can capture a more in-depth picture of mental health inequities. Comparing ethnic minority women to the rest of the population (rather than just within ethnic minorities) can show the combined effect of sex and ethnic minority status. This aligns with the intersectional perspective, recognising that the experience of being both a woman and an ethnic minority may lead to unique mental health challenges. Furthermore, this broader analysis complements the causal insights from Chapter 3 to explore how various social determinants of health contribute to mental health gaps across different population subgroups.

4.3 Methods

This study adopts a decomposition approach to investigate the mental health disparity among ethnic minorities, sex groups, and the intersectionality of both while also assessing the influence of social determinants on health inequities.

4.3.1 Data

The present study's dataset comprised 431,803 and 432,201 valid responses for the SF-12 and GHQ questionnaires, respectively (University of Essex, 2022). The analytical sample was derived from the final 12 waves of the UK Household Longitudinal Study (UKHLS) to leverage the ethnicity booster. Subsequently, earlier waves from the British Household Panel Survey (BHPS) were omitted from the empirical strategy due to the limited representation of ethnic minority groups in those samples.

4.3.2 Variables

Outcome variables

This chapter uses the same instruments as the previous chapter: the SF-12 and the GHQ. These instruments have been discussed in section 1.3.1 above. The average SF-12 score is 49.06 (unweighted) and 48.26 (weighted). The unweighted average of the GHQ-Likert is 11.18, and the weighted average is 11.35.

Table 4.1 Number of observations with valid answers for SF-12

Years	Wave	Number of non-missing observations
2009-10	1	47,400
2010-11	2	39,888
2011-12	3	40,586
2012-13	4	39,236
2013-14	5	37,130
2014-15	6	35,197
2015-16	7	36,996
2016-17	8	35,295
2017-18	9	32,218
2018-19	10	30,926
2020-21	11	29,379
2021-22	12	27,552
Total		**431,803**

Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

Table 4.2 Number of observations with valid answers for GHQ

Years	Wave	Number of non-missing observations
2009-10	1	39,700
2010-11	2	43,414
2011-12	3	40,576
2012-13	4	38,781
2013-14	5	37,133
2014-15	6	38,865
2015-16	7	37,175
2016-17	8	35,472
2017-18	9	32,440
2018-19	10	31,222
2020-21	11	29,688
2021-22	12	27,735
Total		**432,201**

Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

Mental health gap

The mental health gap is computed between two ethnic groups, a white majority and a non-white ethnic minority. Ethnicity has been recoded into white and non-white as set out in Table 4.3.

Table 4.3 Recoding of ethnicity into two major groups

Ethnic group	White	Non-White
British/English/Scottish/Welsh/Northern Irish	388,030	
Irish	9,117	
Any other white background	13,620	
Gypsy or Irish traveler		193
White and black Caribbean		3,606
White and black African		1,301
White and Asian		1,947
Any other mixed background		2,182
Indian		18,655
Pakistani		16,276
Bangladeshi		9,962
Chinese		2,219
Any other Asian background		5,385
Caribbean		9,192
African		10,890
Any other black background		845
Arab		1,490
Any other ethnic group		3,548
Total	**410,767**	**87,691**

Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

Socio-determinants of health (SDOH)

The analysis incorporates several demographic variables as socio-determinants of health: age, neighbourhood cohesion, long-lasting limiting illnesses, experienced attacks or avoided places for fear of being attacked (a proxy for potentil discrimination), and religion identity, as detailed below.

Age and date of birth. Age is a continuous variable derived from birth and measured in completed years at the interview. This variable is also used to derive five and 10-year intervals. The youngest individual in the sample is 16, and the oldest is 103. Month and year of birth were combined to create a variable month-year of birth, which was used as the running variable for the RD design.

Sex. This is a derived variable and is checked across waves. It takes 1 for males if all the information in the survey suggests so and 2 for females. The variable would take 0 if there were any inconsistencies in the available information and the forename in the administration database did not suggest a specific gender. The number of inconsistencies is relatively low. In waves 1 to 12, there are at most two individuals with a value equal to 0. These were coded as missing in the analytical sample. For the model, a new variable named 'Female' was created assuming 1 if female and 0 if male.

Neighbourhood cohesion. This is captured through the Buckner's Neighbourhood cohesion instrument (short α ±= .88). Neighbourhood cohesion, derived from Buckner's Neighbourhood Cohesion Instrument (Buckner, 1988), is calculated as the mean reverse-coded response (rounded to one decimal point) from the original variables. Higher values indicate greater cohesion, ranging from 1 ("lowest cohesion") to 5 ("highest cohesion"). Cronbach's Alpha is reported in the variable label.

Long-lasting limiting or chronic illness. The variable takes three ordinal values:1 "no illness", 2 "non-limiting illness" and 3 "long lasting limiting or chronic illness".

Attacked or avoided places by fear of attacks based on racial, religious or sex (discrimination). This variable records attacks in the last 12 months or avoided places by fear of attacks due to some discrimination based on racial/gender or any other reason. This binary variable assumes 0 "neither attacked nor avoided" and 1 "either attacked or avoided". This variable is termed 'discrimination' as a proxy for that.

Rural/urban residence. This is a binary variable coded as 0 "urban" and 1 "rural".

Religious identity. This is a binary variable coded as "0" if respondent does not practice or identify with any religion and 1 if the opposite.

Income. This has been added to the model as a binary variable indicating whether the household was above the median net household income. Net household income was equivalised by the OECD scale and adjusted by inflation. Moreover, few negative observations have been recoded to 0.

Employment and job status. This dimension was incorporated as a binary variable indicating 1 if employed (full-time or part-time) or student, and 0 otherwise.

Higher educational attainment. Education has been added as a binary variable, denoting 1 if higher education is attained and 0 if not.

Housing tenure. This was a binary variable indicating 1 if ownership status and 0 otherwise.

Behavioural factors. Three behavioural factors were used as indicators of healthy lifestyles in this study: the quantity of fruit consumed, smoking status, and alcohol consumption. The quantity of fruit consumed is represented by a continuous variable ranging from 0 to 10, signifying the daily intake amount. Smoking status is presented as a binary variable, taking the value of 1 for smokers and 0 for non-smokers. As for alcohol consumption, it is expressed as an ordinal variable on a scale from 1 to 5, where 1 indicates never drinking, and 5 corresponds to a frequency of more than four times per week.

4.3.3 Descriptive statistics

Table 4.4 Descriptive statistics by ethnic group

Mean	**Ethnic group**	
	White	**Non-White**
SF-12	49.24	48.08
GHQ-Likert scale	11.17	11.25
Female	0.54	0.55
Age	49.73	40.33
Limiting/chronic illness	1.60	1.41
Attacked/avoided places (discrimination)	0.02	0.07
Above median HH income	0.53	0.37
Employed/student	0.61	0.66
Rural	0.29	0.02
Higher education	0.35	0.41
Own house	0.74	0.56
Neighbourhood cohesion	3.58	3.50
Religion identity	0.15	0.31
Daily fruit	2.29	2.25

Alcohol consumption	3.36	2.89
Smoker	0.15	0.11
Total number of observations	**365,440**	**66,111**

Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

Table 4.5 Descriptive statistics by sex

Mean	**Male**	**Female**
SF-12	50.27	48.1
GHQ-Likert scale	10.52	11.71
Ethnic minority	0.17	0.18
Age	48.06	48.06
Limiting/chronic illness	1.53	1.6
Attacked/avoided places (discrimination)	0.02	0.03
Above median HH income	0.52	0.48
Employed/student	0.66	0.58
Rural	0.24	0.24
Higher education	0.35	0.37
Own house	0.72	0.69
Neighbourhood cohesion	3.53	3.6
Religion identity	0.16	0.2
Daily fruit	2.19	2.36
Alcohol consumption	3.49	3.16
Smoker	0.15	0.13
Total number of observations	**191,678**	**240,099**

Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

Table 4.6 Descriptive statistics by ethnicity and sex

Mean	**Rest of the population**	**Female-BME**
SF-12	49.25	47.09
GHQ-Likert scale	11.14	11.7
Age	48.91	40.21
Limiting/chronic illness	1.58	1.44
Attacked/avoided places (discrimination)	0.02	0.08
Above median HH income	0.51	0.36
Employed/student	0.62	0.59
Rural	0.26	0.02
Higher education	0.36	0.41
Own house	0.72	0.56
Neighborhood cohesion	3.58	3.48
Religion identity	0.17	0.32
Daily fruit	2.29	2.3
Alcohol consumption	3.34	2.77
Smoker	0.15	0.07

Total number of observations	**394,391**	**37,160**

Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

4.3.4 The Oaxaca-Blinder decomposition approach

The Oaxaca-Blinder decomposition is an appropriate modelling technique to evaluate the factors contributing to mean differences in a continuous outcome between two groups (Oaxaca, 1973).

This method can be viewed as a blend of t-tests and multiple regression models (Rahimi & Hashemi Nazari, 2021). Assuming an outcome Y explained by K variables $(x_1, \dots, x_k)$ in a linear regression setting, the mean predicted outcome for group g (g_1) can be formulated in the following manner:

$$\bar{Y}^g = \beta_0^g + \sum_{j=1}^{k} \beta_j^g \bar{x}_j^g$$

where $\bar{x}$ and β corresponds to the mean value of each predictor and the estimated regression coefficient, respectively. Hence, the average difference in outcome between both groups can be defined as:

$$\Delta\bar{Y} = (\beta_0^1 - \beta_0^2) + \sum_{j=1}^{k} (\beta_j^1 \bar{x}_j^1 - \beta_j^2 \bar{x}_j^2) \qquad \textbf{(1)}$$

This formula says that the mean outcome difference can be decomposed into three parts:

1. The mean difference between the level of each contributing factor (x_j);
2. the differential effects (β_j) of these factors on the mean difference between both groups;
3. A residual of unknown factors that are not included in the model.

One of the main aims of an Oaxaca-Blinder approach is to assess the magnitude of each component. For this purpose, the levels of explanatory variables and regression coefficients in the two groups are sequentially assumed to be identical to identify the net effect of each component. This involves adopting a counterfactual approach, where the coefficients and variable levels in the equation for one group are replaced with the corresponding values for the other group (reference). Consequently, the anticipated alteration in a group's mean outcome is determined when this group adopts the reference group's predictor values and regression coefficients. Thus, this methodology can estimate the contribution of each component (Jann, 2008; Jones & Kelley, 1984).

Four-way decomposition

It is often helpful to decompose the mean outcome difference into four components. Such decomposition is done by expressing, for example, Equation 1 from the perspective of group 1 as the reference. The group 1 equation is:

$$\bar{Y}^1 = \beta_0^1 + \sum_{j=1}^{k} \beta_j^1 \bar{x}_j^1$$

$$= \beta_0^1 + \sum_{j=1}^{k} [\beta_j^2 + (\beta_j^1 - \beta_j^2)] \sum_{j=1}^{k} [\bar{x}_j^2 + (\bar{x}_j^1 - \bar{x}_j^2)]$$

$$= \beta_0^1 + \sum_{j=1}^{k} \beta_j^2 \bar{x}_j^2 + \sum_{j=1}^{k} \beta_j^2 (\bar{x}_j^1 - \bar{x}_j^2) + \sum_{j=1}^{k} \bar{x}_j^2 (\beta_j^1 - \beta_j^2) + \sum_{j=1}^{k} (\bar{x}_j^1 - \bar{x}_j^2)(\beta_j^1 - \beta_j^2)$$

The above equation means that $\beta_j^1 = \beta_j^2 + (\beta_j^1 - \beta_j^2)$ and $\bar{x}_j^1 = \bar{x}_j^2 + (\bar{x}_j^1 - \bar{x}_j^2)$ and replacing this into Equation 1, the mean outcome difference is decomposed into four components as below:

$$\Delta\bar{Y} = \underbrace{(\beta_0^1 - \beta_0^2)}_{B} + \underbrace{\sum_{j=1}^{k} \beta_j^2 (\bar{x}_j^1 - \bar{x}_j^2)}_{E} + \underbrace{\sum_{j=1}^{k} \bar{x}_j^2 (\beta_j^1 - \beta_j^2)}_{C} + \underbrace{\sum_{j=1}^{k} (\bar{x}_j^1 - \bar{x}_j^2)(\beta_j^1 - \beta_j^2)}_{I} \qquad (2)$$

Equation 2 shows a decomposition of the mean outcome (D) from the perspective of group 2, with group 1 as the reference. As depicted in Figure 4.1, D is broken down into components B, E, C, and I. The interpretation of each part is the following:

1. **Component B** captures basic differences, including the unobservable factors not incorporated into the model.

2. **Component E** captures the change in group 2's mean predicted outcome if it had the covariates levels of group 1 (reference). In simpler terms, E corresponds to the portion of D attributed to variations between groups in the levels of observable explanatory variables. Such an "explained" component is also known as the "**endowments effect**".
3. Component C corresponds to the change in group 2's mean predicted outcome caused by replacing the coefficients of one group in the equation of the other group. This is known as the "**coefficients effect**".
4. Component I correspond to the interaction between E and C caused by the simultaneous effect of differences in endowments and coefficients. This part is the "**interaction effect**" (Daymont & Andrisani, 1984; Jones & Kelley, 1984).

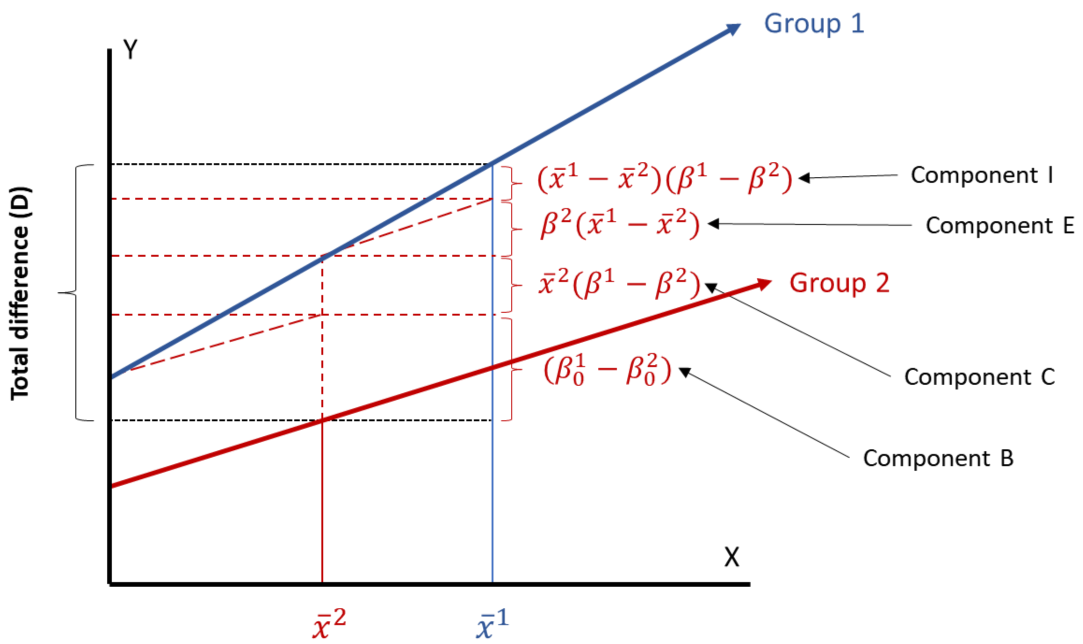


Figure 4.1 Four-way decomposition of the group difference in mean predicted outcome (interaction model) with group 1 as reference
Source: Adapted from Rahimi and Hashemi Nazari (2021)

Three-way decomposition

The four-way decomposition is not the only one, as discussed by Rahimi and Hashemi Nazari (2021). It is possible to arrive at a three-way decomposition, with further arrangements, distinguishing between endowments (E), unexplained (U), and interactions (I). In Equation 2, component (B) captures differences between two groups that cannot be accounted for by the observed covariates (X). Essentially, this disparity arises from unobserved variables. Moreover, component C is not explained either by these differences. Components (B and C) can be grouped into an "unexplained" part (U), giving the three-fold decomposition. Therefore, Equation 2 becomes:

$$\Delta\bar{Y} = \underbrace{\sum_{j=1}^{k}\beta_j^1\left(\bar{x}_j^1 - \bar{x}_j^2\right)}_{\text{E}} + \underbrace{\sum_{j=1}^{k}\bar{x}_j^1\left(\beta_j^1 - \beta_j^2\right)}_{\text{U}} - \underbrace{\sum_{j=1}^{k}\left(\bar{x}_j^1 - \bar{x}_j^2\right)\left(\beta_j^1 - \beta_j^2\right)}_{\text{I}} \qquad (3)$$

In a three-way decomposition, D decomposes into component E – representing differences in the level of covariates. U captures the differential effects of unobserved variables, while I corresponds to the simultaneous interaction between E and U.

Two-way decomposition

Further arrangements can reduce the decomposition into two components: explained and unexplained, which is relatively more convenient to interpret and draw inference for policy recommendations.

The previous decompositions assumed that one group performs better than the other in the given outcome and that the group lagging should catch up. However, a non-discriminatory condition could be postulated to be reached by both groups. If β^* is such a non-discriminatory condition, the corresponding equation for D becomes:

$$\underbrace{\Delta\bar{Y}}_{\text{D}} = \underbrace{\sum_{j=1}^{k}\beta_j^*\left(\bar{x}_j^1 - \bar{x}_j^2\right)}_{\text{Endowments effect}} + \underbrace{\left[\sum_{j=1}^{k}\bar{x}_j^1\left(\beta_j^1 - \beta_j^*\right) + \sum_{j=1}^{k}\bar{x}_j^2\left(\beta_j^* - \beta_j^2\right)\right]}_{\text{Discrimination effect}} \qquad (4)$$

The interpretation of components is the following. The first component corresponds to variations attributed to differences in the levels of observed characteristics, commonly known as the "endowment effects." In contrast, the second component pertains to distinctions in coefficients concerning the non-discriminatory β^*. This component not only captures variations in the levels of unobservable variables but also their differential effects. Hence, it is termed the "unexplained portion of disparity", or discrimination effect.

There is a direct link between components in the different decompositions. The unexplained/discrimination effect in Equation 4 is similar to the U component in Equation 3 but includes also component B in Equation 2. The "endowment effect" in Equation 4 is a combination of component E and I in Equation 3.

4.3.5 Empirical strategy

The empirical analysis starts with testing the association between social determinants of health and the ethnic mental health gap through weighted and unweighted regression analysis (OLS). The weighted regressions incorporate the complex survey design through the -svy prefix commands in Stata© v.17. The remaining of the section shows results for Oaxaca-Blidner decomposition by ethnicity, sex, and the intersection of both. The Oaxaca-Blinder decomposition is implemented through the user-written Stata© command -oaxaca (Jann, 2008).

4.4 Results

This section presents the results of the regression analysis (tables) and data visualisation of the Oaxaca-Blinder decompositions. After considering various decomposition methods (four-way, three-way, and two-way), this study employs the two-way decomposition approach for several reasons. Primarily, the two-way decomposition offers a more straightforward and more interpretable division between explained and unexplained components of the mental health gap. This clarity is crucial for both analytical precision and policy relevance.

Methodologically, the two-way decomposition reduces the complexity of multiple interaction terms in higher-order decompositions. From a policy perspective, the two-way approach provides a more actionable framework. By clearly delineating between differences attributable to observable characteristics (the explained component) and those due to differential returns to these characteristics or unobserved factors (the unexplained component), policymakers can have a more direct path for intervention. The explained component can guide targeted policies addressing specific social determinants of health, while the unexplained component can highlight areas requiring further research or potential structural inequalities. Moreover, the two-way decomposition aligns well with the research questions, showing the relative contributions of observed factors and potential discrimination or other unobserved influences to mental health inequities. This approach balances analytical depth and practical applicability, making it the most suitable choice for addressing our research objectives and informing policy decisions. Tables for decomposition in detail are displayed in Annex III.

4.4.1 The social determinants of ethnic mental health inequities

The regression analysis was conducted to explore the association between socio-determinants of mental health and mental health outcomes. The dependent variables were the mental health status SF12 and the GHQ-Likert scale, while the independent variables included a range of social determinants of health, sex, ethnicity and other demographic variables.

Table 4.7 shows the results from a series of linear regression models of the SF-12 on a set of socio-determinants of health. The sample included 22,944 to 216,273 observations, both weighted and unweighted, of adults in the UK. The SF-12 is an instrument used to assess mental health, which ranges from 0 to 100, where a higher score of 100 indicates better mental health, and a lower score of 0 indicates the opposite.

