LANCASTER UNIVERSITY

DOCTORAL THESIS

The Impact of Economic Shocks on Health and Health Inequalities

Author:
Mario Martínez-Jiménez
BSc Economics (University Pompeu Fabra)
MSc Health Economics (Erasmus University Rotterdam)
MRes Applied Economics (Autonomous University Barcelona)

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"Good economics can be a source of hope – a way to understand what went wrong but also to explain how our world can be put back together, as long as we are honest in our diagnosis of the problems."

Esther Duflo & Abhijit Banerjee

Declaration of Authorship

I, Mario Martínez-Jiménez, declare that this thesis titled, *"The Impact of Economic Shocks on Health and Health Inequalities"* and the work presented in it are my own. I confirm that:

- This work was done while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed: **Mario Martínez-Jiménez**

Date: 30th June, 2022

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During my PhD, I organised the Health Economics at Lancaster (HEAL) seminar series (what was then known as a Lancaster NOVA seminars in Health Economics and Policy). I was the Deputy Chair of the NIHR SPHR Researchers' Network (ResNet) during 2021-22, co-organising the annual ResNet meeting in Birmingham. I have participated in mentoring programs organised by the UK Health Economist's Study Group (HESG) and the Spanish Health Economics Association (AES). My mentors in these programmes were Heather Brown and Beatriz Lopez-Gonzalez, respectively. I discussed scientific articles at three conferences: the UK Health Economics Study Group (HESG) summer meeting at the University of Cambridge; the 2^{nd} Centre for Health Economics APHEC workshop at the University of Genoa (Italy); and the 29^{th} European Workshop on Econometrics and Health Economics at Fribourg (Switzerland). I also peer-reviewed articles in top international journals, such as Journal of Economic Behavior & Organization; Health Economics; International Journal of Health Economics & Management. I have submitted my portfolio of evidence against the UKPSF, Descriptor 1 and been awarded recognition as an *Associate Fellow*. This outcome will be formally ratified at the assessment board on 12^{th} July 2022. In September 2021, I visited *Imperial College Business School* thanks to the *NIHR Short Placement Award for Research Collaboration (NIHR SPARC 07-20-07)*. Pedro Rosa-Dias kindly supervised this placement.

LANCASTER UNIVERSITY

Abstract

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The Impact of Economic Shocks on Health and Health Inequalities

by Mario Martínez-Jiménez

This thesis explores the effects of economic shocks on health and health inequalities using multiple datasets from the United Kingdom. The second chapter studies the effects of retirement on both physical and mental ill-health and whether these change in the presence of economic shocks. Inverse probability weighting regression adjustment is used to examine the mechanisms influencing the relationship between retirement and health, and a difference-in-differences approach combined with matching to investigate whether the health effects of retirement are affected by the Great Recession. Models are estimated on the English Longitudinal Study of Ageing (ELSA) dataset. The third chapter focuses on the effects of parental unemployment spells experienced during early, mid and late childhood on long-term child mental and physical health. This chapter exploits merged data drawn from the British Household Panel Survey (BHPS) and the UK Household Longitudinal Study (UKHLS), linking detailed parental socioeconomic information with key health variables on their children. In this analysis, a Correlated Random Effects (CRE) probit model accounts for unobserved heterogeneity while a non-linear Generalized Estimating Equations (GEE) random effects estimator for the dependency structure of the data. The fourth chapter explores associations between adolescent health and socioeconomic deprivation by income and small-area levels in England. This study uses administrative data drawn from the Health Episode Statistics (HES) linked to Next Steps, a longitudinal survey including a cohort of adolescents born in 1990. Erreygers' corrected concentration index and Shapley-Shorrocks decomposition techniques are employed to measure and explore the relative contributions of a set of childhood circumstances in the adolescent health and health care utilisation inequalities. In addition, an Interrupted Time-Series (ITS) analysis is implemented to examine changes in health care utilisation in the emergency and outpatient departments during the years of the Great Recession and subsequent austerity policies. The last chapter summarises the main findings of the PhD, discusses the policy implications of these findings, reviews the limitations and unanswered questions from the analyses, and provides recommendations for future research.