Table 4.7 SF-12 Regression results – Weighted and unweighted

	(1) SF12-OLS-Unweighted	(2) SF12-OLS-Unweighted (no behavioural variables)	(3) SF12-OLS-Weighted	(4) SF12-OLS-Weighted (no behavioural variables)
Ethnic minority	-.155	-.173*	.841	.562*
	(.337)	(.1)	(.827)	(.318)

	(1) SF12-OLS-Unweighted	(2) SF12-OLS-Unweighted (no behavioural variables)	(3) SF12-OLS-Weighted	(4) SF12-OLS-Weighted (no behavioural variables)
Female	-1.904***	-2.017***	-1.896***	-1.922***
	(.129)	(.049)	(.273)	(.135)
Female and ethnic minority	.199	.423***	-2.705**	-.625
	(.457)	(.134)	(1.207)	(.452)
Age	.01	-.154***	0	-.118***
	(.021)	(.007)	(.04)	(.018)
Age squared	.001***	.003***	.002***	.003***
	(0)	(0)	(0)	(0)
Limiting/chronic illness	-2.466***	-2.649***	-2.274***	-2.599***
	(.088)	(.033)	(.191)	(.085)
Attacked/avoided places (discrimination)	-4.202***	-2.23***	-5.109***	-2.559***
	(.47)	(.184)	(1.182)	(.498)
Above median HH income	.846***	.597***	.186	.421***
	(.136)	(.05)	(.293)	(.129)
Employed/student	1.287***	2.091***	1.278***	1.985***
	(.189)	(.066)	(.416)	(.182)
Rural	.319**	.374***	-.006	.322**
	(.136)	(.053)	(.289)	(.144)
Higher education	.043	.04	.157	.005
	(.128)	(.049)	(.252)	(.135)
Own house	1.209***	1.099***	1.825***	1.329***
	(.176)	(.059)	(.398)	(.172)
Neighbourhood cohesion	2.091***	2.361***	1.994***	2.633***
	(.092)	(.036)	(.219)	(.098)
Religion identity	2.179**	.476***	3.603*	-1.53***
	(.959)	(.059)	(2.136)	(.197)
Daily fruit	.147***		.211**	
	(.047)		(.104)	
Alcohol consumption	-.171***		-.157	
	(.062)		(.126)	

	(1) SF12-OLS-Unweighted	(2) SF12-OLS-Unweighted (no behavioural variables)	(3) SF12-OLS-Weighted	(4) SF12-OLS-Weighted (no behavioural variables)
Smoker	-1.627***		-1.486***	
	(.213)		(.473)	
_cons	39.924***	43.593***	39.813***	41.203***
	(.584)	(.199)	(1.206)	(.541)
Observations	22,944	172,093	145,093	216,273
R-squared	.167	.138	.176	.156

Standard errors are in parentheses.

**** p<.01, ** p<.05, * p<.1*

Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

The results suggest that mental health measured by the SF12 instrument tends to be substantially lower for those facing disabilities, discrimination[2], or socioeconomic disadvantages. Having a long-lasting limiting or chronic illness and experiencing discrimination were most strongly associated with reduced SF-12 scores, by estimates of 2.3 to 2.6 and 2.2 to 5.1 points across models. In addition, mental health seems to be consistently worse among women versus men (gaps around -1.9 points) and those lacking economic resources such as employment or being below the median household income (gaps of 1.3 to 2.1 points). Other markers such as home ownership (1.1 to 1.8 points) and neighbourhood cohesion (2.0 to 2.6 points higher) also robustly predicted better mental health.

There was more mixed evidence regarding any crude differences by ethnic minority status or rural/urban residence itself - estimates ranged from positive to negative across models but lost statistical significance in some weighted specifications after adjusting for socioeconomic factors. This finding suggests complex relationships between race/ethnicity, geography, social disadvantage, and

[2] Attacked/avoided places (discrimination)

health. Overall, the results highlight substantial inequities in mental health along demographic and socioeconomic markers within the UK adult population.

Table 4.8 presents the results of the factors associated with mental health and psychosocial distress in UK adults, using the 12-item General Health Questionnaire (GHQ-12) Likert Scale as the dependent variable. Across both weighted and unweighted regressions on samples ranging from 22,059 to 216,388 observations, results indicate substantially higher distress levels for those facing disabilities, discrimination, or economic disadvantages.

The presence of a long-lasting and limiting or chronic illness and experiencing discrimination were most strongly linked to worse GHQ scores, by gaps of 1.5 to 1.7 points and 1.2 to 2.2 points higher, respectively. Results also suggest psychosocial distress consistently elevated among women relative to men by 1.0 to 1.2 points. Lacking economic resources again emerged as a significant predictor, with above median household income and employment status associated with lower GHQ scores (-0.3 to -1.2 points), signalling more significant distress when income and work are absent. By contrast, markers of social integration like home ownership and neighbourhood cohesion predicted substantially lower psychological distress in all models (-0.4 to -1.4 points).

There was less evidence for GHQ that rural residency or minority status independently predicted higher distress after adjusting for other factors. Moreover, religious identity was associated with lower distress when sample weights were applied, suggesting complex relationships between mental health, demographics, geography, and social disadvantage. On the whole, however, inequities again emerge in psychosocial outcomes across markers of sex, illness level, discrimination, and economic integration like income and employment.

Table 4.8 GHQ-Likert Scale Regression results – Weighted and unweighted

	(1)	(2)	(3)	(4)
	GHQ-OLS-Unweighted	GHQ-OLS-Unweighted (no behavioural variables)	GHQ-OLS-Weighted	GHQ-OLS-Weighted (no behavioural variables)
Ethnic minority	.267	.089	.25	-.032
	(.191)	(.055)	(.396)	(.179)

	(1) GHQ-OLS-Unweighted	(2) GHQ-OLS-Unweighted (no behavioural variables)	(3) GHQ-OLS-Weighted	(4) GHQ-OLS-Weighted (no behavioural variables)
Female	1.088***	1.134***	.951***	1.186***
	(.067)	(.026)	(.139)	(.067)
Female and ethnic minority	-.562**	-.548***	.244	.059
	(.264)	(.074)	(.594)	(.247)
Age	.066***	.136***	.067***	.13***
	(.011)	(.004)	(.019)	(.009)
Age squared	-.001***	-.002***	-.001***	-.002***
	(0)	(0)	(0)	(0)
Limiting/chronic illness	1.622***	1.742***	1.515***	1.723***
	(.048)	(.018)	(.102)	(.045)
Attacked/avoided places (discrimination)	2.236***	1.23***	2.177***	1.242***
	(.279)	(.108)	(.574)	(.29)
Above median HH income	-.34***	-.344***	-.256*	-.268***
	(.071)	(.027)	(.156)	(.07)
Employed/student	-.647***	-1.203***	-.844***	-1.249***
	(.103)	(.036)	(.218)	(.102)
Rural	.001	-.003	.225	.063
	(.071)	(.029)	(.157)	(.077)
Higher education	-.047	-.059**	.003	-.097
	(.069)	(.027)	(.137)	(.073)
Own house	-.493***	-.372***	-.712***	-.42***
	(.094)	(.032)	(.21)	(.09)
Neighbourhood cohesion	-1.068***	-1.311***	-.934***	-1.414***
	(.052)	(.02)	(.126)	(.056)
Religion identity	-.017	.161***	-.734	.748***
	(.686)	(.031)	(1.427)	(.107)
Daily fruit	-.03		-.058	
	(.025)		(.05)	
Alcohol consumption	.093***		.093	

	(1) GHQ-OLS-Unweighted	(2) GHQ-OLS-Unweighted (no behavioural variables)	(3) GHQ-OLS-Weighted	(4) GHQ-OLS-Weighted (no behavioural variables)
	(.033)		(.064)	
Smoker	.564***		.544**	
	(.114)		(.258)	
_cons	12.369***	11.938***	12.593***	12.513***
	(.307)	(.108)	(.687)	(.291)
Observations	23,059	172,082	145,050	216,388
R-squared	.134	.139	.13	.148

Standard errors are in parentheses.

**** p<.01, ** p<.05, * p<.1*

Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

4.4.2 Oaxaca-Blinder decomposition by ethnicity

Figure 4.2 shows the Oaxaca-blinder decomposition for the mental health gap between ethnic groups through the SF12 measure. **The mean score for the white majority is 48.94 and 46.34 for the non-white minority. The gap is 2.588 and is statistically significant (p=0.001) —see panel a**. This means the white majority is relatively better off in mental health compared to the non-white ethnic minority. **About 79% of the overall difference is explained by the levels of observed covariates** —see panel b. Of the explained portion, age, discrimination, neighbourhood cohesion, and house ownership are the most significant contributions, as shown in panel c. The effect of age is important because both ethnic groups show different age distributions, with the ethnic minority mostly skewed towards younger intervals. An alternative model without age is shown in Annex III. Excluding age, most of the explained part is due to discrimination, employment/student status, neighbourhood cohesion and house ownership, all with positive signs. Thus, the results do not change remarkably in relative terms.

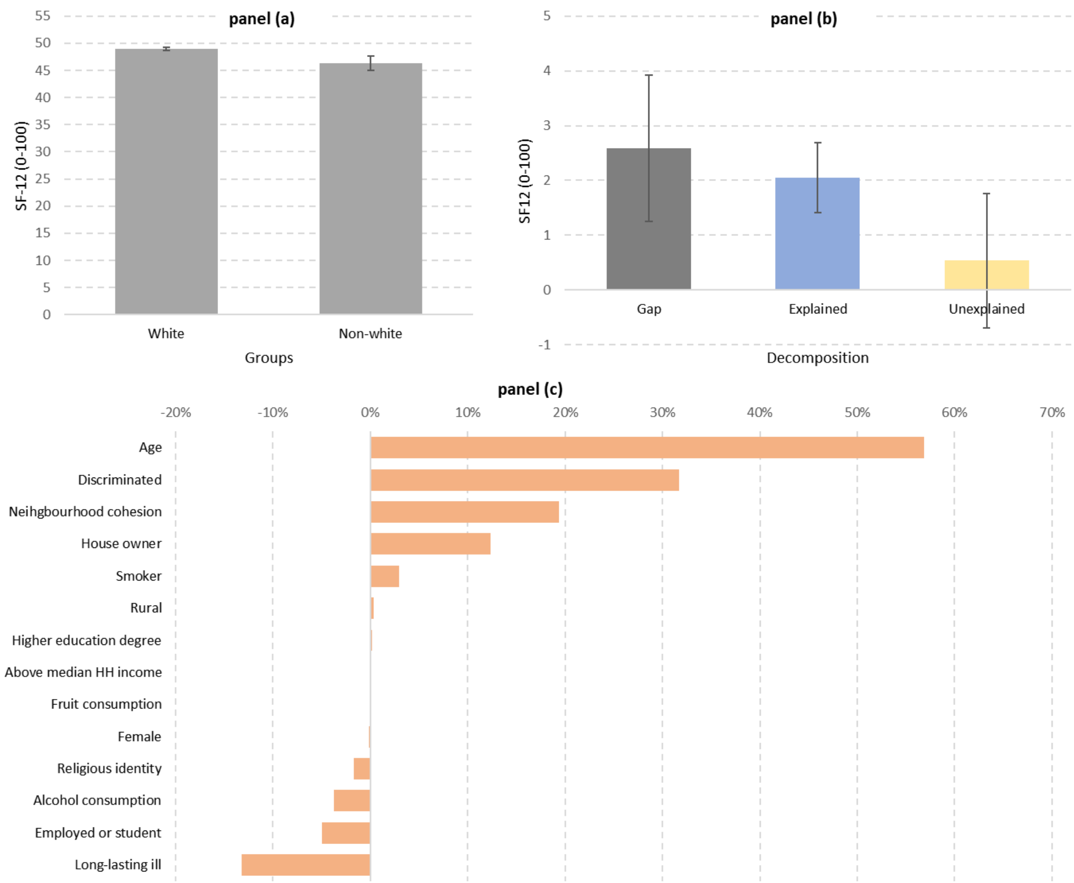


Figure 4.2 Oaxaca-Blinder decomposition for differences in the SF12 according to ethnicity

Note: The figure shows the mental health gap measured by the SF12 instrument according to ethnicity groups (White majority versus Non-white minority) in panel a. Panel b shows the decomposition of the gap into explained and unexplained. The % contribution of each factor to the explained part are displayed in panel c. The error bars display 95% confidence intervals and data estimations has incorporated the sampling design (weights and stratification). The variable discriminated means they experienced attacks or avoided places because of fears of attack based on discrimination. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

Figure 4.3 shows the same Oaxaca-blinder decomposition of mental health measured by the GHQ-Likert scale. **The mean score for the white majority is 11.07 and 12.15 for the non-white minority. The gap is -1.079 and is statistically significant (p=0.001)** as shown in panel a. Likewise to previous results, the white majority is relatively better off in mental health compared to the non-white ethnic minority, with a reverse sign considering the GHQ is an indicator of distress. **About 68% of the gap is explained by observed covariates**. An alternative model without age shows similar results, with discrimination, neighbourhood cohesion, and house ownership playing a pivotal role.

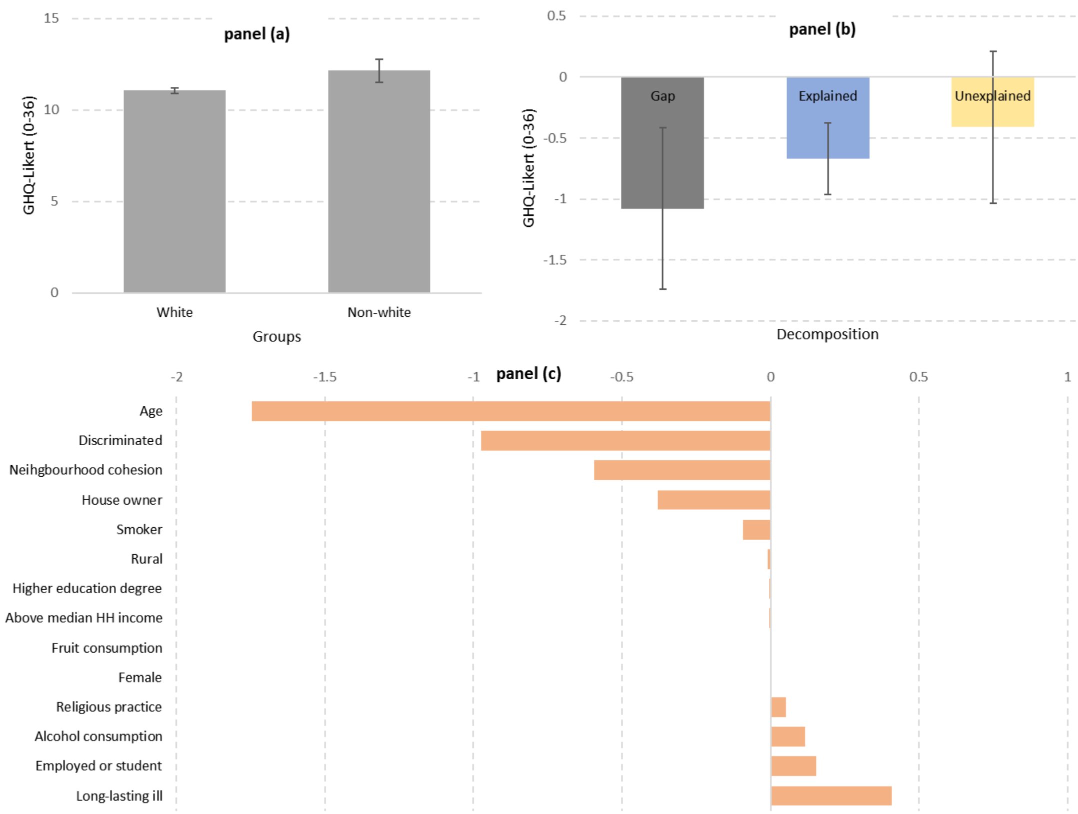


Figure 4.3 Oaxaca-Blinder decomposition for differences in the GHQ-Likert scale according to ethnicity

Note: The figure shows the mental health gap measured by the GHQ-Likert instrument according to ethnicity groups (White majority versus Non-white minority) in panel a. Panel b shows the decomposition of the gap into explained and unexplained. The % contribution of each factor to the explained part are displayed in panel c. The error bars display 95% confidence intervals and data estimations has incorporated the sampling design (weights and stratification). The variable discriminated means they experienced attacks or avoided places because of fears of attack based on discrimination. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

4.4.3 Oaxaca-Blinder decomposition by sex

Figure 4.4 and Figure 4.5 shows the decomposition of the same variables and both outcomes but by sex groups. The mean SF12 score was 47.7 for females and 49.81 for males. **This gap of 2.12 points was statistically significant (p=0.001), reflecting worse mental health for females**. **Approximately 99% of the total gap is not explained by differences in covariates between sexes**, and the explained part is not statistically significant. Within the unexplained part, ethnic minority and age are the statistically significant determinants.

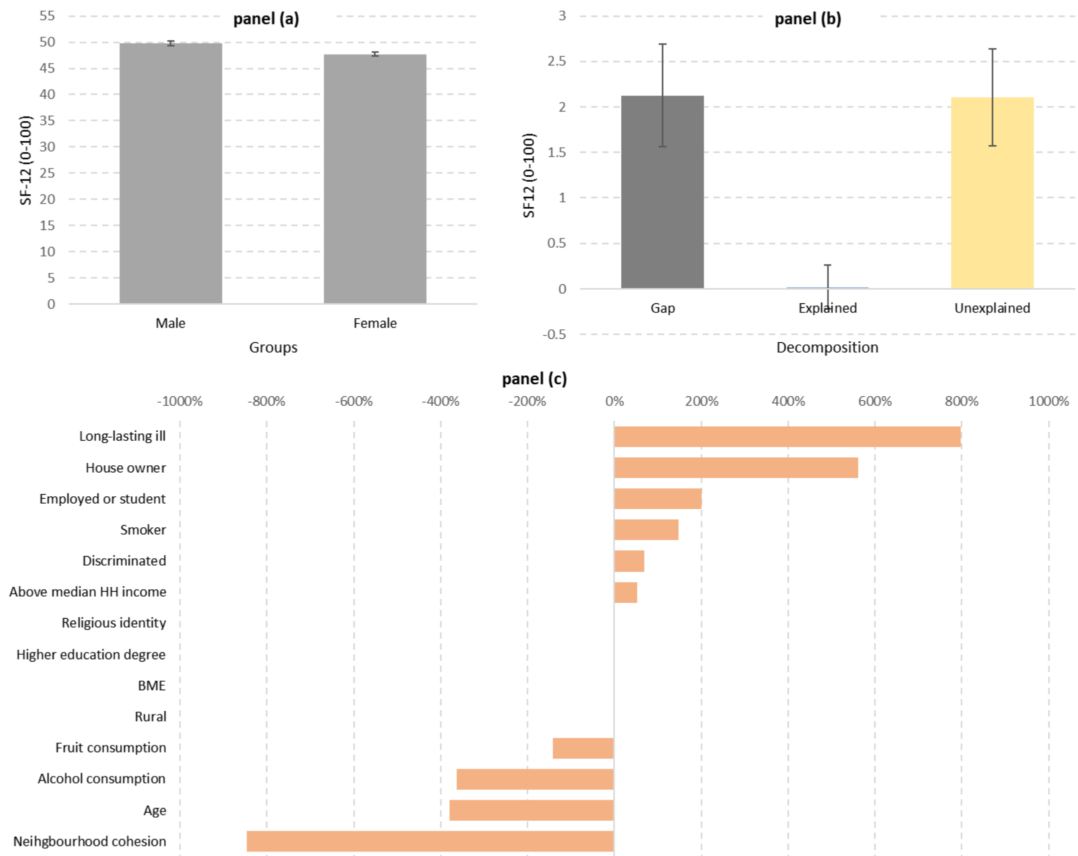


Figure 4.4 Oaxaca-Blinder decomposition for differences in the SF12 according to sex

Note: The figure shows the mental health gap measured by the SF12 instrument according to sex groups (Female versus Male) in panel a. Panel b shows the decomposition of the gap into explained and unexplained. The % contribution of each factor to the explained part are displayed in panel c. The error bars display 95% confidence intervals and data estimations has incorporated the sampling design (weights and stratification). The variable discriminated means they experienced attacks or avoided places because of fears of attack based on discrimination. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

Results for the GHQ-Likert scale in Figure 4.5 below align with previous results for the SF12. **The mean GHQ-Likert score was 11.6 for females and 10.63 for males**. The gap of -1.03 points was significant (p=0.001), indicating greater psychosocial distress among females. **About 94% of the total gap is due to the unexplained part**. None of the social determinants of health are statistically significant within the unexplained part.

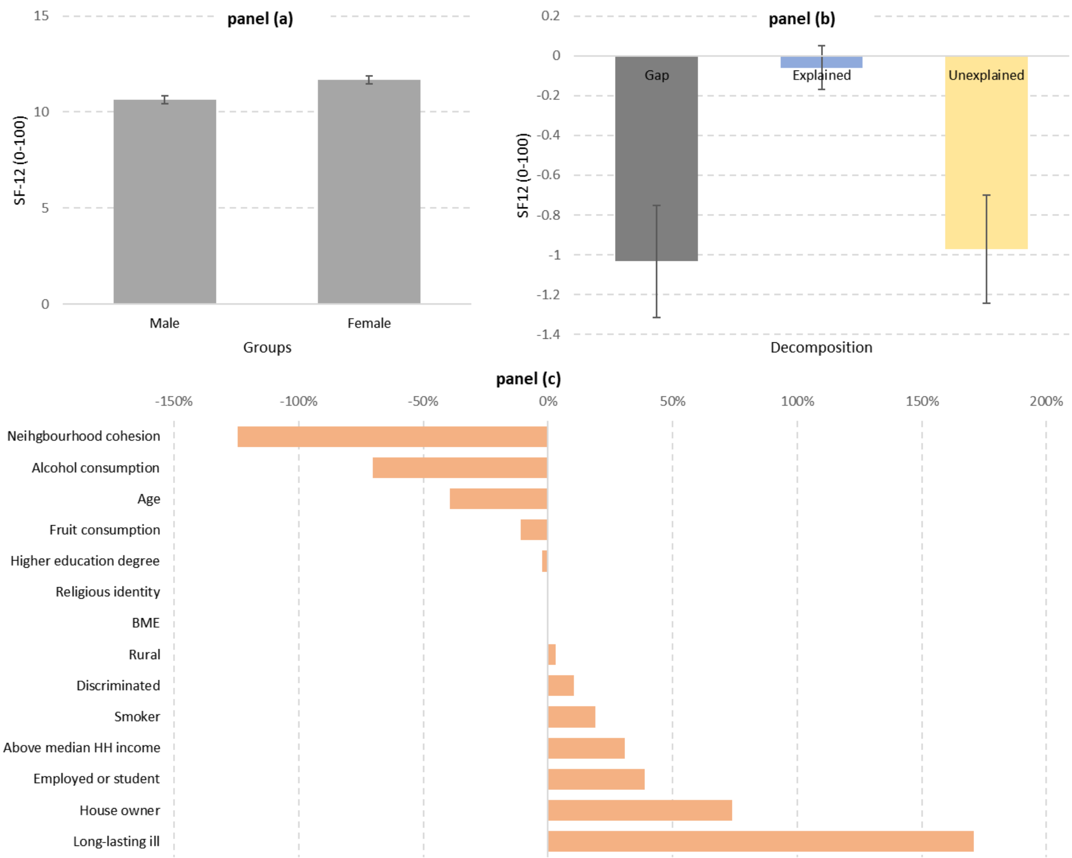


Figure 4.5 Oaxaca-Blinder decomposition for differences in the GHQ-Likert scale according to sex

Note: The figure shows the mental health gap measured by the GHQ-Likert instrument according to sex groups (Female versus Male) in panel a. Panel b shows the decomposition of the gap into explained and unexplained. The % contribution of each factor to the explained part are displayed in panel c. The error bars display 95% confidence intervals and data estimations has incorporated the sampling design (weights and stratification). The variable discriminated means they experienced attacks or avoided places because of fears of attack based on discrimination. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

4.4.4 Intersectional Oaxaca-blinder decomposition by ethnicity and sex

This section shows the same results as the previous models but decomposes the gap by the intersection of sex and ethnicity. Hence, there are two groups: women from ethnic minorities versus the rest of the population.

As shown in Figure 4.6, the mean SF12 score was 43.33 for females from ethnic minorities and 48.95 for the rest of the population. **This gap of 5.62 points was statistically significant (p=0.001), reflecting worse mental health for females from ethnic minorities. Approximately 47% of the total gap is explained by differences in covariates between both sub-populations, and both parts are statistically**

significant. In the explained part, age, discrimination, neighbourhood cohesion, and house ownership are statistically significant.

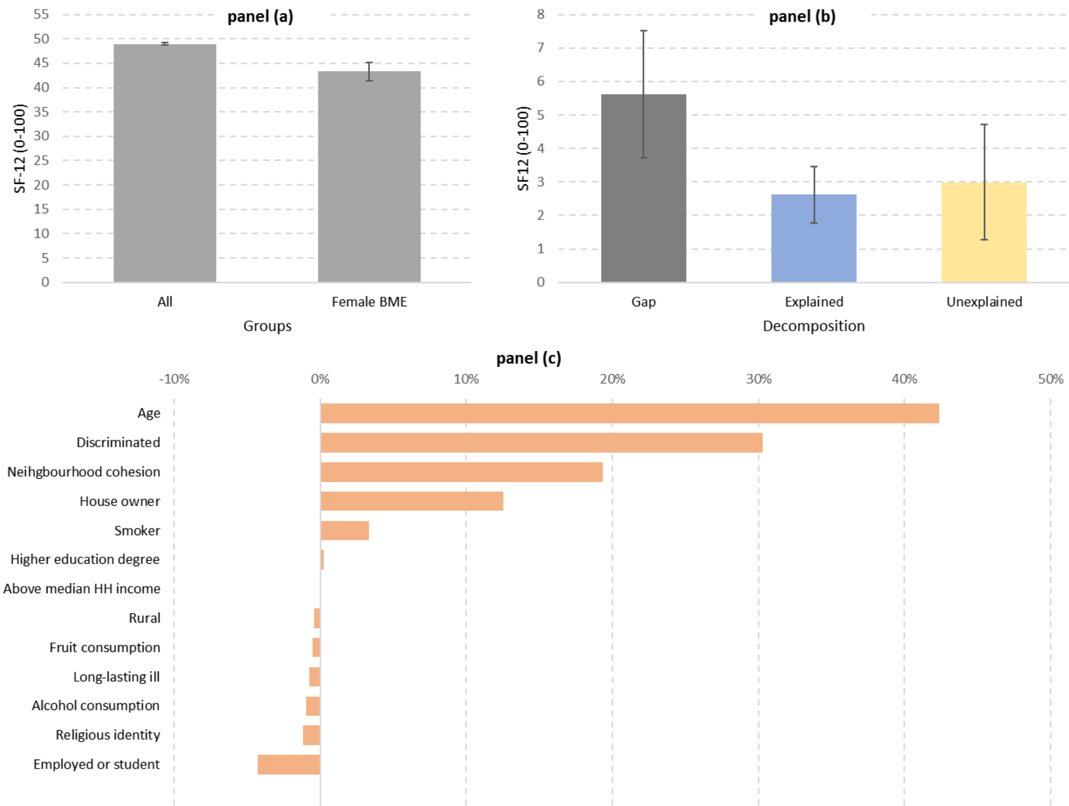


Figure 4.6 Oaxaca-Blinder decomposition for differences in the SF12 according to sex and ethnicity

Note: The figure shows the mental health gap measured by the SF12 instrument according to intersectional groups of sex and ethnicity (Female BME versus all population) in panel a. Panel b shows the gap decomposition into explained and unexplained. The % contribution of each factor to the explained part are displayed in panel c. The error bars display 95% confidence intervals and data estimations has incorporated the sampling design (weights and stratification). The variable discriminated means they experienced attacks or avoided places because of fears of attack based on discrimination. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

Similar results are observed for the GHQ-Likert scale outcome, as shown in Figure 4.7. **The mean GHQ score was 13.13 for females from ethnic minorities and 11.07 for the rest of the population. This gap of -2.05 points was statistically significant (p=0.001), reflecting worse mental health for females from ethnic minorities. Approximately 50% of the total gap is explained by differences in covariates between both sub-populations**, and both parts are statistically significant. In the explained part, age, discrimination, neighbourhood cohesion, and house ownership are statistically significant and relatively significant in magnitude.

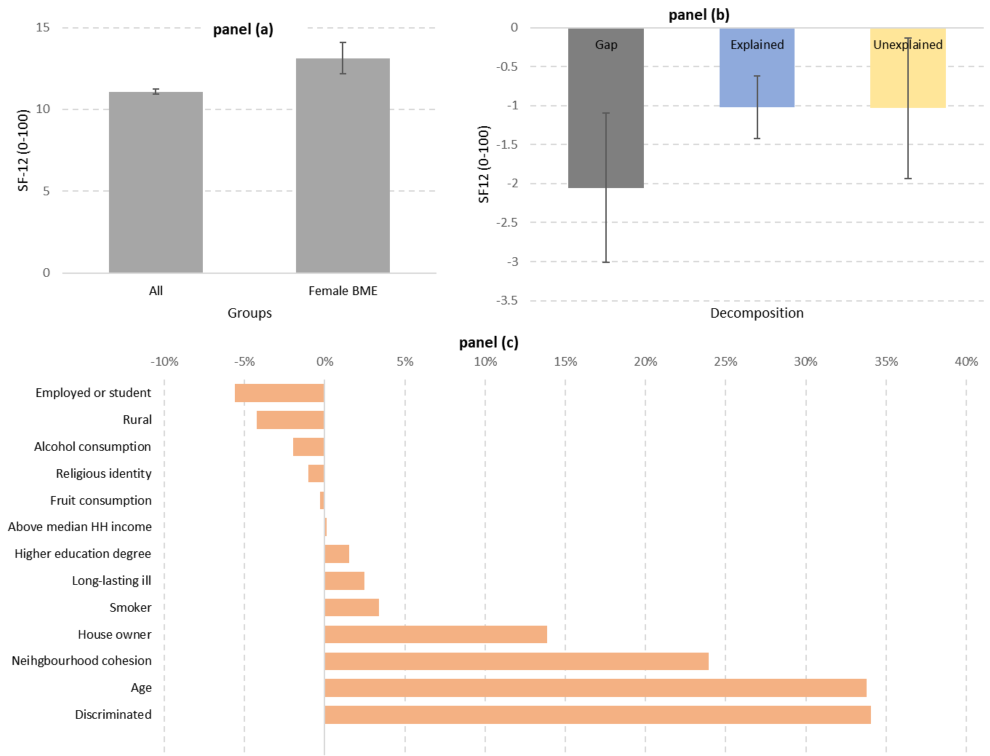


Figure 4.7 Oaxaca-Blinder decomposition for differences in the GHQ-Likert according to sex and ethnicity

Note: The figure shows the mental health gap measured by the GHQ-Likert instrument according to intersectional groups of sex and ethnicity (Female BME versus all population) in panel a. Panel b shows the decomposition of the gap into explained and unexplained. The % contribution of each factor to the explained part are displayed in panel c. The error bars display 95% confidence intervals and data estimations has incorporated the sampling design (weights and stratification). The variable discriminated means they experienced attacks or avoided places because of fears of attack based on discrimination. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931

4.5 Discussions

4.5.1 Key findings

This study aimed to disentangle the intersectional effect of sex and ethnicity on mental health measured by the SF12 and GHQ-Likert by decomposing the mental health gap into explained and unexplained and exploring the contribution of social determinants of inequity on the explained portion of the gap. This analysis was done through an Oaxaca-Blinder decomposition by ethnicity, sex, and the intersection of sex and ethnicity. The empirical analysis started with regression analysis to explore the association between social determinants of health inequity and mental health outcomes.

4.5.1.1 Reflection of outcome measures

The analysis employed two distinct measures of mental health, the SF12 and the GHQ-Likert scale. The SF12 provides a broader measure of mental health-related quality of life, while the GHQ-Likert scale is more sensitive to symptoms of common mental disorders. The disparities observed in the GHQ-Likert scale suggest that these findings may be particularly relevant to detecting and preventing common mental disorders among ethnic minorities.

Using these two complementary measures helps capture a more comprehensive picture of mental health disparities. The SF12 results provide insights into overall mental well-being and functioning, which is crucial for understanding the broader impact of mental health on quality of life. The GHQ-Likert scale results, on the other hand, offer a more clinically oriented perspective, highlighting areas where interventions might be most urgently needed to prevent the development or exacerbation of mental health disorders.

4.5.1.2 The intersectional effects of ethnicity and sex

The intersectional Oaxaca-Blinder decomposition reveals several key insights into the drivers of mental health inequities between women from ethnic minorities and the overall UK population. First, the results demonstrate that differences in endowments (observed characteristics) explain nearly half (47-50%) of the total mental health gap as measured by SF-12 and GHQ scores. This suggests that unequal distributions of socioeconomic resources, social capital, and exposure to discrimination substantively contribute to poorer mental health outcomes for minority women.

In particular, differences in age distribution, experiences of discrimination, neighbourhood cohesion, and home ownership emerge as the most statistically significant drivers of the endowments portion of the gap. The overrepresentation of minority women in younger age groups where mental health issues are more prevalent appears to be a significant contributing factor. Beyond demographics, the higher levels of discrimination faced by minority women coupled with lower access to protective resources like neighbourhood belonging and housing security also detrimentally impact their mental health relative to the general population.

At the same time, over 50% of the total gap remains unexplained by differences in observed characteristics. The results align with critical realism's stratified ontology. The explained portion of the mental health gap represents the 'empirical' domain - observable differences in socioeconomic resources and experiences. However, the substantial unexplained portion (over 50%) points to the existence of 'deep structures' in the 'real' domain, which may not be directly observable but exert a significant influence on mental health outcomes. These could include institutionalised racism, cultural biases, or other systemic factors that interact with ethnicity and gender. These findings can be better understood in light of critical realism's emphasis on looking beyond empirical observations to understand the underlying mechanisms generating observed inequities, highlighting social reality's complex, multi-layered nature (Collier, 1994).

In particular, the decomposition highlights the complex intersectional influences on minority women's mental health, stemming from both unequal distributions of risk and protective factors as well as unobserved processes linked to systemic marginalisation. A dual strategy of strengthening socioeconomic resources and mitigating systemic biases and discrimination may be needed to promote mental health equity across ethnic and gender lines effectively. The unexplained portion also suggests that further research into structural and psychosocial mechanisms is warranted to understand intersectional disparities fully.

4.5.1.3 Model selection and interpretation of results

The main results presented models with behavioural variables (smoking, alcohol consumption, and fruit intake). While incorporating these variables reduced the sample size due to their availability in fewer waves, the models with behavioural factors offer the most comprehensive and reliable insights. Despite the smaller sample, it remains sufficiently large to yield meaningful results. Importantly, including these variables mitigates potential omitted variable bias, providing a more complete picture of the factors influencing mental health disparities. The behavioural variables capture important lifestyle factors that can affect mental health.

Table 4.9 and Table 4.10 present the results of various Oaxaca-Blinder decomposition models for both SF-12 and GHQ-Likert outcomes. This tests the sensitivity of results when excluding behavioural variables or age, considering that age consistently accounted for a large percentage of the explained component in all models. However, the results show that excluding behavioural variables substantially impacts the explained-unexplained gap, while excluding age has a relatively minor effect. This pattern is consistent across both SF-12 and GHQ-Likert outcomes. Notably, in the model excluding behavioural variables, the explained portion increases significantly for both outcomes, suggesting these variables play a crucial role in understanding ethnic mental health disparities. This underscores the importance of including behavioural factors in analyses of mental health inequities despite the reduction in sample size their inclusion may cause. Detailed outputs are displayed in Annex III.

Table 4.9 All models for SF-12

Model	Groups	Explained	Unexplained	Sample size	Variables
Full	Ethnicity	79.3%	20.7%	175,833	All variables, including behavioural
Full	Sex	0.9%	99.1%	287,809	All variables, including behavioural
Full	Intersection	46.7%	53.3%	171,130	All variables, including behavioural
Reduced	Ethnicity	119.0%	-19.0%	258,627	Excluding behavioural
Reduced	Ethnicity	76.1%	23.9%	175,833	Excluding age

Table 4.10 All models for GHQ

Model	Groups	Explained	Unexplained	Sample size	Variables
Full	Ethnicity	61.9%	38.1%	175,949	All variables, including behavioural
Full	Sex	58.0%	42.0%	287,801	All variables, including behavioural
Full	Intersection	49.6%	50.4%	171,247	All variables, including behavioural
Reduced	Ethnicity	95.2%	4.8%	258,836	Excluding behavioural
Reduced	Ethnicity	60.1%	39.9%	175,949	Excluding age

4.5.1.4 Links to related literature

Reflecting on the relation of the findings to other studies, no other study in the UK has used an Oaxaca-Blinder decomposition to explore the ethnic or sex gap in mental health. However, other studies attempted similar strategies in other countries, such as those of Mrejen et al. (2022), which aimed to identify the determinants of depression and treatment disparities over time in Brazil using national survey data. The results showed a 10.8% depression prevalence in 2019, with over 70% not receiving care. Racial disparities were found, with higher depression among black/brown/mixed groups, and regional differences were a key factor.

Similarly, Platt et al. (2016) investigated associations between the gender wage gap and mood disorders in employed US adults. The results revealed higher odds of depression and anxiety when women's income was lower than men's, suggesting an impact of structural discrimination on mental health. Moreover, Brydsten et al. (2019a) examined mental health disparities between native Swedes and migrants, emphasising social integration. The findings showed that social factors like activity, trust and support explained significant disparities, highlighting the need to address social and economic inequality.

Their finding consistently finds that a substantial portion (47-50% in this study) of mental health disparities is explained by differences in socioeconomic resources and exposures. This reinforces how unequal distributions of social determinants drive inequities. Furthermore, the significant contributions of age, discrimination, neighbourhood factors, and housing to mental health disparities align with evidence from other studies, which stress the importance of social integration, experiences of exclusion, income/wealth, and migrant status as primary drivers. Moreover, this study's findings underscore the intersectional impacts of sex and ethnicity, further illuminating the complex dynamics at play in mental health inequalities.

4.5.2 Limitations

The Oaxaca-Blinder decomposition method has limitations worth noting. It is sensitive to model specification, with results dependent on the chosen regression model and sample sizes. This was addressed by testing different model specifications, including variations that excluded or included key variables like age and behaviours, and finding consistent robustness.

The method's additive nature does not consider interactions between independent variables. Consequently, it cannot differentiate the joint effect of variables like ethnicity and gender from their individual effects. This shortcoming motivated the creating of an intersectional group for decomposition and capturing nuanced interactions.

Interpreting the "unexplained" portion is complex, as it may signify omitted variables, unobserved differences, or model misspecification rather than discrimination effects. Caution is needed when concluding the unexplained gap. This quantitative decomposition, while revealing, also highlights the limitations of such methods in fully capturing intersectional experiences, aligning with critical realism's view on the partial nature of scientific knowledge (Zachariadis, 2013). While the Oaxaca-Blinder technique helps identify and quantify disparities, it may not fully capture multiple identities' lived experiences and complex interactions. The substantial unexplained portion of the gap serves as a reminder of the challenges in empirically measuring all aspects of intersectional disadvantage. This limitation underscores the need for complementary qualitative approaches to provide a more comprehensive understanding of how intersecting identities shape mental health outcomes, consistent with critical realism's advocacy for methodological pluralism.

Lastly, the observational nature of the decomposition precludes establishing causal relationships. Making definitive claims about factors driving observed gaps without additional causal evidence is unwarranted.

4.5.3 Implications for practice, policy, and future research

The sizable unexplained portion of the mental health gap indicates that additional research is needed to uncover omitted factors driving inequities. Quantitative and qualitative approaches could provide further insight into structural and psychosocial mechanisms not captured in the current data. For example, primary data collection through interviews or focus groups may identify cultural or experiential drivers.

More complex statistical approaches, such as structural equation modelling or causal mediation analysis, could better elucidate the pathways linking ethnicity, gender, socioeconomic resources, discrimination, and mental health. Testing the mediation effects of factors like discrimination could quantify indirect effects. Moderation analysis could also reveal subgroups experiencing disproportionate impacts at the intersection of multiple marginalised identities.

The cross-sectional nature of the analysis limits claims about causal ordering. Study designs leveraging quasi-experiments, instrument variables, or longitudinal panel data would strengthen causal inference about the factors contributing to mental health gaps across ethnic and gender lines.

Further ethnographic or phenomenological inquiry focused on lived experiences would provide vital context to complement the quantitative findings. Mixed methods approaches drawing on community-based participatory research principles could enhance cultural relevance.

Research expanding beyond the UK to incorporate the experiences of ethnic minority women globally would offer additional perspective. Comparative work could assess generalisability while illuminating region-specific nuances.

In summary, integrating varied methods and data sources, causal analysis of indirect effects, intersectional subgroup analysis, and cross-national research could all help advance this line of inquiry and develop more definitive insights into mental health inequities.

5 Chapter V: Conclusions

5.1 Overall findings

This thesis explored the relationship between ethnicity and mental health inequities in the UK, guided by critical realism, intersectionality from a decolonial perspective, and the Diderichsen model of health inequities.

Critical realism, which posits an objective reality shaped by social, cultural, and historical contexts, informed the research design and discussion of findings. This framework prompted the selection of research questions that probe beyond surface-level associations to examine generative mechanisms. It guided the mixed-methods approach, combining quantitative analysis with systematic review, to capture both empirical regularities and contextual factors. In interpreting results, this perspective was useful in reflecting how structural factors like institutional racism, socioeconomic stratification, and differential access to social determinants of health might generate observed mental health inequities.

An intersectional perspective, informed by decolonial thought, complemented this approach. It facilitated the examination of how multiple, interconnected systems of power and oppression could shape mental health outcomes for ethnic minorities in the UK. This lens prompted consideration of how historical legacies and contemporary social structures intersect to produce complex patterns of mental health inequities that extend beyond simple additive models of identity categories.

The Diderichsen model of pathways to health inequities provided a comprehensive framework for understanding the complex pathways through which ethnic inequities in mental health arise and persist. Its emphasis on social stratification, differential exposure, vulnerability, consequences, and broader societal impacts facilitated a nuanced examination of how social determinants operate at multiple levels, offering clear entry points for potential policy interventions.