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List of Abbreviations

A&E	**A**ccident **&** **E**mergency
APE	**A**verage **P**artial **E**ffects
ATET	**A**verage **T**reatment **E**ffects on the **T**reated
BMI	**B**ody **M**ass **I**ndex
BHPS	**B**ritish **H**ousehold **P**anel **S**urvey
CCI	**C**orrected **C**oncentration **I**ndices
CRE	**C**orrelated **R**andom **E**ffects
DD	**D**ifference-in-**D**ifferences
ELSA	**E**nglish **L**ongitudinal **S**tudy of **A**geing
GOR	**G**overnment **O**ffice **R**egion
GHQ-12	**G**eneral **H**ealth **Q**uestionnaire**-12**
GEE	**G**eneralized **E**stimating **E**quations
GR	**G**reat **R**ecession
HES	**H**ospital **E**pisodes **S**tatistics
HSE	**H**ealth **S**urvey of **E**ngland
IOp	**I**nequality of **Op**portunity
ITS	**I**nterrupted **T**ime-**S**eries
IPWRA	**I**nverse **P**robability **W**eighting **R**egression **A**djustment
IDACI	**I**ncome **D**eprivation **A**ffecting **C**hildren **I**ndex
ISCED	**I**nternational **S**tandard **C**lassification of **E**ducation
IMD	**I**ndex of **M**ultiple **D**eprivation
IV	**I**nstrumental **V**ariable
IES	**I**nstitute for **E**mployment **S**tudies
KPSM-DD	**K**ernel **P**ropensity **S**core **M**atching **D**ifference-in-**D**ifferences
LSYPE	**L**ongitudinal **S**tudy of **Y**oung **P**eople in **E**ngland
LSOA	**L**ower-Layer **S**uper **O**utput **A**reas
MLE	**M**aximum **L**ikelihood **E**stimation
NS-SEC	**N**ational **S**tatistics **S**ocio-**E**conomic **C**lassification
NHS	**N**ational **H**ealth **S**ystem
ONS	**O**ffice of **N**ational **S**tatistics
OECD	**O**rganization for **E**conomic **C**o-operation and **D**evelopment
OP	**O**ut**P**atient
QMLE	**Q**uasi-**M**aximum **L**ikelihood **E**stimation
RDD	**R**egression **D**iscontinuity **D**esign
SHARE	**S**urvey of **H**ealth, **A**geing and **R**etirement in **E**urope
SPA	**S**tate **P**ension **A**ge
SOEP	German **So**cio-**E**conomic **P**anel
SES	**S**ocio**E**conomic **S**tatus
UK	**U**nited **K**ingdom
UKHLS	**UK** **H**ousehold **L**ongitudinal **S**tudy
UR	**U**nemployment **R**ate
US	**U**nited **S**tates
WHO	**W**orld **H**ealth **O**rganisation

To my Mother
- Apolonia Jiménez Guirado -
my light and inspiration. . .

1 Introduction

1.1 Overview

This thesis consists of three articles investigating the effect of economic shocks on health and health inequalities using data from the United Kingdom. The thesis contributes to the economics literature on the effects of economic shocks on the health of three subpopulation groups: adolescents, young adults, and retired individuals. In particular, the first article studies the effects of retirement on both physical and mental ill-health and whether these change in the presence of economic shocks. The second article focuses on the effects of parental unemployment spells experienced during childhood on children's long-term health (when they become young adults, 18-33). Finally, the third article explores associations between adolescent health inequalities related to socioeconomic deprivation in England and examines the evolution of health care utilisation during the years of the 2008 Great Recession and subsequent austerity policies. This thesis employs several rich datasets coupled with modern econometric methods and economic perspective to contribute to the analysis of these issues. The association between economic recessions and health is a well-established topic in the fields of economics and public health. The ground-breaking work of Ruhm (2000) found strong evidence of procyclical mortality by examining data from the United States in the 1970s and the 2000s. Yet, studies focusing on more recent data provide less conclusive evidence, suggesting the presence of potentially countervailing mechanisms (Bellés-Obrero and Castelló, 2018).[1]