The methodological pluralism employed - a systematic review, quasi-experimental analysis, and Oaxaca-Blinder decomposition - allowed for a comprehensive exploration of ethnic mental health inequities. This approach moved beyond mere empirical observations to probe deeper, often unobservable social structures and mechanisms, offering a richer understanding of the phenomenon while acknowledging the limitations inherent in empirical investigation of complex social realities.

Chapter II's systematic review synthesised evidence from nine observational studies, showing that social determinants like housing, education, and employment considerably mediate the effect of ethnicity on mental health. It highlighted the need for research on modifiable social determinants to inform targeted policy interventions and noted the absence of intersectional analyses in existing studies.

Chapter III's quasi-experimental analysis, using the 1972 Raising of the School Leaving Age (ROSLA) policy, found no significant causal effect of an additional year of compulsory schooling on long-term mental health within ethnic minorities. This contrasts with some studies showing mental health improvements in the general population, underscoring the need to ensure that education systems empower diverse communities.

Chapter IV's Oaxaca-Blinder decomposition revealed that differences in socioeconomic endowments explain nearly half of the mental health gap between minority women and the overall UK population. The substantial unexplained portion suggests unobserved systemic biases linked to intersectional disadvantage drive inequities.

Overall, this thesis demonstrates the multifaceted nature of ethnic mental health inequities in the UK, pointing to complex interactions between ethnicity, socioeconomic factors, and systemic inequities. The findings emphasise the need for coordinated policy efforts addressing upstream social determinants and structural reforms to promote health equity. Further research incorporating causal frameworks and intersectional perspectives can continue unravelling the intricate pathways underlying these inequities, maintaining a resolute commitment to social justice.

5.2 Main limitations

One of the limitations of this research, viewed through a critical realist lens, is the challenge of fully capturing social reality's complex, multi-layered nature using primarily quantitative methods. While our approaches, particularly the Oaxaca-Blinder decomposition, reveal key patterns and associations, they may not fully uncover the 'deep structures' and generative mechanisms in the 'real' domain that critical realism posits as crucial for understanding social phenomena.

The substantial unexplained portions in the analyses, especially in the intersectional decomposition, highlight the limitations of quantitative data in fully representing the lived experiences of individuals facing multiple intersecting forms of disadvantage. This aligns with critical realism's acknowledgment of the partial nature of scientific knowledge and the challenges in empirically measuring all aspects of complex social realities.

While the study attempted to incorporate an intersectional perspective, particularly in the systematic review and decomposition analysis, data availability and methodological limitations constrained the ability to fully explore the multiplicative effects of various identities and social positions. This underscores the need for more nuanced, mixed-methods approaches in future research.

The quasi-experimental design, while valuable for exploring causal relationships, was limited in its ability to account for the full range of intersecting factors that may influence mental health outcomes. This reflects the broader challenge of balancing methodological rigor with the need to capture complex social realities.

Panel attrition in the longitudinal data used may have introduced some bias, although the UKHLS compares favourably to other household panels in retention rates. Future research could benefit from more robust techniques to address potential attrition biases.

Despite these limitations, the mixed methods approach employed in this thesis, combining rigorous empirical analysis with critical perspectives, provides a strong foundation for further investigating the complex phenomena of ethnic mental health inequities. It also points to valuable directions for future research that could more fully embrace critical realist and intersectional frameworks.

5.3 Policy Implications

The research findings yield critical policy implications for fostering social inclusivity and equity. Firstly, recognising the significance of socioeconomic resources for ethnic minorities, policies should prioritise initiatives to bolster access to education, employment opportunities, affordable housing, and improving neighbourhood environments. Secondly, targeted mental health promotion and prevention programs are imperative, necessitating policy interventions to ensure early intervention and robust support systems tailored to minority communities' unique needs. Additionally, policies must prioritise the implementation of anti-racism training and robust reporting mechanisms within public services like healthcare to combat interpersonal discrimination effectively. Diversifying the mental health workforce should be a key policy objective to mitigate cultural and institutional biases in care delivery. Moreover, policy efforts must centre on comprehensive ethnicity data collection and monitoring across public sectors to identify disparities systematically and facilitate evidence-based interventions to promote equity and social justice.

Lastly, adopting an intersectional lens in policymaking can be invaluable for tackling health inequities in the UK context. This involves recognising how multiple axes of advantage and disadvantage related to ethnicity, gender, socioeconomic status, disability, sexual orientation, and other factors intersect to produce varied experiences of marginalisation and privilege. Using intersectional analysis tools to collect disaggregated data and assess how policy impacts diverse subgroups can reveal disparities conventional approaches miss. An intersectional mindset prompts exploring varied perspectives through the meaningful participation of affected communities in policy processes. It enables addressing unique challenges faced by individuals at neglected intersections, such as minority women's mental health. Most crucially, intersectionality-informed policies tackle root causes of inequities like systemic racism, discrimination, and exclusion. This promotes universalism and social justice. Making intersectionality an integral part of impact assessments, consultation exercises, budgeting, and implementation monitoring can thus enhance policy equity. The UK can lead intersectional policymaking for diversity, inclusion, and human rights.

5.4 Future research

The future research directions from this thesis encompass various methodologies and inquiries crucial for advancing our understanding and addressing the complexities of mental health inequities among ethnic minority communities. Further longitudinal analyses offer a promising avenue for examining mental health trajectories over time within diverse ethnic groups, providing insights into the underlying predictors and potential interventions needed to promote positive outcomes.

Incorporating mixed methods research that captures the lived experiences and perspectives of minority individuals navigating mental health systems can offer rich contextual insights, guiding the development of more culturally responsive interventions and policies. Comparative studies across UK countries and regions hold the potential for elucidating the nuanced interplay of place-based factors in shaping mental health outcomes, informing targeted interventions tailored to specific geographic contexts. Investigating the effectiveness of targeted policy interventions aimed at specific social determinants or service enhancements through rigorous research methodologies is essential for informing evidence-based policymaking and improving mental health outcomes for ethnic minorities. Leveraging quasi-experimental studies to evaluate the causal impact of policy changes or reforms can provide valuable insights into the effectiveness of interventions, guiding future policy decisions and resource allocation.

Additionally, exploring heterogeneity in effects within ethnic minority groups by factors such as migrant status or religion can deepen our understanding of intersecting identities and inform the development of more tailored and culturally sensitive interventions. These future research directions can significantly contribute to promoting mental health equity and addressing disparities among ethnic minority populations.

Last, future research should critically reassess and modify the Grossman health capital model in the context of ethnic and mental health inequities. While this model has been influential in understanding the relationship between education and health, it fails to adequately account for structural determinants such as systemic racism and discrimination that significantly impact mental health outcomes among ethnic minorities. The model's emphasis on individual choice and investment overlooks how institutional barriers limit these groups' access to education, healthcare, and other resources. Future studies should incorporate these structural factors, cultural sensitivities, and access barriers into a more comprehensive framework. This modified approach could provide a better understanding of the complex interplay between education, systemic inequalities, and mental health outcomes across diverse ethnic groups, potentially informing more effective and equitable policy interventions.

6 REFERENCES

Abed Al Ahad, M., Demšar, U., Sullivan, F., & Kulu, H. (2022). Air pollution and individuals' mental well-being in the adult population in United Kingdom: A spatial-temporal longitudinal study and the moderating effect of ethnicity. *Plos One*, *17*(3), e0264394. https://doi.org/10.1371/journal.pone.0264394

Adams, S. J. (2002). Educational attainment and health: Evidence from a sample of older adults. *Education Economics*, *10*(1), 97-109.

Ahmad, G., McManus, S., Cooper, C., Hatch, S. L., & Das-Munshi, J. (2022). Prevalence of common mental disorders and treatment receipt for people from ethnic minority backgrounds in England: repeated cross-sectional surveys of the general population in 2007 and 2014. *The British Journal of Psychiatry*, *221*(3), 520-527.

Albouy, V., & Lequien, L. (2009). Does compulsory education lower mortality? *Journal of Health Economics*, *28*(1), 155-168.

Alexander, C., & Shankley, W. (2020). Ethnic inequalities in the state education system in England. *Ethnicity, Race and Inequality in the UK*, 93.

Alghamdi, N. A., Dunn, K., Cairns, D., & Melville, C. (2023). Utilising quantitative methods to study the intersectionality of multiple social disadvantages in women with common mental disorders: a systematic review. *International Journal for Equity in Health*, *22*(1), 264.

Amin, V., Fletcher, J. M., Lu, Q., & Song, J. (2023). Re-examining the relationship between education and adult mental health in the UK: A research note. *Economics of Education Review*, *93*, 102354.

Audit, R. D. (2017). Race Disparity Audit. *Cabinet Office*.

Avendano, M., De Coulon, A., & Nafilyan, V. (2020). Does longer compulsory schooling affect mental health? Evidence from a British reform. *Journal of Public Economics*, *183*, 104137. https://doi.org/10.1016/j.jpubeco.2020.104137

Bago d'Uva, T., O'Donnell, O., & Van Doorslaer, E. (2008). Differential health reporting by education level and its impact on the measurement of health inequalities among older Europeans. *International journal of epidemiology*, *37*(6), 1375-1383.

Bajekal, M., Blane, D., Grewal, I., Karlsen, S., & Nazroo, J. (2004). Ethnic differences in influences on quality of life at older ages: a quantitative analysis. *Ageing & Society*, *24*(5), 709-728.

Baker, C. (2021). Mental health statistics for England: prevalence, services and funding.

Banks, J., & Mazzonna, F. (2012). The Effect of Education on Old Age Cognitive Abilities: Evidence from a Regression Discontinuity Design. *The Economic Journal*, *122*(560), 418-448. https://doi.org/10.1111/j.1468-0297.2012.02499.x

Barcellos, S. H., Carvalho, L. S., & Turley, P. (2018). Education can reduce health differences related to genetic risk of obesity. *Proceedings of the National Academy of Sciences*, *115*(42), E9765-E9772.

Barcellos, S. H., Carvalho, L. S., & Turley, P. (2023). Distributional effects of education on health. *Journal of Human Resources*, *58*(4), 1273-1306. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10361687/pdf/nihms-1739756.pdf

Barkhuizen, W., Cullen, A. E., Shetty, H., Pritchard, M., Stewart, R., McGuire, P., & Patel, R. (2020). Community treatment orders and associations with readmission rates and duration of psychiatric hospital admission: a controlled electronic case register study. *Bmj Open*, *10*(3), e035121. https://doi.org/10.1136/bmjopen-2019-035121

Barr, B., Clayton, S., Whitehead, M., Thielen, K., Burström, B., Nylén, L., & Dahl, E. (2010). To what extent have relaxed eligibility requirements and increased generosity of disability benefits acted as disincentives for employment? A systematic review of evidence from countries with well-developed welfare systems. *Journal of Epidemiology & Community Health*, *64*(12), 1106-1114.

Bartley, M. (2017). *Health inequality : an introduction to concepts, theories and methods* (Second edition. ed.).

Baschung Pfister, P., de Bruin, E. D., Bastiaenen, C. H. G., Maurer, B., & Knols, R. H. (2019). Reliability and validity of the German version of the Myositis Activities Profile (MAP) in patients with inflammatory myopathy. *Plos One*, *14*(6), e0217173. https://doi.org/10.1371/journal.pone.0217173

Becares, L., & Nazroo, J. (2015). Social capital, ethnic density and mental health among ethnic minority people in England: a mixed-methods study. In *Handbook of research methods and applications in social capital* (pp. 242-261). Edward Elgar Publishing.

Becares, L., Nazroo, J., Jackson, J., & Heuvelman, H. (2012). Ethnic density effects on health and experienced racism among Caribbean people in the US and England: A cross-national comparison [Article]. *Social science & medicine*, *75*(12), 2107-2115. https://doi.org/10.1016/j.socscimed.2012.03.046

Becares, L., Nazroo, J., & Stafford, M. (2009). The buffering effects of ethnic density on experienced racism and health [Article]. *Health & Place*, *15*(3), 700-708. https://doi.org/10.1016/j.healthplace.2008.10.008

Bécares, L., Nazroo, J., & Stafford, M. (2009). The buffering effects of ethnic density on experienced racism and health. *Health & Place*, *15*(3), 700-708.

Becares, L., Shaw, R. J., Katikireddi, S. V., Irizar, P., Amele, S., Kapadia, D., Nazroo, J., & Taylor, H. (2022). Racism as the fundamental cause of ethnic inequities in COVID-19 vaccine hesitancy: A theoretical framework and empirical exploration using the UK Household Longitudinal Study [Article]. *Ssm-Population Health*, *19*, 10, Article 101150. https://doi.org/10.1016/j.ssmph.2022.101150

Behrman, J. R., Kohler, H.-P., Jensen, V. M., Pedersen, D., Petersen, I., Bingley, P., & Christensen, K. (2011). Does more schooling reduce hospitalization and delay mortality? New evidence based on Danish twins. *Demography*, *48*(4), 1347-1375.

Bhaskar, R. (2013). *A realist theory of science*. Routledge.

Black, D. (1980). Inequalities in health: report/ of a research working group.

Black, S. E., Devereux, P. J., & Salvanes, K. G. (2008). Staying in the classroom and out of the maternity ward? The effect of compulsory schooling laws on teenage births. *The Economic Journal*, *118*(530), 1025-1054.

Blane, D. (1985). An assessment of the Black Report's explanations of health inequalities. *Sociology of Health & Illness*, *7*(3), 423-445. https://doi.org/10.1111/1467-9566.ep10832355

Borras, A. M. (2021). Toward an intersectional approach to health justice. *International Journal of Health Services*, *51*(2), 206-225.

Bowe, A. G. (2017). The immigrant paradox on internalizing symptoms among immigrant adolescents [Article]. *Journal of Adolescence*, *55*, 72-76. https://doi.org/10.1016/j.adolescence.2017.01.002

Braveman, P., & Gottlieb, L. (2014). The Social Determinants of Health: It's Time to Consider the Causes of the Causes. *Public Health Reports*, *129*(1_suppl2), 19-31. https://doi.org/10.1177/00333549141291s206

Bridger, E., & Daly, M. (2019). Cognitive ability as a moderator of the association between social disadvantage and psychological distress: evidence from a population-based sample [Article]. *Psychological Medicine*, *49*(9), 1545-1554. https://doi.org/10.1017/s0033291718002118

Brydsten, A., Rostila, M., & Dunlavy, A. (2019a). Social integration and mental health - a decomposition approach to mental health inequalities between the foreign-born and native-born in Sweden. *International Journal for Equity in Health*, *18*, Article 48. https://doi.org/10.1186/s12939-019-0950-1

Brydsten, A., Rostila, M., & Dunlavy, A. (2019b). Social integration and mental health - a decomposition approach to mental health inequalities between the foreign-born and native-born in Sweden [Article]. *International Journal for Equity in Health*, *18*, 11, Article 48. https://doi.org/10.1186/s12939-019-0950-1

Brzezinski, M. (2019). What accounts for the rise of low self-rated health during the recent economic crisis in Europe? [Article]. *International Journal for Equity in Health*, *18*, 8, Article 21. https://doi.org/10.1186/s12939-019-0926-1

Bubonya, M., Cobb-Clark, D. A., & Wooden, M. (2017). Mental health and productivity at work: Does what you do matter? *Labour Economics*, *46*, 150-165.

Buckner, J. C. (1988). The development of an instrument to measure neighborhood cohesion. *American Journal of Community Psychology*, *16*(6), 771-791.

Byrne, B., Alexander, C., Khan, O., Nazroo, J., & Shankley, W. (2020). *Ethnicity, Race and Inequality in the UK : State of the Nation*.

Calonico, S., Cattaneo, M. D., & Titiunik, R. (2014). Robust data-driven inference in the regression-discontinuity design. *Stata journal*, *14*(4), 909-946. https://www.stata-journal.com/article.html?article=st0366

Campion, J., Javed, A., Saxena, S., & Sharan, P. (2022). Public mental health: An opportunity to address implementation failure. *Indian Journal of Psychiatry*, *64*(2), 113.

Case, A., Fertig, A., & Paxson, C. (2005). The lasting impact of childhood health and circumstance. *Journal of Health Economics*, *24*(2), 365-389.

Cattaneo, M. D., Frandsen, B. R., & Titiunik, R. (2015). Randomization Inference in the Regression Discontinuity Design: An Application to Party Advantages in the U.S. Senate [Article]. *Journal of Causal Inference*, *3*(1), 1-24. https://doi.org/10.1515/jci-2013-0010

Cattaneo, M. D., Idrobo, N., & Titiunik, R. (2019). *A practical introduction to regression discontinuity designs: Foundations*. Cambridge University Press.

Cattaneo, M. D., Idrobo, N., & Titiunik, R. (2023). A practical introduction to regression discontinuity designs: Extensions. *arXiv preprint arXiv:2301.08958*.

Cattaneo, M. D., Jansson, M., & Ma, X. (2018). Manipulation testing based on density discontinuity. *The Stata Journal*, *18*(1), 234-261.

Cattaneo, M. D., Titiunik, R., & Vazquez-Bare, G. (2016). Inference in regression discontinuity designs under local randomization. *The Stata Journal*, *16*(2), 331-367.

Cattaneo, M. D., Titiunik, R., & Vazquez-Bare, G. (2017). Comparing Inference Approaches for RD Designs: A Reexamination of the Effect of Head Start on Child Mortality [Article]. *Journal of Policy Analysis and Management*, *36*(3), 643-+. https://doi.org/10.1002/pam.21985

Cézard, G., Finney, N., Kulu, H., & Marshall, A. (2022). Ethnic differences in self-assessed health in Scotland: The role of socio-economic status and migrant generation. *Population, Space and Place*, *28*(3), e2403.

Chou, S.-Y., Liu, J.-T., Grossman, M., & Joyce, T. (2010). Parental education and child health: evidence from a natural experiment in Taiwan. *American Economic Journal: Applied Economics*, *2*(1), 33-61.

Chum, A., Teo, C., & Azra, K. K. (2022). Does the longitudinal association between neighbourhood cohesion and mental health differ by ethnicity? Results from the UK Household Longitudinal Survey. *Social Psychiatry and Psychiatric Epidemiology*, *57*(4), 859-872. https://doi.org/10.1007/s00127-021-02125-6

Clark, D., & Royer, H. (2010). *The effect of education on adult health and mortality: Evidence from Britain*.

Clark, D., & Royer, H. (2013). The effect of education on adult mortality and health: Evidence from Britain. *American Economic Review*, *103*(6), 2087-2120. https://doi.org/10.1257/aer.103.6.2087

Codjoe, L., Barber, S., & Thornicroft, G. (2019). Tackling inequalities: a partnership between mental health services and black faith communities. In (Vol. 28, pp. 225-228): Taylor & Francis.

Collier, A. (1994). Critical realism: an introduction to Roy Bhaskar's philosophy.

Cornaglia, F., Crivellaro, E., & McNally, S. (2015). Mental health and education decisions. *Labour Economics*, *33*, 1-12.

Courtin, E., Nafilyan, V., Glymour, M., Goldberg, M., Berr, C., Berkman, L. F., Zins, M., & Avendano, M. (2019). Long-term effects of compulsory schooling on physical, mental and cognitive ageing: a natural experiment. *J Epidemiol Community Health*, *73*(4), 370-376.

Cowan, S., McCulloch, G., & Woodin, T. (2012). From HORSA huts to ROSLA blocks: the school leaving age and the school building programme in England, 1943–1972. *History of Education*, *41*(3), 361-380.

Cox, B. D., Huppert, F. A., & Whichelow, M. J. (1993). The health and lifestyle survey: seven years on. *(No Title)*.

Crenshaw, K. (1990). Mapping the margins: Intersectionality, identity politics, and violence against women of color. *Stan. L. Rev.*, *43*, 1241.

Crespo, L., López-Noval, B., & Mira, P. (2014). Compulsory schooling, education, depression and memory: New evidence from SHARELIFE. *Economics of Education Review*, *43*, 36-46.

Crotty, M., & Crotty, M. F. (1998). *The foundations of social research: Meaning and perspective in the research process*. Sage.

Crozier, G. (2023). Reproducing Racism and Maintaining White Supremacy: Experiences in School and University. In *Racism and Education in Britain: Addressing Structural Oppression and the Dominance of Whiteness* (pp. 135-166). Springer.

Cunningham, S. (2018). Causal Inference: The Mixtape. *Unpublished manuscript*.

Curnock, E., Leyland, A. H., & Popham, F. (2016). The impact on health of employment and welfare transitions for those receiving out-of-work disability benefits in the UK [Article]. *Social science & medicine*, *162*, 1-10. https://doi.org/10.1016/j.socscimed.2016.05.042

Currie, J., & Stabile, M. (2006). Child mental health and human capital accumulation: the case of ADHD. *Journal of Health Economics*, *25*(6), 1094-1118.

Cutler, D. M., & Lleras-Muney, A. (2010). Understanding differences in health behaviors by education. *Journal of Health Economics*, *29*(1), 1-28.

Cutler, D. M., & Lleras-Muney, A. (2012). Education and health: insights from international comparisons.

Dahlgren, G., & Whitehead, M. (1993). Tackling inequalities in health: what can we learn from what has been tried.

Dahlgren, G., & Whitehead, M. (2021). The Dahlgren-Whitehead model of health determinants: 30 years on and still chasing rainbows. *Public Health*, *199*, 20-24.

Davies, N. M., Dickson, M., Davey Smith, G., Van Den Berg, G. J., & Windmeijer, F. (2018). The causal effects of education on health outcomes in the UK Biobank. *Nature Human Behaviour*, *2*(2), 117-125. https://doi.org/10.1038/s41562-017-0279-y

Daymont, T. N., & Andrisani, P. J. (1984). Job preferences, college major, and the gender gap in earnings. *Journal of Human Resources*, 408-428.

Devonport, T. J., Ward, G., Morrissey, H., Burt, C., Harris, J., Burt, S., Patel, R., Manning, R., Paredes, R., & Nicholls, W. (2023). A Systematic Review of Inequalities in the Mental Health Experiences of Black African, Black Caribbean and Black-mixed UK Populations: Implications for Action. *J Racial Ethn Health Disparities*, *10*(4), 1669-1681. https://doi.org/10.1007/s40615-022-01352-0

Diderichsen, F., Andersen, I., Manuel, C., Working Group of Danish Review on Social Determinants of, H., Andersen, A. M., Bach, E., Baadsgaard, M., Bronnum-Hansen, H., Hansen, F. K., Jeune, B., Jorgensen, T., & Sogaard, J. (2012). Health inequality--determinants and policies. *Scand J Public Health*, *40*(8 Suppl), 12-105. https://doi.org/10.1177/1403494812457734

Diderichsen, F., Evans, T., & Whitehead, M. (2001). The social basis of disparities in health. *Challenging inequities in health: From ethics to action*, *1*, 12-23.

Diderichsen, F., Whitehead, M., & Dahlgren, G. (2022). Planning for health equity in the crossfire between science and policy. *Scand J Public Health*, *50*(7), 875-881. https://doi.org/10.1177/14034948221082450

Dreger, S., Gerlinger, T., & Bolte, G. (2016). Gender inequalities in mental wellbeing in 26 European countries: do welfare regimes matter? *European Journal of Public Health*, *26*(5), 872-876. https://doi.org/10.1093/eurpub/ckw074

Dursun, B., & Cesur, R. (2016). Transforming lives: the impact of compulsory schooling on hope and happiness. *Journal of Population Economics*, *29*, 911-956.

Egede, L. E. (2006). Race, ethnicity, culture, and disparities in health care. *J Gen Intern Med*, *21*(6), 667-669. https://doi.org/10.1111/j.1525-1497.2006.0512.x

Erens, B., Primatesta, P., & Prior, G. (2001). *Health Survey for England: The Health of Minority Ethnic Groups' 99: a Survey Carried Out on Behalf of the Department of Health*. Stationery Office.

Fonseca de Freitas, D., Pritchard, M., Shetty, H., Khondoker, M., Nazroo, J., Hayes, R. D., & Bhui, K. (2022). Ethnic inequities in multimorbidity among people with psychosis: a retrospective cohort study [Article]. *Epidemiol Psychiatr Sci*, *31*, e52, Article e52. https://doi.org/10.1017/S2045796022000385

Fuchs, V. R. (1980). *Time preference and health: an exploratory study* (0898-2937).

Gagne, T., Nandi, A., & Schoon, I. (2021). Time trend analysis of social inequalities in psychological distress among young adults before and during the pandemic: evidence from the UK Household Longitudinal Study COVID-19 waves. *J Epidemiol Community Health*, *76*(5), 421-427. https://doi.org/10.1136/jech-2021-217266

Gaviria, A., & Raphael, S. (2001). School-based peer effects and juvenile behavior. *Review of Economics and Statistics*, *83*(2), 257-268.

Gehrsitza, M., & Williams Jr, M. C. (2022). The Effects of Compulsory Schooling on Health and Hospitalization over the Life-Cycle.

Gorski, P. S. (2013). "What is Critical Realism? And Why Should You Care?". *Contemporary Sociology: A Journal of Reviews*, *42*(5), 658-670. https://doi.org/10.1177/0094306113499533

Grosfoguel, R. (2007). The Epistemic Decolonial Turn. *Cultural Studies*, *21*(2-3), 211-223. https://doi.org/10.1080/09502380601162514

Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political economy*, *80*(2), 223-255.

Grossman, M. (2006). Education and nonmarket outcomes. *Handbook of the Economics of Education*, *1*, 577-633.

Grossman, M. (2015). *The relationship between health and schooling: What's new?*

Gupta, M., Singh, N., & Verma, S. (2006). South Asians and cardiovascular risk: what clinicians should know. *Circulation*, *113*(25), e924-929. https://doi.org/10.1161/CIRCULATIONAHA.105.583815

Hahn, J., Todd, P., & Van der Klaauw, W. (2001). Identification and estimation of treatment effects with a regression-discontinuity design. *Econometrica*, *69*(1), 201-209.

Harding, S., & Maxwell, R. (1997). Differences in the mortality of migrants' pp108-121 in Health inequalities: Decennial Supplement Series DS No. 15 edited by F Drever and M Whitehead. *London: The Stationery Office*.

Harouni, G. G., Mahdavi, M. R. V., Naghdi, S., Armoon, B., Fazaeli, A. A., Ghiasvand, H., Noroozi, M., & Ahounbar, E. (2018). Decomposing disparity in adult individual's mental health in Tehran among lower and higher economic groups; an Oaxaca- Blinder analysis on urban HEART Survey- round 2 [Article]. *Afr Health Sci*, *18*(4), 1018-1026. https://doi.org/10.4314/ahs.v18i4.23

Hunt, B., Wilson, C. L., Fauzia, G., & Mazhar, F. (2020). The Muslimah Project: A Collaborative Inquiry into Discrimination and Muslim Women's Mental Health in a Canadian Context [Article; Early Access]. *American Journal of Community Psychology*, *66*(3-4), 12. https://doi.org/10.1002/ajcp.12450

Huntington-Klein, N. (2021). *The effect: An introduction to research design and causality*. CRC Press.

Huo, T., Guo, Y., Shenkman, E., & Muller, K. (2018). Assessing the reliability of the short form 12 (SF-12) health survey in adults with mental health conditions: a report from the wellness incentive and navigation (WIN) study. *Health Qual Life Outcomes*, *16*(1), 34. https://doi.org/10.1186/s12955-018-0858-2

Iqbal, N. (2021). Minority Mental Health: Intersections between faith and ethnicity. *Available at SSRN 3767398*.

Irving, P., Barrett, K., Nijher, M., & de Lusignan, S. (2021). Prevalence of depression and anxiety in people with inflammatory bowel disease and associated healthcare use: population-based cohort study. *Evid Based Ment Health*, *24*(3), 102-109. https://doi.org/10.1136/ebmental-2020-300223

Janke, K., Johnston, D. W., Propper, C., & Shields, M. A. (2020). The causal effect of education on chronic health conditions in the UK. *J Health Econ*, *70*, 102252. https://doi.org/10.1016/j.jhealeco.2019.102252

Jann, B. (2008). The Blinder–Oaxaca decomposition for linear regression models. *The Stata Journal*, *8*(4), 453-479.

Jenkinson, C., Chandola, T., Coulter, A., & Bruster, S. (2001). An assessment of the construct validity of the SF-12 summary scores across ethnic groups. *J Public Health Med*, *23*(3), 187-194. https://doi.org/10.1093/pubmed/23.3.187

Jenkinson, C., Stewart-Brown, S., Petersen, S., & Paice, C. (1999). Assessment of the SF-36 version 2 in the United Kingdom. *J Epidemiol Community Health*, *53*(1), 46-50. https://doi.org/10.1136/jech.53.1.46

Jones, F. L., & Kelley, J. (1984). Decomposing differences between groups: A cautionary note on measuring discrimination. *Sociological methods & research*, *12*(3), 323-343.

Joseph-Salisbury, R. (2020). Race and racism in English secondary schools. *Runnymede Perspectives*.

Kaestner, R., & Grossman, M. (2009). Effects of weight on children's educational achievement. *Economics of Education Review*, *28*(6), 651-661.

Kamhöfer, D. A., & Schmitz, H. (2016). Reanalyzing zero returns to education in Germany. *Journal of Applied Econometrics*, *31*(5), 912-919.

Kapadia, D., Zhang, J., Salway, S., Nazroo, J., Booth, A., Villarroel-Williams, N., Becares, L., & Esmail, A. (2022). Ethnic inequalities in healthcare: a rapid evidence review.

Karlsen, S., & Nazroo, J. Y. (2002). Agency and structure: the impact of ethnic identity and racism on the health of ethnic minority people [Article]. *Sociology of Health & Illness*, *24*(1), 1-20. https://doi.org/10.1111/1467-9566.00001

Karlsen, S., Nazroo, J. Y., McKenzie, K., Bhui, K., & Weich, S. (2005). Racism, psychosis and common mental disorder among ethnic minority groups in England [Article]. *Psychol Med*, *35*(12), 1795-1803. https://doi.org/10.1017/S0033291705005830

Kashyap, G. C., & Singh, S. K. (2017). Reliability and validity of general health questionnaire (GHQ-12) for male tannery workers: a study carried out in Kanpur, India. *BMC psychiatry*, *17*(1), 102. https://doi.org/10.1186/s12888-017-1253-y

Katikireddi, S. V., Lal, S., Carrol, E. D., Niedzwiedz, C. L., Khunti, K., Dundas, R., Diderichsen, F., & Barr, B. (2021). Unequal impact of the COVID-19 crisis on minority ethnic groups: a framework for understanding and addressing inequalities. *J Epidemiol Community Health*, *75*(10), 970-974. https://doi.org/10.1136/jech-2020-216061

Kim, Y., & Steiner, P. (2016). Quasi-Experimental Designs for Causal Inference. *Educ Psychol*, *51*(3-4), 395-405. https://doi.org/10.1080/00461520.2016.1207177

King, M., Marston, L., McManus, S., Brugha, T., Meltzer, H., & Bebbington, P. (2013). Religion, spirituality and mental health: results from a national study of English households. *Br J Psychiatry*, *202*(1), 68-73. https://doi.org/10.1192/bjp.bp.112.112003

Knight, M., Kenyon, S., Brocklehurst, P., Neilson, J., Shakespeare, J., & Kurinczuk, J. J. (2017). Saving lives, improving mothers' care: lessons learned to inform future maternity care from the UK and Ireland confidential enquiries into maternal deaths and morbidity 2009-2012.

Kupferberg, A., Bicks, L., & Hasler, G. (2016). Social functioning in major depressive disorder. *Neurosci Biobehav Rev*, *69*, 313-332. https://doi.org/10.1016/j.neubiorev.2016.07.002

Lager, A., Seblova, D., Falkstedt, D., & Lovden, M. (2017). Cognitive and emotional outcomes after prolonged education: a quasi-experiment on 320 182 Swedish boys. *Int J Epidemiol*, *46*(1), 303-311. https://doi.org/10.1093/ije/dyw093

Lamb, D., Gnanapragasam, S., Greenberg, N., Bhundia, R., Carr, E., Hotopf, M., Razavi, R., Raine, R., Cross, S., Dewar, A., Docherty, M., Dorrington, S., Hatch, S., Wilson-Jones, C., Leightley, D., Madan, I., Marlow, S., McMullen, I., Rafferty, A. M.,…Wessely, S. (2021). Psychosocial impact of the COVID-19 pandemic on 4378 UK healthcare workers and ancillary staff: initial baseline data from a cohort study collected during the first wave of the pandemic. *Occup Environ Med*, *78*(11), 801-808. https://doi.org/10.1136/oemed-2020-107276

Lee, D. S. (2008). Randomized experiments from non-random selection in US House elections. *Journal of Econometrics*, *142*(2), 675-697.

Linder, A., Spika, D., Gerdtham, U. G., Fritzell, S., & Heckley, G. (2020). Education, immigration and rising mental health inequality in Sweden [Article]. *Soc Sci Med*, *264*, 113265, Article 113265. https://doi.org/10.1016/j.socscimed.2020.113265

Lleras-Muney, A. (2005). The relationship between education and adult mortality in the United States. *The Review of Economic Studies*, *72*(1), 189-221.

Lynn, P. (2009). Sample design for understanding society. *Underst. Soc. Work. Pap. Ser*, *2009*.

Malik, P., Patel, K., Pinto, C., Jaiswal, R., Tirupathi, R., Pillai, S., & Patel, U. (2022). Post-acute COVID-19 syndrome (PCS) and health-related quality of life (HRQoL)—A systematic review and meta-analysis. *Journal of medical virology*, *94*(1), 253-262.

Marmot, M. (2020). Health equity in England: the Marmot review 10 years on. *Bmj*, *368*, m693. https://doi.org/10.1136/bmj.m693

Marmot, M., Adelstein, A., & Bulusu, L. (1984). Immigrant mortality in England and Wales 1970—78. Office of Population Censuses and Surveys. *Studies of Medical and Population Subjects No 47*, 3-144.

Marmot, M., Allen, J., & Goldblatt, P. (2010). A social movement, based on evidence, to reduce inequalities in health: Fair Society, Healthy Lives (The Marmot Review). *Social science & medicine (1982)*, *71*(7), 1254-1258.

Martinez Dy, A., Martin, L., & Marlow, S. (2015). Developing a Critical Realist Positional Approach to Intersectionality. *Journal of Critical Realism*, *13*(5), 447-466. https://doi.org/10.1179/1476743014z.00000000043

Mazumder, B. (2008). Does education improve health? A reexamination of the evidence from compulsory schooling laws. *Economic Perspectives*, *32*(2).

Mazzonna, F. (2014). The long lasting effects of education on old age health: evidence of gender differences. *Soc Sci Med*, *101*, 129-138. https://doi.org/10.1016/j.socscimed.2013.10.042

McCrary, J., & Royer, H. (2011). The Effect of Female Education on Fertility and Infant Health: Evidence from School Entry Policies Using Exact Date of Birth. *Am Econ Rev*, *101*(1), 158-195. https://doi.org/10.1257/aer.101.1.158

McFall, S., Nandi, A., & Platt, L. (2021). Understanding society: UK household longitudinal study: user guide to ethnicity and immigration research. *Institute for Social and Economic Research*.

Meghir, C., Palme, M., & Simeonova, E. (2018). Education and mortality: Evidence from a social experiment. *American Economic Journal: Applied Economics*, *10*(2), 234-256.

Memon, A., Taylor, K., Mohebati, L. M., Sundin, J., Cooper, M., Scanlon, T., & de Visser, R. (2016). Perceived barriers to accessing mental health services among black and minority ethnic (BME) communities: a qualitative study in Southeast England. *Bmj Open*, *6*(11), e012337. https://doi.org/10.1136/bmjopen-2016-012337

Mirza, H. S., & Warwick, R. (2022). Race and ethnicity. *IFS Deaton Review of Inequalities*.

Mrejen, M., Hone, T., & Rocha, R. (2022). Socioeconomic and racial/ethnic inequalities in depression prevalence and the treatment gap in Brazil: A decomposition analysis. *SSM Popul Health*, *20*, 101266. https://doi.org/10.1016/j.ssmph.2022.101266

Myers, K. (2009). Immigrants and ethnic minorities in the history of education. *Paedagogica Historica*, *45*(6), 801-816.

Nandi, A., Luthra, R., & Benzeval, M. (2020). When does hate hurt the most? Generational differences in the association between ethnic and racial harassment, ethnic attachment, and mental health. *Ethnic and Racial Studies*, *43*(16), 327-347.

Nazroo, J. (2022a). Race/ethnic inequalities in health: moving beyond confusion to focus on fundamental causes.

Nazroo, J. (2022b). Tackling racism: moving beyond rhetoric to turn theory into practice [Editorial Material]. *Bmj*, *378*, o1597, Article o1597. https://doi.org/10.1136/bmj.o1597

Nazroo, J. Y. (1999). *Ethnicity, class and health*. University of London, University College London (United Kingdom).

Nazroo, J. Y., Bhui, K. S., & Rhodes, J. (2020). Where next for understanding race/ethnic inequalities in severe mental illness? Structural, interpersonal and institutional racism [Article]. *Sociol Health Illn*, *42*(2), 262-276. https://doi.org/10.1111/1467-9566.13001

NHS Digital. (2022). *Detentions under the Mental Health Act*. NHS Digital. Retrieved 25/02/2023 from https://www.ethnicity-facts-figures.service.gov.uk/health/mental-health/detentions-under-the-mental-health-act/latest

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International economic review*, 693-709.

Oreopoulos, P. (2006). Estimating average and local average treatment effects of education when compulsory schooling laws really matter. *American Economic Review*, *96*(1), 152-175.

Paccoud, I., Nazroo, J., & Leist, A. K. (2022). Region of birth differences in healthcare navigation and optimisation: the interplay of racial discrimination and socioeconomic position [Article]. *Int J Equity Health*, *21*(1), 106, Article 106. https://doi.org/10.1186/s12939-022-01709-1

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hrobjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S.,…Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *Syst Rev*, *10*(1), 89. https://doi.org/10.1186/s13643-021-01626-4

Paradies, Y., Ben, J., Denson, N., Elias, A., Priest, N., Pieterse, A., Gupta, A., Kelaher, M., & Gee, G. (2015). Racism as a Determinant of Health: A Systematic Review and Meta-Analysis. *Plos One*, *10*(9), e0138511. https://doi.org/10.1371/journal.pone.0138511

Patterson, J. G., Russomanno, J., Teferra, A. A., & Jabson Tree, J. M. (2020). Disparities in food insecurity at the intersection of race and sexual orientation: A population-based study of adult women in the United States. *SSM Popul Health*, *12*, 100655. https://doi.org/10.1016/j.ssmph.2020.100655

Perez, A. E., Gamarel, K. E., van den Berg, J. J., & Operario, D. (2020). Sexual and behavioral health disparities among African American sexual minority men and women [Article]. *Ethnicity & Health*, *25*(5), 653-664. https://doi.org/10.1080/13557858.2018.1444149

Pierce, M., McManus, S., Hope, H., Hotopf, M., Ford, T., Hatch, S. L., John, A., Kontopantelis, E., Webb, R. T., Wessely, S., & Abel, K. M. (2021). Mental health responses to the COVID-19 pandemic: a latent class trajectory analysis using longitudinal UK data. *Lancet Psychiatry*, *8*(7), 610-619. https://doi.org/10.1016/S2215-0366(21)00151-6

Pischke, J.-S., & Von Wachter, T. (2008). Zero returns to compulsory schooling in Germany: Evidence and interpretation. *The Review of Economics and Statistics*, *90*(3), 592-598.

Platt, J., Prins, S., Bates, L., & Keyes, K. (2016). Unequal depression for equal work? How the wage gap explains gendered disparities in mood disorders. *Soc Sci Med*, *149*, 1-8. https://doi.org/10.1016/j.socscimed.2015.11.056

Plotnikov, D., Williams, C., Atan, D., Davies, N. M., Ghorbani Mojarrad, N., Guggenheim, J. A., Eye, U. K. B., & Vision, C. (2020). Effect of Education on Myopia: Evidence from the United Kingdom ROSLA 1972 Reform. *Invest Ophthalmol Vis Sci*, *61*(11), 7. https://doi.org/10.1167/iovs.61.11.7

Prady, S. L., Pickett, K. E., Croudace, T., Fairley, L., Bloor, K., Gilbody, S., Kiernan, K. E., & Wright, J. (2013). Psychological distress during pregnancy in a multi-ethnic community: findings from the born in Bradford cohort study. *Plos One*, *8*(4), e60693. https://doi.org/10.1371/journal.pone.0060693

Proto, E., & Quintana-Domeque, C. (2021). COVID-19 and mental health deterioration by ethnicity and gender in the UK. *Plos One*, *16*(1), e0244419. https://doi.org/10.1371/journal.pone.0244419

Race Disparity Audit. (2017). *Race Disparity Audit. Cabinet Office*.

Rahimi, E., & Hashemi Nazari, S. S. (2021). A detailed explanation and graphical representation of the Blinder-Oaxaca decomposition method with its application in health inequalities. *Emerg Themes Epidemiol*, *18*(1), 12. https://doi.org/10.1186/s12982-021-00100-9

Raymond, A., Watt, T., Douglas, H. R., Head, A., Kypridemos, C., & Rachet-Jacquet, L. (2024). REAL Centre.

Richman, L. S., & Zucker, A. N. (2019). Quantifying intersectionality: An important advancement for health inequality research. *Soc Sci Med*, *226*, 246-248. https://doi.org/10.1016/j.socscimed.2019.01.036

Rudat, K. (1994). Black and minority ethnic groups in England. 1994. *London: Health Education Authority*, 1-178.

Salway, S., Mir, G., Turner, D., Ellison, G. T., Carter, L., & Gerrish, K. (2016). Obstacles to "race equality" in the English National Health Service: Insights from the healthcare commissioning arena. *Social science & medicine*, *152*, 102-110.