Severe economic recessions are typically defined by a sudden increase in unemployment. Previous evidence suggests that newly unemployed individuals may suffer short run earning losses that might persist in the long run during economic recessions, and their health could also deteriorate (Mroz and Savage (2006); Clark and Lepinteur (2019)). Income losses experienced during economic shocks may affect individual and household decision-making, potentially generating negative spillovers to other family members, including children. Beyond job losses, economic recessions often lead to a deterioration in employment quality. For instance, globally, a large proportion of those workers who remained employed during the 2008 Great Recession were forced to accept reduced working hours as well as lower wages and benefits (Clark, Knabe, and Rätzel, 2010). Therefore, those who remain employed may still suffer from work-related stress, depression from a higher risk of unemployment, and

[1] Ruhm (2000), in his work titled *"Are recessions good for your health"*, uses panel data and controls for time-invariant state-specific effect to overcome some of the omitted variable biases. This study documents a strong inverse relationship between macroeconomic conditions and health. Yet, Ruhm (2015) claims that the strong procyclical pattern of mortality present in the 1970s and 1980s has been largely eliminated in recent years, and that so, deaths became less procyclical or more countercyclical during the last macroeconomic shocks. For instance, reduced economic activity as a result of a recession may also have some positive health impacts (see Adda, Banks, and Von Gaudecker (2009); Griffith, O'Connell, and Smith (2016)).

overall increased uncertainty around the value of their assets. Higher levels of anxiety, depression, and uncertainty may have affected individuals' labour force status (e.g., early exits from the labour market), and this may have had an impact on an individual's health in both the short- and long run.

Periods of economic recessions may also increase income inequalities (Ollivaud and Turner, 2014). The 2008 Great Recession exacerbated both income and wealth inequality, and these widening gaps have endured for a decade in countries such as the UK. In 2018, households in the bottom 20% of the population had a mean equivalised disposable income of £12,798, whilst the top 20% earned £69,126, according to data from the Office for National Statistics (ONS). The recession caused by the COVID-19 pandemic has further increased these inequalities, mostly due to rising prices for many families and their children (Buheji, Costa Cunha, et al. (2020); Perry, Aronson, and Pescosolido (2021)). Thus, this recent period of successive economic recessions has impacted children and young adults' living conditions and wellbeing in high-income countries.[2] Yet, the health needs of young people are often overlooked by policymakers and academics (Kieling, Baker-Henningham, et al. (2011); Currie and Alemán-Díaz (2015)), although experiencing poor health during adolescence may have long-term impacts in their labour and educational status (Lesner, 2018).

Using three independent longitudinal datasets from the UK, this thesis aims at identifying the effect of economic shocks on the health of three subgroups of the population – adolescents, young adults, and retired individuals. More specifically, Chapter 2 contributes to the literature on the health effects of retirement by exploring the potential mechanisms driving this relationship and examining whether these effects might be affected by economic shocks. This chapter also provides evidence on whether work-related stress suffered by workers during economic recessions may affect health. Chapter 3 then focuses on the long-term health effects of parental unemployment experienced during childhood and early adolescence on long-term children's mental and physical health. This chapter contributes to the literature by investigating a largely unexplored set of potential mechanisms driving this relationship with potentially important implications for the design of public policies aimed at alleviating the (negative) effects of unemployment. Overall, estimates presented in this chapter help to better understand whether intrahousehold (economic) shocks may have an impact on child health in the longer run. Chapter 4 explores associations between adolescent health inequalities related to socioeconomic deprivation at income and small-area levels in England. This chapter also examines changes in health care utilisation in emergency and outpatient care during the years of the Great Recession and subsequent austerity policies. To this end, this study uses both administrative and survey datasets from a cohort of individuals born in 1990, the millennial generation.[3]

The rest of Chapter 1 is organised as follows. The following section provides background and key references for each of the three analyses corresponding to chapters 2-4. First, it reviews the motivation and context by focusing on the health effects of retirement during economic shocks and how these can be used to predict similar effects during future and inevitable recessions. Second, it discusses how parental investment may influence children's production function of health and cognitive achievement. It also reviews evidence on how

[2] Van Den Berg, Lindeboom, and Portrait (2006) examine the Dutch population born between 1812 and 1912 and find that the state of the business cycle at birth affects mortality: being born in a recession reduces lifespan by about 5%.