Scharron-del Rio, M. R., & Aja, A. A. (2020). Latinx: Inclusive Language as Liberation Praxis [Article]. *Journal of Latinx Psychology*, *8*(1), 7-20. https://doi.org/10.1037/lat0000140

Sekhon, J. S., & Titiunik, R. (2017). On Interpreting the Regression Discontinuity Design as a Local Experiment. In M. D. Cattaneo & J. C. Escanciano (Eds.), *Regression Discontinuity Designs* (Vol. 38, pp. 1-28). Emerald Group Publishing Ltd. https://doi.org/10.1108/s0731-905320170000038001

Shangani, S., Gamarel, K. E., Ogunbajo, A., Cai, J., & Operario, D. (2020). Intersectional minority stress disparities among sexual minority adults in the USA: the role of race/ethnicity and socioeconomic status [Article]. *Culture Health & Sexuality*, *22*(4), 398-412. https://doi.org/10.1080/13691058.2019.1604994

Shankley, W., & Laurence, J. (2022). Community ethnic density, ethnic segregation, and ethnic minorities' common mental disorders in the UK. *Health & Place*, *73*, 102723. https://doi.org/10.1016/j.healthplace.2021.102723

Simkhada, B., Vahdaninia, M., van Teijlingen, E., & Blunt, H. (2021). Cultural issues on accessing mental health services in Nepali and Iranian migrants communities in the UK. *Int J Ment Health Nurs*, *30*(6), 1610-1619. https://doi.org/10.1111/inm.12913

Simpson, J., Albani, V., Bell, Z., Bambra, C., & Brown, H. (2021). Effects of social security policy reforms on mental health and inequalities: A systematic review of observational studies in high-income countries. *Soc Sci Med*, *272*, 113717. https://doi.org/10.1016/j.socscimed.2021.113717

Smith, G. D., Bartley, M., & Blane, D. (1990). The Black report on socioeconomic inequalities in health 10 years on. *Bmj*, *301*(6748), 373-377. https://doi.org/10.1136/bmj.301.6748.373

Sproston, K., & Mindell, J. (2006). Health Survey for England 2004. The health of minority ethnic groups.

Su, J. G., Jerrett, M., de Nazelle, A., & Wolch, J. (2011). Does exposure to air pollution in urban parks have socioeconomic, racial or ethnic gradients? *Environ Res*, *111*(3), 319-328. https://doi.org/10.1016/j.envres.2011.01.002

Sun, J., & Lyu, S. (2020). Social participation and urban-rural disparity in mental health among older adults in China [Article]. *J Affect Disord*, *274*, 399-404. https://doi.org/10.1016/j.jad.2020.05.091

Thimm-Kaiser, M., Benzekri, A., & Guilamo-Ramos, V. (2023). Conceptualizing the Mechanisms of Social Determinants of Health: A Heuristic Framework to Inform Future Directions for Mitigation. *Milbank Q*, *101*(2), 486-526. https://doi.org/10.1111/1468-0009.12642

Thistlethwaite, D. L., & Campbell, D. T. (1960). Regression-discontinuity analysis: An alternative to the ex post facto experiment. *Journal of Educational Psychology*, *51*(6), 309.

Titiunik, R. (2021). Natural experiments. *Advances in experimental political science*, 103-129.

UK Government. (2021). *Commission on Race and Ethnic Disparities: The Report*.

University of Essex. (2022). *Institute for Social and Economic Research, Understanding Society: Waves 1–12, 2009–2021 and Harmonised BHPS: Waves 1-18, 1991-2009. [data collection]. 17th Edition. UK Data Service. SN: 6614, DOI: http://doi.org/10.5255/UKDA-SN-6614-18* (

University of Essex, & Institute for Social and Economic Research. (2023). *Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931* (https://doi.org/http://doi.org/10.5255/UKDA-SN-6931-15

Vahdaninia, M., Simkhada, B., Van Teijlingen, E., Blunt, H., & Mercel-Sanca, A. (2020). Mental health services designed for Black, Asian and Minority Ethnics (BAME) in the UK: a scoping review of case studies. *Mental Health and Social Inclusion*, *24*(2), 81-95.

van Ingen, M., Grohmann, S., & Gunnarsson, L. (2020). *Critical Realism, Feminism, and Gender: A Reader*. Routledge.

Van Kippersluis, H., O'Donnell, O., & Van Doorslaer, E. (2011). Long-run returns to education: Does schooling lead to an extended old age? *Journal of Human Resources*, *46*(4), 695-721.

Vazquez-Bare, G., Cattaneo, M., & Titiunik, R. (2016). rdlocrand: a Stata Package for Inference in Regression Discontinuity Designs under Local Randomizati. 2016 Stata Conference,

Wallace, M., & Kulu, H. (2015). Mortality among immigrants in England and Wales by major causes of death, 1971-2012: A longitudinal analysis of register-based data. *Soc Sci Med*, *147*, 209-221. https://doi.org/10.1016/j.socscimed.2015.10.060

Wallace, S., Nazroo, J., & Becares, L. (2016). Cumulative Effect of Racial Discrimination on the Mental Health of Ethnic Minorities in the United Kingdom. *Am J Public Health*, *106*(7), 1294-1300. https://doi.org/10.2105/AJPH.2016.303121

Ware, J., Jr., Kosinski, M., & Keller, S. D. (1996). A 12-Item Short-Form Health Survey: construction of scales and preliminary tests of reliability and validity. *Med Care*, *34*(3), 220-233. https://doi.org/10.1097/00005650-199603000-00003

Ware, J., Kosinski Jr, M., Turner-Bowker, D., & Gandek, B. (2002). How to score version 2 of the SF-12 Health Survey (with a supplement documenting version 1). Lincoln, RI: QualityMetric. *Inc Google Scholar*.

Watson, H., Harrop, D., Walton, E., Young, A., & Soltani, H. (2019). A systematic review of ethnic minority women's experiences of perinatal mental health conditions and services in Europe. *Plos One*, *14*(1), e0210587. https://doi.org/10.1371/journal.pone.0210587

Weich, S., Nazroo, J., Sproston, K., McManus, S., Blanchard, M., Erens, B., Karlsen, S., King, M., Lloyd, K., Stansfeld, S., & Tyrer, P. (2004). Common mental disorders and ethnicity in England: the EMPIRIC study. *Psychol Med*, *34*(8), 1543-1551. https://doi.org/10.1017/s0033291704002715

Welch, V., Dewidar, O., Tanjong Ghogomu, E., Abdisalam, S., Al Ameer, A., Barbeau, V. I., Brand, K., Kebedom, K., Benkhalti, M., Kristjansson, E., Madani, M. T., Antequera Martin, A. M., Mathew,

C. M., McGowan, J., McLeod, W., Park, H. A., Petkovic, J., Riddle, A., Tugwell, P.,…Wells, G. A. (2022). How effects on health equity are assessed in systematic reviews of interventions. *Cochrane Database Syst Rev*, *1*(1), MR000028. https://doi.org/10.1002/14651858.MR000028.pub3

Whitehead, M. (1991). The concepts and principles of equity and health. *Health promotion international*, *6*(3), 217-228.

Whitehead, M. (2007). A typology of actions to tackle social inequalities in health. *J Epidemiol Community Health*, *61*(6), 473-478. https://doi.org/10.1136/jech.2005.037242

Wild, S. H., Fischbacher, C., Brock, A., Griffiths, C., & Bhopal, R. (2007). Mortality from all causes and circulatory disease by country of birth in England and Wales 2001-2003. *J Public Health (Oxf)*, *29*(2), 191-198. https://doi.org/10.1093/pubmed/fdm010

Wilson, T. (2017). Compulsory education and teenage motherhood.

Zachariadis, M., Scott, S. and Barrett, M. (2013). Methodological implications of critical realism for mixed-methods research. *MIS quarterly*, pp.855-879. https://doi.org/10.2307/43826004

Zhang, Y., Qu, B., Lun, S. S., Guo, Y., & Liu, J. (2012). The 36-item short form health survey: reliability and validity in Chinese medical students. *Int J Med Sci*, *9*(7), 521-526. https://doi.org/10.7150/ijms.4503

7 ANNEXES

7.1 Annex I – Systematic Literature Review

7.1.1 PRISMA checklist

Section and Topic	Item #	Checklist item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	24
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	N/A
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	25-26
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	26
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	27
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	28-29
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	29 and 128
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	30-31
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	30-31

Section and Topic	Item #	Checklist item	Location where item is reported
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	30-31
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	30-31
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	31
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	N/A
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	31
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	N/A
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	31
	13d	Describe any methods used to synthesise results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	31
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	31
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesised results.	N/A
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	N/A
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	N/A
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	32-33
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	N/A
Study characteristics	17	Cite each included study and present its characteristics.	33
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	37
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	N/A

Section and Topic	Item #	Checklist item	Location where item is reported
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	37
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	N/A
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	N/A
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesised results.	N/A
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	N/A
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	N/A
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	38-42
	23b	Discuss any limitations of the evidence included in the review.	42
	23c	Discuss any limitations of the review processes used.	42
	23d	Discuss implications of the results for practice, policy, and future research.	42
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	N/A
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	N/A
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	N/A
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	N/A
Competing interests	26	Declare any competing interests of review authors.	N/A
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	24-42

7.1.2 Search strings

PubMed

("medical outcomes study SF-12"[Title/Abstract] OR "medical outcomes study SF12"[Title/Abstract] OR "medical outcomes study SF 12"[Title/Abstract] OR "medical outcomes study short form-12"[Title/Abstract] OR "medical outcomes study short form 12"[Title/Abstract] OR "SF-12"[Title/Abstract] OR "SF12"[Title/Abstract] OR "SF 12"[Title/Abstract] OR "short-form-12"[Title/Abstract] OR "MOS SF-12"[Title/Abstract] OR "MOS SF12"[Title/Abstract] OR "MOS SF 12"[Title/Abstract] OR "MOS short form-12"[Title/Abstract] OR "MOS short form 12"[Title/Abstract] OR "SF-36"[Title/Abstract] OR "SF36"[Title/Abstract] OR "SF 36"[Title/Abstract] OR "short form 36"[Title/Abstract] OR "SF-36 health survey"[Title/Abstract] OR "SF-36 questionnaire"[Title/Abstract] OR "SF-36 measurement"[Title/Abstract] OR "SF-36 assessment"[Title/Abstract] OR "SF-36 score"[Title/Abstract] OR "SF-36 health outcomes"[Title/Abstract] OR "SF-36 utility"[Title/Abstract] OR "SF-36 quality of life"[Title/Abstract] OR "SF-36 health-related quality of life"[Title/Abstract] OR "SF-36 HRQoL"[Title/Abstract] OR "SF-36 outcomes"[Title/Abstract] OR "SF-36 functional status"[Title/Abstract] OR "SF-36 functional health"[Title/Abstract] OR "SF-36 health status"[Title/Abstract] OR "SF-36 medical outcomes study"[Title/Abstract] OR "SF-36 MOS"[Title/Abstract] OR "SF-36 physical component summary"[Title/Abstract] OR "SF-36 mental component summary"[Title/Abstract] OR "SF-36 PCS"[Title/Abstract] OR "SF-36 MCS"[Title/Abstract] OR "SF-36 domains"[Title/Abstract] OR "SF-36 subscales"[Title/Abstract] OR "General Health Questionnaire"[Title/Abstract] OR "GHQ"[Title/Abstract] OR "GHQ-28"[Title/Abstract] OR "GHQ 28"[Title/Abstract] OR "GHQ-12"[Title/Abstract] OR "GHQ 12"[Title/Abstract] OR "GHQ score"[Title/Abstract] OR "GHQ assessment"[Title/Abstract] OR "GHQ measurement"[Title/Abstract] OR "GHQ questionnaire"[Title/Abstract] OR "GHQ outcomes"[Title/Abstract] OR "GHQ mental health"[Title/Abstract] OR "GHQ psychiatric"[Title/Abstract] OR "GHQ psychological"[Title/Abstract] OR "GHQ well-being"[Title/Abstract] OR "GHQ functional health"[Title/Abstract] OR "GHQ functional status"[Title/Abstract] OR "GHQ health status"[Title/Abstract] OR "GHQ domain"[Title/Abstract] OR "GHQ subscales"[Title/Abstract]) AND ("ethnic"[Title/Abstract] OR "ethnicity"[Title/Abstract] OR "race"[Title/Abstract] OR "racial"[Title/Abstract] OR "bame"[Title/Abstract] OR "discrimination"[Title/Abstract] OR "racism"[Title/Abstract]) AND ("quantitative"[Title/Abstract] OR "natural experiment"[Title/Abstract] OR "quasi-experimental"[Title/Abstract] OR "difference-in-difference"[Title/Abstract] OR "multi-level"[Title/Abstract] OR "regression"[Title/Abstract] OR "longitudinal"[Title/Abstract] OR "time-series"[Title/Abstract] OR "logistic"[Title/Abstract] OR "linear"[Title/Abstract] OR "Poisson"[Title/Abstract] OR "synthetic control"[Title/Abstract] OR "propensity score"[Title/Abstract] OR "instrumental variable"[Title/Abstract] OR "decomposition"[Title/Abstract] OR "cross-sectional"[Title/Abstract] OR "quasi-natural"[Title/Abstract] OR "natural policy experiment"[Title/Abstract] OR "confounding"[Title/Abstract] OR "fixed-effects"[Title/Abstract])AND ("UK"[Title/Abstract] OR "United Kingdom"[Title/Abstract] OR "Great Britain"[Title/Abstract] OR "England"[Title/Abstract] OR "Scotland"[Title/Abstract] OR "Wales"[Title/Abstract] OR "Northern Ireland"[Title/Abstract] OR "British"[Title/Abstract] OR "London"[Title/Abstract])

Web of Science

(TS=("medical outcomes study SF-12") OR TS=("medical outcomes study SF12") OR TS=("medical outcomes study SF 12") OR TS=("medical outcomes study short form-12") OR TS=("medical outcomes study short form 12") OR TS=("SF-12") OR TS=("SF12") OR TS=("SF 12") OR TS=("short-form-12") OR TS=("MOS SF-12") OR TS=("MOS SF12") OR TS=("MOS SF 12") OR TS=("MOS short form-12") OR TS=("MOS short form 12") OR TS=("SF-36") OR TS=("SF36") OR TS=("SF 36") OR TS=("short form 36") OR TS=("SF-36 health survey") OR TS=("SF-36 questionnaire") OR TS=("SF-36 measurement") OR TS=("SF-36 assessment") OR TS=("SF-36 score") OR TS=("SF-36 health outcomes") OR TS=("SF-36 utility") OR TS=("SF-36 quality of life") OR TS=("SF-36 health-related quality of life") OR TS=("SF-36 HRQoL") OR TS=("SF-36 outcomes") OR TS=("SF-36 functional status") OR TS=("SF-36 functional health") OR TS=("SF-36 health status") OR TS=("SF-36 medical outcomes study") OR TS=("SF-36 MOS") OR TS=("SF-36 physical component summary") OR TS=("SF-36 mental component summary") OR TS=("SF-36 PCS") OR TS=("SF-36 MCS") OR TS=("SF-36 domains") OR TS=("SF-36 subscales") OR TS=("General Health Questionnaire") OR TS=("GHQ") OR TS=("GHQ-28") OR TS=("GHQ 28") OR TS=("GHQ-12") OR TS=("GHQ 12") OR TS=("GHQ score") OR TS=("GHQ assessment") OR TS=("GHQ measurement") OR TS=("GHQ questionnaire") OR TS=("GHQ outcomes") OR TS=("GHQ mental health") OR TS=("GHQ psychiatric") OR TS=("GHQ psychological") OR TS=("GHQ well-being") OR TS=("GHQ functional health") OR TS=("GHQ functional status") OR TS=("GHQ health status") OR TS=("GHQ domain") OR TS=("GHQ subscales")) AND (TS=("ethnic") OR TS=("ethnicity") OR TS=("race") OR TS=("racial") OR TS=("bame") OR TS=("discrimination") OR TS=("racism")) AND (TS=("quantitative") OR TS=("natural experiment") OR TS=("quasi-experimental") OR TS=("difference-in-difference") OR TS=("multi-level") OR TS=("regression") OR TS=("longitudinal") OR TS=("time-series") OR TS=("logistic") OR TS=("linear") OR TS=("Poisson") OR TS=("synthetic control") OR TS=("propensity score") OR TS=("instrumental variable") OR TS=("decomposition") OR TS=("cross-sectional") OR TS=("quasi-natural") OR TS=("natural policy experiment") OR TS=("confounding") OR TS=("fixed-effects")) AND (TS=("UK") OR TS=("United Kingdom") OR TS=("Great Britain") OR TS=("England") OR TS=("Scotland") OR TS=("Wales") OR TS=("Northern Ireland") OR TS=("British") OR TS=("London"))

EBSCO: APA PsycArticles, APA PsycInfo, CINAHL, EconLit, ERIC, MEDLINE Complete, SocINDEX with Full Text

(AB("medical outcomes study SF-12") OR TI("medical outcomes study SF-12") OR AB("medical outcomes study SF12") OR TI("medical outcomes study SF12") OR AB("medical outcomes study SF 12") OR TI("medical outcomes study SF 12") OR AB("medical outcomes study short form-12") OR TI("medical outcomes study short form-12") OR AB("medical outcomes study short form 12") OR TI("medical outcomes study short form 12") OR AB("SF-12") OR TI("SF-12") OR AB("SF12") OR TI("SF12") OR AB("SF 12") OR TI("SF 12") OR AB("short-form-12") OR TI("short-form-12") OR AB("MOS SF-12") OR TI("MOS SF-12") OR AB("MOS SF12") OR TI("MOS SF12") OR AB("MOS SF 12") OR TI("MOS SF 12") OR AB("MOS short form-12") OR TI("MOS short form-12") OR AB("MOS short form 12") OR TI("MOS short form 12") OR AB("SF-36") OR TI("SF-36") OR AB("SF36") OR TI("SF36") OR AB("SF 36") OR TI("SF 36") OR AB("short form 36") OR TI("short form 36") OR AB("SF-36 health survey") OR TI("SF-36 health survey") OR AB("SF-36 questionnaire") OR TI("SF-36 questionnaire") OR AB("SF-36 measurement") OR TI("SF-36 measurement") OR AB("SF-36 assessment") OR TI("SF-36 assessment") OR AB("SF-36 score") OR TI("SF-36 score") OR AB("SF-36 health outcomes") OR TI("SF-36 health outcomes") OR AB("SF-36 utility") OR TI("SF-36 utility") OR AB("SF-36 quality of life") OR TI("SF-36 quality of life") OR AB("SF-36 health-related quality of life") OR TI("SF-36 health-related quality of life") OR AB("SF-36 HRQoL") OR TI("SF-36 HRQoL") OR AB("SF-36 outcomes") OR TI("SF-36 outcomes") OR AB("SF-36 functional status") OR TI("SF-36 functional status") OR AB("SF-36 functional health") OR TI("SF-36 functional health") OR AB("SF-36 health status") OR TI("SF-36 health status") OR AB("SF-36 medical outcomes study") OR TI("SF-36 medical outcomes study") OR AB("SF-36 MOS") OR TI("SF-36 MOS") OR AB("SF-36 physical component summary") OR TI("SF-36 physical component summary") OR AB("SF-36 mental component summary") OR TI("SF-36 mental component summary") OR AB("SF-36 PCS") OR TI("SF-36 PCS") OR AB("SF-36 MCS") OR TI("SF-36 MCS") OR AB("SF-36 domains") OR TI("SF-36 domains") OR AB("SF-36 subscales") OR TI("SF-36 subscales") OR AB("General Health Questionnaire") OR TI("General Health Questionnaire") OR AB("GHQ") OR TI("GHQ") OR AB("GHQ-28") OR TI("GHQ-28") OR AB("GHQ 28") OR TI("GHQ 28") OR AB("GHQ-12") OR TI("GHQ-12") OR AB("GHQ 12") OR TI("GHQ 12") OR AB("GHQ score") OR TI("GHQ score") OR AB("GHQ assessment") OR TI("GHQ assessment") OR AB("GHQ measurement") OR TI("GHQ measurement") OR AB("GHQ questionnaire") OR TI("GHQ questionnaire") OR AB("GHQ outcomes") OR TI("GHQ outcomes") OR AB("GHQ mental health") OR TI("GHQ mental health") OR AB("GHQ psychiatric") OR TI("GHQ psychiatric") OR AB("GHQ psychological") OR TI("GHQ psychological") OR AB("GHQ well-being") OR TI("GHQ well-being") OR AB("GHQ functional health") OR TI("GHQ functional health") OR AB("GHQ functional status") OR TI("GHQ functional status") OR AB("GHQ health status") OR TI("GHQ health status") OR AB("GHQ domain") OR TI("GHQ domain") OR AB("GHQ subscales") OR TI("GHQ subscales")) AND (AB("ethnic") OR TI("ethnic") OR AB("ethnicity") OR TI("ethnicity") OR AB("race") OR TI("race") OR AB("racial") OR TI("racial") OR AB("bame") OR TI("bame") OR AB("discrimination") OR TI("discrimination") OR AB("racism") OR TI("racism")) AND (AB("quantitative") OR TI("quantitative") OR AB("natural experiment") OR TI("natural experiment") OR AB("quasi-experimental") OR TI("quasi-experimental") OR AB("difference-in-difference") OR TI("difference-in-difference") OR AB("multi-level") OR TI("multi-level") OR AB("regression") OR TI("regression") OR AB("longitudinal") OR TI("longitudinal") OR AB("time-series") OR TI("time-series") OR AB("logistic") OR TI("logistic") OR AB("linear") OR TI("linear") OR AB("Poisson") OR TI("Poisson") OR AB("synthetic control") OR TI("synthetic control") OR AB("propensity score") OR TI("propensity score") OR AB("instrumental variable") OR TI("instrumental variable") OR AB("decomposition") OR TI("decomposition") OR AB("cross-sectional") OR TI("cross-sectional") OR AB("quasi-natural") OR TI("quasi-natural") OR AB("natural policy experiment") OR TI("natural policy experiment") OR AB("confounding") OR TI("confounding") OR AB("fixed-effects") OR TI("fixed-effects")) AND (AB("UK") OR TI("UK") OR AB("United Kingdom") OR TI("United Kingdom") OR AB("Great Britain") OR TI("Great Britain") OR AB("England") OR TI("England") OR AB("Scotland") OR TI("Scotland") OR AB("Wales") OR TI("Wales") OR AB("Northern Ireland") OR TI("Northern Ireland") OR AB("British") OR TI("British") OR AB("London") OR TI("London"))

7.1.3 Data extraction tool at title/abstract screening stage

Question	Responses
Q1. Is the study based in the UK?	Yes/No/Maybe
Q2. Is the study observational/quantitative?	Yes/No/Maybe
Q3. Is the study focused on mental health outcomes measured by either SF12, SF36 or GHQ?	Yes/No/Maybe
Q4. Is ethnicity incorporated as one of the predictors?	Yes/No/Maybe
Q5. Is the study published in 2013 or later?	Yes/No/Maybe

If any of the study had a No for any of the questions, it would be excluded from the full-text review.

7.1.4 Data extraction tool at the full-text screening stage

Question	Rules for Responses	Decision
Q1. Is ethnicity incorporated to allow estimation effect by each sub-group?	Yes/No	If No, exclude from the final review
Q2. Is the SF12, SF36 or GHQ used to measure mental health across ethnic groups?	Yes/No	If No, exclude from the final review
Q3. Are sample sizes enough for power analysis?	Yes/No	If No, exclude from the final review

7.1.5 Data extraction tool for reports at the final stage

Item	**Description**
Citation (Author, year))	
Study design	Cross-sectional, longitudinal, etc
Aims, research questions, hypotheses	
Participants	Eligibility criteria, age,
Setting	Location, and relevant dates such as recruitment follow-up
Data sources	
Sample size	
Mental health outcomes	
Predictor variables	
Covariates	exposures, confounders, mediators/moderators

Ethnicity variable	Describe the groups
How is ethnicity incorporated in the analysis?	E.g., as dummy, categorical, or modelled separately by each group
Statistical methods	Modelling approach
Main results	
Limitations	

7.1.6 Validity Assessment Form of econometric studies

The form to assess validity is based on similar approaches adopted in systematic reviews with similar study design types (Barr et al., 2010; Simpson et al., 2021).

Table 7.1 Validity Assessment Form

Criteria	**Rationale**	**Score**
Unit of analysis	Three analysis units were utilised in the studies - aggregate (ecological), individual, and repeated measures on the same individuals (panel). Among these, panel data is considered the most reliable as it accounts for unmeasured confounding variables that do not change within individuals over time.	3- Longitudinal (panel) data 2-Individual data 1-Ecological (aggregate data)

	On the other hand, ecological studies are deemed the least robust as they may lead to ecological bias when using aggregate data to infer about individuals.	
Comparison approach	The studies examined either cross-sectional disparities in outcomes, changes over time, or a combination of both using a difference-in-differences approach. Cross-sectional comparisons are particularly vulnerable to unmeasured confounding factors. Studies examining changes within the same group over time can mitigate this to some extent, but other secular trends may still affect the results.	3-Difference in Differences 2-Interupted time series 1-Cross sectional
Sample selection	The quality of the sample selection relies on the complexity of the sampling approach.	3- Nationally recognised survey, based on random sampling 2-Non random sample that it is representative 1- Non random sample that is not representative
Number of points of data	Many data points allow for a more robust analysis that considers long-term trends in exposed and unexposed groups.	3- >5 time points with at least 2 after policy start 2- 3-5 with at least two after policy 1-One time point only after the policy start
Response/follow-up bias	A response/follow-up risk of greater than 80% is considered low-risk, 60-79% is considered moderate-risk, and less than 60% or non-reported is considered high-risk. Measures such as using weights to adjust for response bias/attrition can decrease the risk.	3- Response & follow-up rate >80% 2- Response & follow-up rate 60-80%, data weighted for non-response/loss to follow-up 1- Response/follow-up rate <60% or non-reported, not weighted for non-response/loss of follow-up
Exogeneity of policy exposure	The level of bias present will be determined by the degree to which the variation in exposure is exogenous, meaning it is not likely to be associated	3- Policy variation is as good as random, un-targeted roll-out/ arbitrary eligibility criteria

	with other factors that could influence the outcome and instead appears almost random.	2- Policy variation depends on administrative decisions unlikely to be associated with outcomes (e.g. different jurisdictions) 1-Policy variation relates to targeting/uptake/differential adoption of policy – likely to be associated with outcomes. E.g. targeting areas with poor initial outcomes
Confounding	The quality is likely to be higher to the extent the analysis adjusted adequately for potential confounders such as age, sex, health status, labour market conditions, wage, education, and occupation.	3- All major confounders included in analysis 2-Missing 1-2 confounders 1-missing >2 confounders
Sample size/power	The chances of the analysis yielding biased estimates will also depend on the study's strength, which primarily relies on the sample size.	3-Priori sample size calculations performed/large sample size, >500 observations 2- No power calculations – sample size 100-500 1- No power calculations – sample size <100
Analysis	An assessment of the potential for bias in the analysis was conducted, which included evaluating the sample size and the use of appropriate statistical techniques.	3- large sample size and an appropriate statistical technique was used 2-Either an inappropriate statistical technique was used or the sample size was small. 1.-Both an inappropriate statistical technique was used and the sample was small.
<u>Total Validity Score (out of 27)</u>		

7.2 Annex II – RDD

7.2.1 First stage estimates ROSLA on education leaving age

Table 7.2 Effects of ROSLA on education among ethnic minorities – local random approach with optimal window selection

	Age left school			**>= 16 Leaving age**			**>= 17 Leaving age**			**>= 18 Leaving age**		
	Pooled	**Female**	**Male**	**Pooled**	**Female**	**Male**	**Pooled**	**Female**	**Male**	**Pooled**	**Female**	**Male**
1975 ROSLA	2.049***	2.093***	2.000***	0.685***	0.704***	0.667***	0.322***	0.352**	0.285*	0.104	0.074	0.143
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.014	0.076	0.160	0.690	0.476
Eff. Obs <c	31	18	13	31	18	13	31	18	13	31	18	13
Eff. Obs >c	48	27	21	48	27	21	48	27	21	48	27	21
Tot.Obs<c	185	94	91	185	94	91	185	94	91	185	94	91
Tot.Obs>c	526	283	243	530	284	246	530	284	246	530	284	246
Mean<c	14.097	14.167	14.000	0.065	0.323	0.000	0.032	0.236	0.000	0.000	0.000	0.000
Mean>c	16.146	16.259	16.000	0.750	0.396	0.667	0.354	0.501	0.286	0.104	0.267	0.359

*Note: These estimations were conducted using the local randomisation approach with optimal bandwith (-12,10) using the Stata© command -rdrandinf. Tot.Obs,><c corresponds to the total number of observations to the left/rigth of the cut-off, while Eff.Obs><c are the effective number of observations used for the estimation following the optimal bandwith. Mean><c is the mean value of the outcome variable to the left and right of the cut-off, respectively. The p-values correspond to the finite sample estimation. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931. *** p<0.001, ** p<0.05, * p<0.1*

7.2.2 Reduced form – effect of ROSLA on mental health

Table 7.3 Effects of ROSLA on education among ethnic minorities

(ITT)		**SF-12**			**GHQ-Likert scale**	
	Pooled	**Female**	**Male**	**Pooled**	**Female**	**Male**
1975 ROSLA	0.753	0.814	0.818	-0.760	-1.729	0.316
p-value	0.784	0.764	0.828	0.556	0.376	0.880
Eff. Obs <c	31	18	13	38	20	18
Eff. Obs >c	48	27	21	53	28	25
Tot.Obs<c	185	94	91	218	109	109
Tot.Obs>c	530	284	246	568	308	260
Mean<c	48.511	49.972	46.488	12.684	13.800	11.444

Mean>c	49.263	50.786	47.306	11.925	12.071	11.760

*Note: These estimations were conducted using the local randomisation approach with optimal bandwith (-12,10) using the Stata© command -rdrandinf. Tot.Obs><c corresponds to the total number of observations to the left/rigth of the cut-off, while Eff.Obs><c are the effective number of observations used for the estimation following the optimal bandwith. Mean>< is the mean value of the outcome variable to the left and right of the cut-off, respectively. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931. *** p<0.001, ** p<0.05, * p<0.1*

7.2.3 Causal effect of education on mental health (LATE)

Table 7.4 Effects of education on mental health among ethnic minorities - optimal bandwidth

(2SLS)	**SF-12**			**GHQ-Likert scale**		
	Pooled	**Female**	**Male**	**Pooled**	**Female**	**Male**
Left FT education at 16 or older	1.098	1.157	1.228	-1.094	-2.396	0.475
p-value	0.784	0.764	0.828	0.556	0.376	0.880
Eff. Obs <c	31	18	13	38	20	18
Eff. Obs >c	48	27	21	53	28	25
Tot.Obs<c	185	94	91	218	109	109
Tot.Obs>c	530	284	246	568	308	260

Mean<c	48.511	49.972	46.488	12.684	13.800	11.444
Mean>c	49.263	50.786	47.306	11.925	12.071	11.760

*Note: These estimations were conducted using the local randomisation approach with optimal bandwidth (-12,10) using the Stata© command -rdrandinf. Tot.Obs><c corresponds to the total number of observations to the left/right of the cut-off, while Eff.Obs><c are the effective number of observations used to estimate following the optimal bandwidth. Mean>< is the outcome variable's mean value to the cut-off's left and right, respectively. Data: Understanding Society: Waves 1-12, 2009-2021 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 16th Edition. UK Data Service. SN: 6931. *** p<0.001, ** p<0.05, * p<0.1*

Table 7.5 Effects of education on mental health among ethnic minorities – maximum sample size

	SF-12	**GHQ-Likert scale**
1975 ROSLA	-0.686	0.049
p-value	0.622	0.916
Eff. Obs <c	185	218
Eff. Obs >c	530	568
Tot.Obs<c	185	218
Tot.Obs>c	530	568
Mean<c	48.43	11.89
Mean>c	47.953	11.93

7.3 Annex III – Oaxaca-Blinder

7.3.1 Oaxaca-Blinder (OB) decomposition

The tables in this section show the estimated results of the Oaxaca-Blinder decomposition across sex and ethnicity and the intersection of both. Section 7.3.1.4 displays results for the decomposition by ethnicity with other specifications, such as excluding behavioural variables or age.

7.3.1.1 Decomposition by ethnicity

Table 7.6 Oaxaca-Blinder decomposition for SF12 by ethnic groups

SF12	Coefficient	SE	t	P>|t|	[95% conf. interval]	
Overall						
White	48.9359	0.15291	320.03	0	48.636	49.2357
Non-white	46.3476	0.65885	70.35	0	45.0558	47.6394
Gap	2.58822	0.6806	3.8	0	1.25376	3.92268
Explained	2.05229	0.32416	6.33	0	1.41671	2.68788
Unexplained	0.53593	0.62796	0.85	0.393	-0.6953	1.76717
Explained						
Female	-0.0031	0.06157	-0.05	0.96	-0.1238	0.11768
Age	1.16682	0.1506	7.75	0	0.87155	1.46209
Long-lasting ill	-0.2721	0.10074	-2.7	0.007	-0.4696	-0.0745
Attacked/avoided places (discrimination)	0.65064	0.17708	3.67	0	0.30344	0.99783
Above median HH income	0.00222	0.0065	0.34	0.733	-0.0105	0.01497
Employed or student	-0.1026	0.05779	-1.77	0.076	-0.2159	0.01074
Rural	0.00677	0.05448	0.12	0.901	-0.1	0.11359
Higher education degree	0.00302	0.03409	0.09	0.929	-0.0638	0.06987
House owner	0.2529	0.08074	3.13	0.002	0.09459	0.41122
Neighbourhood cohesion	0.39671	0.09696	4.09	0	0.2066	0.58683
Religious identity	-0.0352	0.02148	-1.64	0.101	-0.0773	0.00691
Fruit consumption	0.00198	0.0136	0.15	0.884	-0.0247	0.02864
Alcohol consumption	-0.077	0.05176	-1.49	0.137	-0.1785	0.02452
Smoker	0.06109	0.04272	1.43	0.153	-0.0227	0.14486
Unexplained						
Female	1.19234	0.56855	2.1	0.036	0.07758	2.30709
Age	0.41372	1.73293	0.24	0.811	-2.984	3.81147
Long-lasting ill	0.43073	1.2127	0.36	0.722	-1.947	2.80846

Attacked/avoided places (discrimination)	0.4646	0.19491	2.38	0.017	0.08243	0.84676
Above median HH income	-0.2391	0.70035	-0.34	0.733	-1.6123	1.13403
Employed or student	-0.483	1.33961	-0.36	0.718	-3.1096	2.14353
Rural	-0.1743	0.17512	-1	0.32	-0.5177	0.16904
Higher education degree	0.43727	0.60877	0.72	0.473	-0.7564	1.63089
House owner	0.99067	0.87701	1.13	0.259	-0.7289	2.71021
Neighbourhood cohesion	-5.4817	3.26075	-1.68	0.093	-11.875	0.91165
Religious practice	-0.0002	0.01564	-0.01	0.992	-0.0308	0.0305
Fruit consumption	-0.2385	1.12849	-0.21	0.833	-2.4511	1.97416
Alcohol consumption	0.3432	1.42316	0.24	0.809	-2.4472	3.13358
Smoker	-0.2748	0.20599	-1.33	0.182	-0.6787	0.12907
_cons	3.15503	4.22269	0.75	0.455	-5.1244	11.4345
Observations	175,833					

Table 7.7 Oaxaca-Blinder decomposition for GHQ-Likert by ethnic groups

GHQ-Likert	**Coefficient**	**SE**	**t**	**P>|t|**	**[95% conf. interval]**	
overall						
White	11.073	0.0767	144.41	0	10.922	11.223
Non-white	12.152	0.3294	36.89	0	11.506	12.798
Gap	-1.079	0.3386	-3.19	0.001	-1.743	-0.415
Explained	-0.668	0.1501	-4.45	0	-0.962	-0.374
Unexplained	-0.411	0.318	-1.29	0.196	-1.035	0.2122
Explained						
Female	-0.002	0.0286	-0.07	0.947	-0.058	0.0542
Age	-0.371	0.058	-6.4	0	-0.485	-0.257
Long-lasting ill	0.1622	0.068	2.38	0.017	0.0288	0.2955
Attacked/avoided places (discrimination)	-0.268	0.0809	-3.32	0.001	-0.427	-0.11
Above median HH income	-0.004	0.008	-0.53	0.594	-0.02	0.0114
Employed or student	0.0587	0.0298	1.97	0.049	0.0002	0.1173
Rural	0.0372	0.03	1.24	0.215	-0.022	0.096
Higher education degree	-0.019	0.0183	-1.06	0.29	-0.055	0.0165
House owner	-0.106	0.0385	-2.76	0.006	-0.182	-0.031
Neighbourhood cohesion	-0.188	0.0475	-3.97	0	-0.282	-0.095
Religious identity	0.0118	0.0117	1.01	0.313	-0.011	0.0346
Fruit consumption	0.0001	0.0032	0.04	0.964	-0.006	0.0065
Alcohol consumption	0.0455	0.0263	1.73	0.083	-0.006	0.097
Smoker	-0.024	0.0181	-1.31	0.19	-0.059	0.0118
Unexplained						
Female	-0.076	0.2886	-0.26	0.793	-0.642	0.4901
Age	-0.068	0.9639	-0.07	0.944	-1.957	1.8224
Long-lasting ill	0.3994	0.7333	0.54	0.586	-1.038	1.8372

Attacked/avoided places (discrimination)	-0.292	0.104	-2.81	0.005	-0.496	-0.088
Above median HH income	0.0314	0.3876	0.08	0.935	-0.728	0.7913
Employed or student	0.2525	0.6622	0.38	0.703	-1.046	1.551
Rural	0.0621	0.0824	0.75	0.451	-0.099	0.2237
Higher education degree	-0.314	0.3452	-0.91	0.363	-0.991	0.3627
House owner	-0.016	0.501	-0.03	0.974	-0.998	0.9662
Neighbourhood cohesion	1.5712	1.7308	0.91	0.364	-1.822	4.9648
Religious practice	0.0114	0.0128	0.9	0.371	-0.014	0.0365
Fruit consumption	0.5679	0.5649	1.01	0.315	-0.54	1.6755
Alcohol consumption	0.2263	0.8374	0.27	0.787	-1.416	1.8682
Smoker	0.0405	0.1219	0.33	0.74	-0.198	0.2795
_cons	-2.808	2.2318	-1.26	0.208	-7.184	1.5675
Observations	175,949					

7.3.1.2 Decomposition by sex

Table 7.8 Oaxaca-Blinder decomposition for SF12 by sex

SF12	Coefficient	SE	t	P>|t|	[95% conf. interval]	
Overall						
Male	49.80799	0.214163	232.57	0	49.38809	50.2279
Female	47.68286	0.198352	240.4	0	47.29396	48.07177
Gap	2.125132	0.28733	7.4	0	1.561771	2.688494
Explained	0.0193567	0.123489	0.16	0.875	-0.22276	0.261478
Unexplained	2.105776	0.272003	7.74	0	1.572465	2.639086
Explained						
BME	-0.000213	0.004303	-0.05	0.961	-0.00865	0.008223
Age	-0.0734412	0.074112	-0.99	0.322	-0.21875	0.071868
Long-lasting ill	0.1543935	0.049849	3.1	0.002	0.056655	0.252132
Attacked/avoided places (discrimination)	0.0133864	0.024007	0.56	0.577	-0.03368	0.060457
Above median HH income	0.0102449	0.02309	0.44	0.657	-0.03503	0.055517
Employed or student	0.0390419	0.022583	1.73	0.084	-0.00524	0.083321
Rural	-0.0003683	0.00298	-0.12	0.902	-0.00621	0.005474
Higher education degree	-0.0001737	0.00198	-0.09	0.93	-0.00406	0.003708
House owner	0.1087005	0.032027	3.39	0.001	0.045906	0.171495
Neighbourhood cohesion	-0.163867	0.044478	-3.68	0	-0.25107	-0.07666
Religious identity	0.0004088	0.002483	0.16	0.869	-0.00446	0.005277
Fruit consumption	-0.0272425	0.015671	-1.74	0.082	-0.05797	0.003483
Alcohol consumption	-0.0701984	0.046193	-1.52	0.129	-0.16077	0.020371
Smoker	0.0286848	0.018166	1.58	0.114	-0.00693	0.064302
Unexplained						
BME	0.1898161	0.093585	2.03	0.043	0.006326	0.373306

Age	-2.902615	1.002321	-2.9	0.004	-4.86785	-0.93739
Long-lasting ill	-0.3315704	0.581478	-0.57	0.569	-1.47166	0.808521
Attacked/avoided places (discrimination)	0.0271596	0.04672	0.58	0.561	-0.06444	0.118762
Above median HH income	-0.1057993	0.332248	-0.32	0.75	-0.75723	0.545633
Employed or student	-0.6414702	0.508489	-1.26	0.207	-1.63845	0.355514
Rural	0.2402869	0.141105	1.7	0.089	-0.03638	0.516949
Higher education degree	-0.3742076	0.22115	-1.69	0.091	-0.80781	0.059397
House owner	-0.6383627	0.554615	-1.15	0.25	-1.72578	0.449059
Neighbourhood cohesion	0.9088711	1.492	0.61	0.542	-2.01646	3.834205
Religious practice	-0.0014871	0.003602	-0.41	0.68	-0.00855	0.005575
Fruit consumption	-0.0824701	0.45764	-0.18	0.857	-0.97976	0.814816
Alcohol consumption	0.5348899	0.792853	0.67	0.5	-1.01964	2.08942
Smoker	0.0167897	0.12239	0.14	0.891	-0.22318	0.256758
_cons	5.265945	2.089613	2.52	0.012	1.168883	9.363007
Observations	287,809					