[3] Millennials are people born between 1981 and 1996, according to the definition by the *Pew Research Center*.

intrahousehold shocks (such as parental job losses) occurring during childhood and early adolescence may impact children's health in the long run. The last section explores the idea that adolescents' and young people's health needs to be at the core of the political debate since adolescence is a crucial period of human development where the social determinants of health could have long-lasting effects on health and wellbeing trajectories. Finally, a summary of the three main articles of the thesis is presented.

1.2 Background

1.2.1 Economic shocks and retirement

Recent economic crises tend to have an immediate negative effect on the labour market, particularly in high-income countries (Ollivaud and Turner, 2014). For instance, the 2008 Great Recession led to a sharp increase in the unemployment rate, particularly among low-skilled workers aged over-50. Yet, for many who remained employed, the quality of employment deteriorated with increased job insecurity due to the recession – leading to many workers in low-paid or physically demanding sectors to exit the labour force earlier than expected (i.e., before the state pension age). This job insecurity resulted in sustained and potentially harmful impacts on individuals, families, and households. Similarly, the recent COVID-19 pandemic and the subsequent economic crisis have resulted in a rise in the proportion of older people without a college degree deciding exiting the labour force (while those with a college degree were less likely to do so). The former resulted from harsher working conditions for low-skilled workers, whereas the latter was due to the working from home benefits that those in high-skilled jobs experienced.[4]

The 2008 financial crisis resulted in an increased unemployment rate as well as a sharp devaluation in asset prices. The group of older people approaching retirement were likely to have been particularly vulnerable to these changes in asset prices. Moreover, those aged betwwen 55 and 65 experienced more extended unemployment periods due to the economic downturn (Coile, Levine, and McKnight, 2014).[5] Unlike those who have not yet reached the state pension age, already retired individuals on a state pension were less exposed to movements in the stock market and had not experienced the hasher employment conditions (e.g., work-related stress or fear of losing employment) that working individuals have. Therefore, those individuals reaching the state pension age during an economic recession may have experienced improvements in their health and wellbeing status. In contrast, those older workers not yet approaching retirement age during the financial crisis may decide to work more years to build their retirement resources.

[4] See the opinion article titled *"Covid retirees show work-from-home revolution has not benefited everyone"*, published in November 2021 in the *Financial Times*.

[5] This was mostly caused by older age groups generally experiencing greater barriers to developing and retaining digital and technological skills, as well as to receive workplace training or participate in learning.

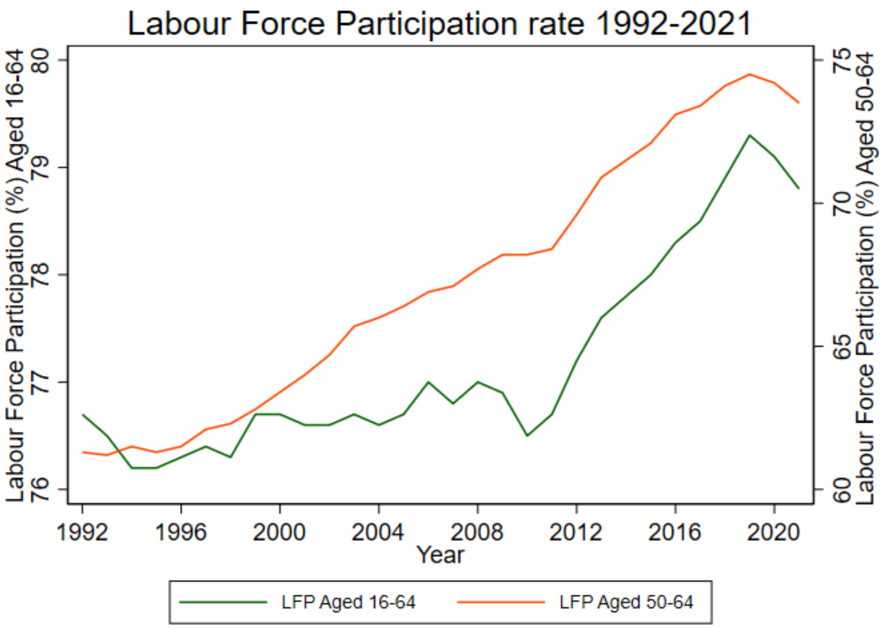
FIGURE 1.1: Population projections in the United Kingdom

Source: Figure created using data from Office for National Statistics (`ons.gov.uk`).

The English population is ageing, and projections estimate that around 24% of the UK population will be aged 65 and over in the next 25 years (see Figure 1.1). Consequently, retirement ages are being pushed out by governments, concerned at affordability. Reforms in recent decades in Organisation for Economic Co-operation and Development (OECD) countries include increases in the Statutory Pension Age (SPA) and less generous early retirement schemes. However, policymakers need to be aware of the complexities of encouraging older people to remain in the labour market. For instance, does increasing the SPA improve public financial sustainability during economic recessions? Potentially a higher SPA may exacerbate the prevalence of the health conditions associated with old age as well as the total amount of individuals with ill-health and disabilities in the population since an extension of the retirement age might result in too heavy a burden in terms of physical and psychological strain for older manual workers.

Changes in the labour market structures in terms of labour market participation rates have been observed after the Great Recession and over the course of the COVID-19 pandemic. In the UK, the Institute for Employment Studies (IES) estimates that there are roughly 310,000 fewer older people (especially older women) in the labour market due to the COVID-19 pandemic than one would have expected if pre-pandemic trends had continued. Similar patterns were experienced after the Great Recession when the labour force participation rate decreased due to the movement of a large fraction of over-50 from work to inactivity (see Figure 1.2). The decision of older adults to leave the workforce after economic shocks not only has consequences on public finance sustainability but also on the health and wellbeing of retired individuals – further research is needed to better understand how.

FIGURE 1.2: Labour force participation rate in the United Kingdom (1992-2021)



Notes: The labour force participation rate is the number of employed and unemployed persons looking for a job divided by the total working-age population. *Source:* Figure created using data from Office for National Statistics (ons.gov.uk) – Labour force survey.

Chapter 2 examines the health effects of retirement soon after an economic shock. Findings suggest that retiring right after a financial crisis may positively impact the health of blue-collar workers who live in the regions most affected by the Great Recession. This chapter brings together evidence that may help policymakers develop new policies accounting for population ageing in the presence of frequent economic shocks, across the range of socio economic status..

1.2.2 Child development and parental investment

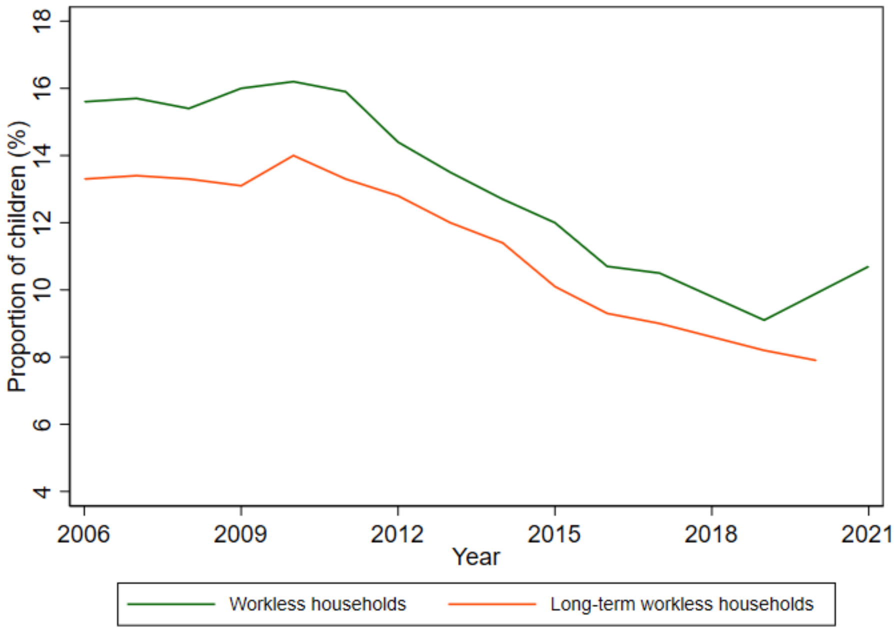
In 2021, over 30% of the world's young people lived in poverty and faced many challenges, including insufficient living standards. Furthermore, 10-20% of children and adolescents worldwide experience mental health problems, which may impact long-term educational, employment and economic outcomes (Kessler, Angermeyer, et al., 2007). Extensive research suggests that poverty is associated with mental illness among adolescents and young adults (Reiss, 2013), although the mechanisms underlying this relationship are not yet well understood.[6] In turn, parental unemployment increases exposure to mental illness risk factors among children living in the same household, such as financial distress, violence, or intra-household conflict.