Table 7.9 Oaxaca-Blinder decomposition for GHQ-Likert by sex

GHQ	Coefficient	SE	t	P>|t|	[95% conf. interval]	
Overall						
Male	10.63651	0.105109	101.2	0	10.43042	10.84259
Female	11.66917	0.102216	114.16	0	11.46876	11.86959
Gap	-1.032668	0.143646	-7.19	0	-1.31431	-0.75102
Explained	-0.0598939	0.056663	-1.06	0.291	-0.17099	0.051203
Unexplained	-0.9727737	0.13851	-7.02	0	-1.24435	-0.7012
Explained						
BME	-0.0002231	0.003337	-0.07	0.947	-0.00677	0.00632
Age	0.0235887	0.02453	0.96	0.336	-0.02451	0.071683
Long-lasting ill	-0.102347	0.032626	-3.14	0.002	-0.16632	-0.03838
Attacked/avoided places (discrimination)	-0.0062561	0.00993	-0.63	0.529	-0.02573	0.013214
Above median HH income	-0.0184675	0.012688	-1.46	0.146	-0.04334	0.00641
Employed or student	-0.0232882	0.012139	-1.92	0.055	-0.04709	0.000513
Rural	-0.0017966	0.00237	-0.76	0.449	-0.00644	0.002851
Higher education degree	0.0013922	0.002314	0.6	0.547	-0.00314	0.005929
House owner	-0.0443474	0.015235	-2.91	0.004	-0.07422	-0.01448
Neighbourhood cohesion	0.0745764	0.021177	3.52	0	0.033055	0.116098
Religious identity	-0.0000566	0.000803	-0.07	0.944	-0.00163	0.001518
Fruit consumption	0.0066213	0.007248	0.91	0.361	-0.00759	0.020833
Alcohol consumption	0.0421496	0.023609	1.79	0.074	-0.00414	0.08844
Smoker	-0.0114398	0.007942	-1.44	0.15	-0.02701	0.004131
Unexplained						
BME	-0.0182903	0.045828	-0.4	0.69	-0.10814	0.071564
Age	0.641664	0.537711	1.19	0.233	-0.41261	1.695942
Long-lasting ill	-0.2967098	0.309699	-0.96	0.338	-0.90393	0.31051

Attacked/avoided places (discrimination)	-0.0135496	0.023533	-0.58	0.565	-0.05969	0.03259
Above median HH income	-0.0681687	0.169228	-0.4	0.687	-0.39997	0.263633
Employed or student	0.0236406	0.27387	0.09	0.931	-0.51333	0.560612
Rural	-0.0855294	0.078464	-1.09	0.276	-0.23937	0.068313
Higher education degree	0.1858471	0.118649	1.57	0.117	-0.04679	0.41848
House owner	0.0670794	0.284023	0.24	0.813	-0.4898	0.623957
Neighbourhood cohesion	-0.2014245	0.837874	-0.24	0.81	-1.84423	1.441378
Religious practice	0.0017732	0.002439	0.73	0.467	-0.00301	0.006555
Fruit consumption	-0.2497415	0.228528	-1.09	0.275	-0.69781	0.198329
Alcohol consumption	0.195514	0.408178	0.48	0.632	-0.60479	0.995821
Smoker	-0.0455947	0.065233	-0.7	0.485	-0.1735	0.082306
_cons	-1.109284	1.197542	-0.93	0.354	-3.45728	1.238712
Observations	287,801					

7.3.1.3 Decomposition by the intersection of sex and ethnicity

Table 7.10 Oaxaca-Blinder decomposition for SF12 by sex and ethnicity

SF12	Coefficient	std. err.	t	P>|t|	[95% conf. interval]	
Overall						
All	48.95184	0.151058	324.06	0	48.65567	49.24802
Female BME	43.33546	0.954683	45.39	0	41.46363	45.20728
Gap	5.61639	0.970529	5.79	0	3.713494	7.519286
Explained	2.624003	0.428558	6.12	0	1.783737	3.464268
Unexplained	2.992387	0.877168	3.41	0.001	1.272541	4.712233
Explained						
Age	1.111373	0.186344	5.96	0	0.746013	1.476734
Long-lasting ill	-0.0201633	0.145974	-0.14	0.89	-0.30637	0.266045
Attacked/avoided places (discrimination)	0.7952798	0.247777	3.21	0.001	0.309468	1.281092
Above median HH income	-0.0005422	0.009804	-0.06	0.956	-0.01977	0.018681
Employed or student	-0.1121448	0.056532	-1.98	0.047	-0.22299	-0.0013
Rural	-0.0114915	0.056931	-0.2	0.84	-0.12311	0.100131
Higher education degree	0.0062484	0.023952	0.26	0.794	-0.04071	0.05321
House owner	0.3295885	0.10242	3.22	0.001	0.128775	0.530402
Neighbourhood cohesion	0.5082611	0.125277	4.06	0	0.262633	0.753889
Religious identity	-0.0311204	0.019375	-1.61	0.108	-0.06911	0.006868
Fruit consumption	-0.0145612	0.019571	-0.74	0.457	-0.05293	0.023811
Alcohol consumption	-0.0249021	0.062176	-0.4	0.689	-0.14681	0.097004
Smoker	0.0881773	0.057833	1.52	0.127	-0.02521	0.201569
Unexplained						
Age	-2.491131	2.359027	-1.06	0.291	-7.11643	2.134165
Long-lasting ill	1.999506	1.79719	1.11	0.266	-1.52421	5.52322
Attacked/avoided places (discrimination)	0.3933341	0.338661	1.16	0.246	-0.27067	1.057339

Above median HH income	-0.0346008	1.139295	-0.03	0.976	-2.2684	2.199193
Employed or student	0.8996643	1.964082	0.46	0.647	-2.95127	4.750601
Rural	0.1856964	0.184488	1.01	0.314	-0.17603	0.547418
Higher education degree	-0.8610289	0.786953	-1.09	0.274	-2.40399	0.681933
House owner	1.23145	1.234257	1	0.318	-1.18853	3.651432
Neighbourhood cohesion	-7.930937	4.487745	-1.77	0.077	-16.73	0.868095
Religious practice	0.0113641	0.026126	0.43	0.664	-0.03986	0.062589
Fruit consumption	-0.4584499	1.676068	-0.27	0.784	-3.74468	2.827784
Alcohol consumption	1.804685	1.854434	0.97	0.331	-1.83127	5.440637
Smoker	-0.400365	0.326233	-1.23	0.22	-1.04	0.239274
_cons	8.6432	5.927298	1.46	0.145	-2.97833	20.26473
Observations	171,130					

Table 7.11 Oaxaca-Blinder decomposition for GHQ by sex and ethnicity

GHQ	Coefficient	std. err.	t	P>|t|	[95% conf. interval]	
Overall						
All	11.07626	0.075419	146.86	0	10.92839	11.22414
Female BME	13.13036	0.483503	27.16	0	12.18236	14.07835
Gap	-2.054094	0.488352	-4.21	0	-3.0116	-1.09659
Explained	-1.019482	0.204293	-4.99	0	-1.42004	-0.61893
Unexplained	-1.034612	0.459449	-2.25	0.024	-1.93544	-0.13378
Explained						
Age	-0.3442279	0.068718	-5.01	0	-0.47896	-0.20949
Long-lasting ill	-0.0252513	0.100558	-0.25	0.802	-0.22241	0.171911
Attacked/avoided places (discrimination)	-0.3469709	0.116492	-2.98	0.003	-0.57537	-0.11857
Above median HH income	-0.0011288	0.011541	-0.1	0.922	-0.02376	0.0215
Employed or student	0.0569719	0.028176	2.02	0.043	0.001728	0.112216
Rural	0.0431729	0.031329	1.38	0.168	-0.01825	0.104599
Higher education degree	-0.0157227	0.013642	-1.15	0.249	-0.04247	0.011025
House owner	-0.141501	0.049407	-2.86	0.004	-0.23837	-0.04463
Neighbourhood cohesion	-0.2438713	0.062178	-3.92	0	-0.36578	-0.12196
Religious identity	0.0104256	0.010053	1.04	0.3	-0.00929	0.030137
Fruit consumption	0.003026	0.006287	0.48	0.63	-0.0093	0.015353
Alcohol consumption	0.0200079	0.030872	0.65	0.517	-0.04052	0.080538
Smoker	-0.0344122	0.02484	-1.39	0.166	-0.08312	0.014292
Unexplained						
Age	0.1217838	1.260087	0.1	0.923	-2.34884	2.592411
Long-lasting ill	-0.2644702	1.025502	-0.26	0.797	-2.27515	1.746211
Attacked/avoided places (discrimination)	-0.3688657	0.173672	-2.12	0.034	-0.70938	-0.02835
Above median HH income	-0.0885492	0.659915	-0.13	0.893	-1.38243	1.205333
Employed or student	-0.6161646	0.980386	-0.63	0.53	-2.53839	1.306058
Rural	-0.1337571	0.11638	-1.15	0.251	-0.36194	0.094427
Higher education degree	-0.1098909	0.452743	-0.24	0.808	-0.99757	0.777792
House owner	-0.7101143	0.729556	-0.97	0.33	-2.14054	0.720312

Neighbourhood cohesion	3.72237	2.181074	1.71	0.088	-0.55402	7.998757
Religious practice	0.0131343	0.01628	0.81	0.42	-0.01879	0.045055
Fruit consumption	0.2030329	0.739246	0.27	0.784	-1.24639	1.652458
Alcohol consumption	1.165036	1.139232	1.02	0.307	-1.06863	3.398705
Smoker	-0.0761795	0.200605	-0.38	0.704	-0.4695	0.317143
_cons	-3.891977	2.929598	-1.33	0.184	-9.63598	1.852027
Observations	171,247					

7.3.1.4 Other model specifications – robustness tests

Table 7.12 Oaxaca-Blinder decomposition for SF12 between ethnic groups, excluding behavioural variables

SF12	Coefficient	SE	t	P>|t|	[95% conf. interval]	
Overall						
White	49.0459	0.08105	605.12	0	48.887	49.2048
Non-white	47.9066	0.24811	193.08	0	47.4202	48.393
difference	1.13932	0.26291	4.33	0	0.6239	1.65475
explained	1.35633	0.12618	10.75	0	1.10896	1.60369
unexplained	-0.217	0.24996	-0.87	0.385	-0.70705	0.27305
Explained						
Female	-0.00862	0.02771	-0.31	0.756	-0.06294	0.04569
Age	1.17575	0.07124	16.5	0	1.03608	1.31542
Long-lasting ill	-0.56376	0.05022	-11.23	0	-0.66221	-0.4653
Attacked/avoided places (discrimination)	0.25356	0.05174	4.9	0	0.15213	0.35499
Above median HH income	0.02723	0.01078	2.53	0.012	0.0061	0.04836
Employed or student	-0.15113	0.02507	-6.03	0	-0.20027	-0.10199
Rural	0.07913	0.0312	2.54	0.011	0.01797	0.1403
Higher education degree	0.03836	0.01823	2.1	0.035	0.00263	0.07409
House owner	0.1854	0.03307	5.61	0	0.12057	0.25023
Neighbourhood cohesion	0.22996	0.04898	4.69	0	0.13394	0.32599
Religious identity	0.09044	0.01532	5.9	0	0.0604	0.12048
Unexplained						
Female	0.3478	0.22892	1.52	0.129	-0.10099	0.7966
Age	1.37247	0.62709	2.19	0.029	0.14307	2.60186
Long-lasting ill	1.1053	0.48762	2.27	0.023	0.14933	2.06128
Attacked/avoided places (discrimination)	-0.03896	0.03438	-1.13	0.257	-0.10637	0.02844
Above median HH income	-0.17437	0.20653	-0.84	0.399	-0.57926	0.23052
Employed or student	0.01794	0.40336	0.04	0.965	-0.77283	0.80872
Rural	-0.04668	0.06222	-0.75	0.453	-0.16865	0.0753
Higher education degree	-0.51514	0.21486	-2.4	0.017	-0.93637	-0.09392

House owner	1.13228	0.29276	3.87	0	0.55833	1.70624
Neighbourhood cohesion	-2.12597	1.11511	-1.91	0.057	-4.31211	0.06016
Religious identity	-0.04746	0.06109	-0.78	0.437	-0.16722	0.0723
_cons	-1.24423	1.44641	-0.86	0.39	-4.07987	1.59141
Observations	258,627					

Table 7.13 Oaxaca-Blinder decomposition for GHQ-Likert between ethnic groups, excluding behavioural variables

GHQ-Likert	Coefficient	SE	t	P>|t|	[95% conf. interval]	
Overall						
White	11.123	0.040588	274.04	0	11.04342	11.20257
Non-white	11.42517	0.145527	78.51	0	11.13986	11.71047
difference	-0.30217	0.151471	-1.99	0.046	-0.59913	-0.00522
explained	-0.28772	0.066964	-4.3	0	-0.419	-0.15644
unexplained	-0.01446	0.142634	-0.1	0.919	-0.29409	0.265173
Explained						
Female	0.004885	0.016648	0.29	0.769	-0.02775	0.037523
Age	-0.37569	0.029276	-12.83	0	-0.43308	-0.3183
Long-lasting ill	0.373263	0.032808	11.38	0	0.308944	0.437582
Attacked/avoided places (discrimination)	-0.12346	0.02993	-4.12	0	-0.18214	-0.06478
Above median HH income	-0.01727	0.0061	-2.83	0.005	-0.02923	-0.00531
Employed or student	0.088999	0.014275	6.23	0	0.061013	0.116985
Rural	0.005845	0.016576	0.35	0.724	-0.02665	0.038341
Higher education degree	-0.01452	0.009937	-1.46	0.144	-0.034	0.004964
House owner	-0.06389	0.014335	-4.46	0	-0.09199	-0.03579
Neighbourhood cohesion	-0.12339	0.026006	-4.74	0	-0.17438	-0.07241
Religious identity	-0.04249	0.008048	-5.28	0	-0.05827	-0.02671
Unexplained						
Female	-0.02554	0.125867	-0.2	0.839	-0.2723	0.22122
Age	-0.48769	0.374489	-1.3	0.193	-1.22187	0.246485
Long-lasting ill	-0.73714	0.296299	-2.49	0.013	-1.31803	-0.15625
Attacked/avoided places (discrimination)	0.011548	0.017672	0.65	0.513	-0.0231	0.046193
Above median HH income	0.041688	0.120482	0.35	0.729	-0.19451	0.27789
Employed or student	0.272878	0.236243	1.16	0.248	-0.19027	0.736025
Rural	0.005364	0.032982	0.16	0.871	-0.0593	0.070024
Higher education degree	0.277884	0.127733	2.18	0.03	0.027467	0.528301
House owner	-0.43071	0.181103	-2.38	0.017	-0.78576	-0.07567
Neighbourhood cohesion	1.911427	0.688396	2.78	0.006	0.561846	3.261009

Religious identity	0.00709	0.036212	0.2	0.845	-0.0639	0.078083
_cons	-0.86125	0.885372	-0.97	0.331	-2.597	0.874496
Observations	258,836					

Table 7.14 Oaxaca-Blinder decomposition for SF12 between ethnic groups, excluding age

SF12	Coefficient	SE.	t	P>|t|	[95% conf. interval]	
Overall						
White	48.93586	0.152396	321.11	0	48.63706	49.23466
Non-white	46.34764	0.669077	69.27	0	45.03578	47.65949
Gap	2.588222	0.690824	3.75	0	1.233724	3.942719
Explained	1.970292	0.328789	5.99	0	1.325637	2.614947
Unexplained	0.617929	0.644463	0.96	0.338	-0.64567	1.881525
Explained						
Female	-0.00306	0.061792	-0.05	0.96	-0.12422	0.118095
Long-lasting ill	-0.19914	0.075425	-2.64	0.008	-0.34702	-0.05125
Attacked/avoided places (discrimination)	0.739999	0.193232	3.83	0	0.36113	1.118868
Above median HH income	0.00413	0.009282	0.44	0.656	-0.01407	0.022329
Employed or student	0.362167	0.071471	5.07	0	0.222033	0.502301
Rural	0.02948	0.055831	0.53	0.598	-0.07999	0.138948
Higher education degree	0.009464	0.034973	0.27	0.787	-0.05911	0.078037
House owner	0.36209	0.102589	3.53	0	0.160943	0.563237
Neighbourhood cohesion	0.528657	0.12345	4.28	0	0.286609	0.770705
Religious identity	-0.01188	0.017692	-0.67	0.502	-0.04657	0.022803
Fruit consumption	0.002249	0.015406	0.15	0.884	-0.02796	0.032456
Alcohol consumption	0.067119	0.053113	1.26	0.206	-0.03702	0.171257
Smoker	0.079022	0.053711	1.47	0.141	-0.02629	0.184333
Unexplained						
Female	1.119322	0.576006	1.94	0.052	-0.01005	2.248695
Long-lasting ill	0.466352	1.173798	0.4	0.691	-1.83511	2.767814
Attacked/avoided places (discrimination)	0.440927	0.201406	2.19	0.029	0.046031	0.835823
Above median HH income	-0.0201	0.722705	-0.03	0.978	-1.4371	1.39691
Employed or student	-1.54595	1.288928	-1.2	0.23	-4.07314	0.981251
Rural	-0.12249	0.171093	-0.72	0.474	-0.45795	0.212973
Higher education degree	0.195426	0.602837	0.32	0.746	-0.98656	1.377408
House owner	0.999101	0.866479	1.15	0.249	-0.6998	2.698003
Neighbourhood cohesion	-4.45381	3.402694	-1.31	0.191	-11.1255	2.217846
Religious practice	-0.00301	0.015631	-0.19	0.847	-0.03366	0.027633

Fruit consumption	-0.01651	1.14864	-0.01	0.989	-2.26864	2.235631
Alcohol consumption	0.735223	1.457296	0.5	0.614	-2.12209	3.592539
Smoker	-0.35334	0.212898	-1.66	0.097	-0.77077	0.064091
_cons	3.176774	3.991055	0.8	0.426	-4.64848	11.00203
Observations	175,833					

Table 7.15 Oaxaca-Blinder decomposition for GHQ-Likert between ethnic groups, excluding age

GHQ-Likert	Coefficient	std. err.	t	P>|t|	[95% conf. interval]	
Overall						
White	11.07272	0.076972	143.85	0	10.9218	11.22363
Non-white	12.15181	0.331685	36.64	0	11.50148	12.80214
Gap	-1.0791	0.340993	-3.16	0.002	-1.74768	-0.41051
Explained	-0.64818	0.151845	-4.27	0	-0.9459	-0.35046
Unexplained	-0.43091	0.320454	-1.34	0.179	-1.05923	0.197399
Explained						
Female	-0.00192	0.028682	-0.07	0.947	-0.05815	0.05432
Long-lasting ill	0.140636	0.059198	2.38	0.018	0.024566	0.256706
Attacked/avoided places (discrimination)	-0.29818	0.084458	-3.53	0	-0.46378	-0.13258
Above median HH income	-0.00496	0.009151	-0.54	0.588	-0.0229	0.01298
Employed or student	-0.08765	0.027303	-3.21	0.001	-0.14118	-0.03412
Rural	0.029305	0.030339	0.97	0.334	-0.03018	0.088791
Higher education degree	-0.02169	0.018681	-1.16	0.246	-0.05831	0.014941
House owner	-0.14352	0.044652	-3.21	0.001	-0.23107	-0.05597
Neighbourhood cohesion	-0.23383	0.055666	-4.2	0	-0.34298	-0.12469
Religious identity	0.003867	0.011162	0.35	0.729	-0.01802	0.025751
Fruit consumption	0.000173	0.003852	0.04	0.964	-0.00738	0.007725
Alcohol consumption	-0.00094	0.02565	-0.04	0.971	-0.05123	0.049354
Smoker	-0.02948	0.021621	-1.36	0.173	-0.07187	0.012917
Unexplained						
Female	-0.04935	0.289866	-0.17	0.865	-0.61769	0.518987
Long-lasting ill	0.410167	0.70281	0.58	0.56	-0.96783	1.788165
Attacked/avoided places (discrimination)	-0.28712	0.104579	-2.75	0.006	-0.49217	-0.08208
Above median HH income	-0.04151	0.387001	-0.11	0.915	-0.8003	0.717278
Employed or student	0.569937	0.62692	0.91	0.363	-0.65926	1.799136
Rural	0.043663	0.078925	0.55	0.58	-0.11108	0.19841
Higher education degree	-0.24458	0.335535	-0.73	0.466	-0.90246	0.413302
House owner	-0.02427	0.48034	-0.05	0.96	-0.96607	0.917533

Neighbourhood cohesion	1.238252	1.726403	0.72	0.473	-2.1467	4.623206
Religious practice	0.012108	0.012905	0.94	0.348	-0.01319	0.03741
Fruit consumption	0.504302	0.578573	0.87	0.383	-0.6301	1.638708
Alcohol consumption	0.117507	0.852592	0.14	0.89	-1.55417	1.789182
Smoker	0.062843	0.121918	0.52	0.606	-0.1762	0.301888
_cons	-2.74286	2.307429	-1.19	0.235	-7.26702	1.781314
Observations	175,949					