One of the most widely recognised signals of the occurrence of an economic recession is a sudden increase in unemployment rates. In high-income countries, there is evidence of rising long-term unemployment and lower participation rates, even in countries with economic

[6] Kieling, Baker-Henningham, et al. (2011), Clayborne, Kingsbury, et al. (2021) and Ridley, Rao, et al. (2020) reviewed the literature on natural and controlled economic experiments involving individuals living in poverty.

growth (European-Commission, 2020). Indeed, the United Nations (UN) goal of *"decent work and economic growth"* promotes development-oriented policies that support sustained, inclusive, and sustainable job creation for all (Leal Filho, Azul, et al., 2020).[7] Job losses since 2008 have pushed numerous families into financial and economic hardship, resulting in increases in poverty, debt and bankruptcy (Grusky, Western, and Wimer, 2011). Because work is closely related to several dimensions of subjective wellbeing, job losses and economic insecurity have also been associated with increased ill-health, psychological distress as well as family dissolution (Ruiz-Valenzuela, 2021). Therefore, job losses have the potential to generate adverse spillover effects for other members of the household, including children. A substantial body of evidence shows that illnesses during adulthood are more prevalent and appear to be more problematic among those who have experienced adverse early-life conditions.[8] Moreover, evidence suggests that early life interventions (such as (un-)conditional cash transfers) for low-income mothers may prevent disease and promote health.[9]

FIGURE 1.3: Proportion of children living in workless households (UK)



Notes: There are no data available for the proportion of children in long term workless households in 2021. *Source:* Figure created using data from Office for National statistics (`ons.gov.uk`) – Labour force survey.

During the fourth quarter of 2021 in the UK, 10.7% of all children (around 1.35 million) were living in jobless households. This has increased by approximately 110,000 children from

[7] Further details about the United Nations "global goal" and the importance of productive employment and decent work for all can be found here: `https://www.globalgoals.org/goals/8-decent-work-and-economic-growth/`.

[8] Conti, Heckman, and Urzua (2010) examines the early origins of health disparities and establishes a strong relationship between health and education and more generally between early childhood conditions and adult outcomes. Conti, Heckman, and Pinto (2016) analyses the long-term impacts on healthy behaviour and health of two of the oldest and most cited US early childhood interventions. Their results are in line with emerging body of evidence that shows the potential of early life interventions for preventing disease and promoting health.

[9] See more in *The New York Times* new titled *"Cash Aid to Poor mothers Increases Brain Activity in Babies"*.

the previous year. About 8% of all children (around 1 million) lived in long-term jobless households in 2020.[10] As shown in Figure 1.3, a similar pattern occurred in the years after the Great Recession. Increased financial strain is strongly associated with children's mental health. Children with a mental disorder are more than twice as likely to live in a household that has fallen behind with payments.[11] Therefore, financial stress appears to be positively and strongly associated with lower child mental health.

A growing body of literature has established a strong relationship between early childhood conditions and adult outcomes (Almond, Currie, and Duque, 2018). Most of the negative consequences of job loss and poverty directly affect variables that enter both the production function of cognitive achievement and the health production function, which could potentially translate into long(er)-run effects via overall human capital accumulation. During the last decade, many studies have analysed the short-term impact of parental job loss on child outcomes (Ruiz-Valenzuela, 2021). However, long-term consequences, mechanisms and possible heterogeneous effects have been overlooked, primarily because of the lack of appropriate data. Another aspect of this relationship that has not been comprehensively investigated is whether the timing of parental job loss may play a role.[12] In Chapter 3, merged data from two extensive household surveys, the British Household Panel Survey (BHPS) and the UK Household Longitudinal Study (UKHLS), are used to investigate the long-term health consequences for children living in a household where at least one of the parents was unemployed during childhood or early adolescence.

Evidence from this chapter suggests that the effects of parental unemployment could be a substantial and under-emphasized cost of recessions. Therefore, understanding its influence can help formulate appropriate policy responses to tackle widening inequalities as part of levelling up agendas. Many governments in high-income countries react with unprecedented measures to avoid massive employment destruction during economic recessions. For example, in the UK, furloughs and other job schemes were implemented as part of the response to the Covid-19 crisis. Further evidence that helps to prioritise public resources while obtaining improved (health) outcomes may be warranted. Chapter 3 provides an overview of the current evidence and economic theory on the determinants of children's health and its long-run effects. This chapter also highlights one of the major benefits of addressing the job crisis among low-income households and discusses forms of social protection that might be relevant in overcoming the long-term health effects of parental unemployment. Finally, it is clear that there are links between early life events and adult outcomes, such as between adverse childhood experiences and adult health.[13]

[10] These figures come from the *"Improving Lives: Helping Workless Families Indicators 2022: Data for 2005 to 2021"* report published by *Department for Work and Pensions* in the United Kingdom. Available in the following link: `https://www.gov.uk/government/publications/improving-lives-helping-workless-families-indicators-2022/improving-lives-helping-workless-families-indicators-2022-data-for-2005-to-2021`.

[11] These figures are extracted from the Office for National Statistics (ONS) - *Children living in long-term workless households in the UK: 2020* report. Available in the following link: `https://www.ons.gov.uk/employmentandlabourmarket/peoplenotinwork/unemployment/bulletins/childrenlivinginlongtermworklesshouseholdsintheuk/2020`.

[12] Ruiz-Valenzuela (2021) summarises the existing literature on the effects of parental job loss on children's outcomes and the line for future research.

[13] Adverse childhood experiences are highly stressful, and potentially traumatic, events or situations that occur during childhood and/or adolescence (Minds, 2018).

1.2.3 Inequalities in adolescent health and health care utilisation

The World Health Organisation (WHO) estimates that social inequalities account for 50% of inequalities in major non-communicable diseases.[14] However, there has been less research looking specifically at the evidence on the social determinants of health for adolescents and young people as distinct from other age groups. Although it is apparent that health inequalities exist in adolescence and that significant proportions of young people are facing disadvantages (Currie, 2009), the precise relationship between social determinants and health outcomes for this age group is less clear. Much of the data relates to adult samples only or does not distinguish young people from younger children or adults. However, the specific challenges of life as a teenager and young adult can be markedly different from those experienced by individuals at different life-cycle stages.[15]

One of the key messages from the *Key data on young people (2019)* report is that the gap in health between the rich and poor in society is already apparent between the ages of 10–24, and for some key health indicators, that gap is widening over time.[16] Adolescence is a critical stage of human development, and fundamental aspects of an individual's health and health behaviours are formed during this stage of life. Young people experience substantial physical, psychological and behavioural changes as they move from adolescence into adulthood. Socioeconomic factors at this stage of life may uniquely affect an individual's health trajectories with potential long-term impacts.[17]

Accident and emergency hospital admissions have increased over the last decade (Keeble and Kossarova, 2017). However, a large proportion of these admissions, particularly those for conditions such as asthma, could have been prevented with early access to high-quality child and paediatrics health care services (Kossarova, Devakumar, and Edwards, 2016). Children with low socioeconomic status are not only more likely to have worse health status and more injuries but also to have significantly less access to routine medical care (Newacheck, Hughes, and Stoddard, 1996). For instance, Figure 1.4 shows that people residing in the "most deprived 10%" areas in England have the largest number of attendances at accident and emergency departments with just over 3 million in 2018-19, whereas the "least deprived 10%" have the lowest number of attendances (1.5 million), an attendance rate around half that of the "most deprived 10%". In many cases, the difference between the health care use of children living in deprived households and that of other children growing up in less deprived circumstances is more marked than ever (Cookson, Propper, et al., 2016).

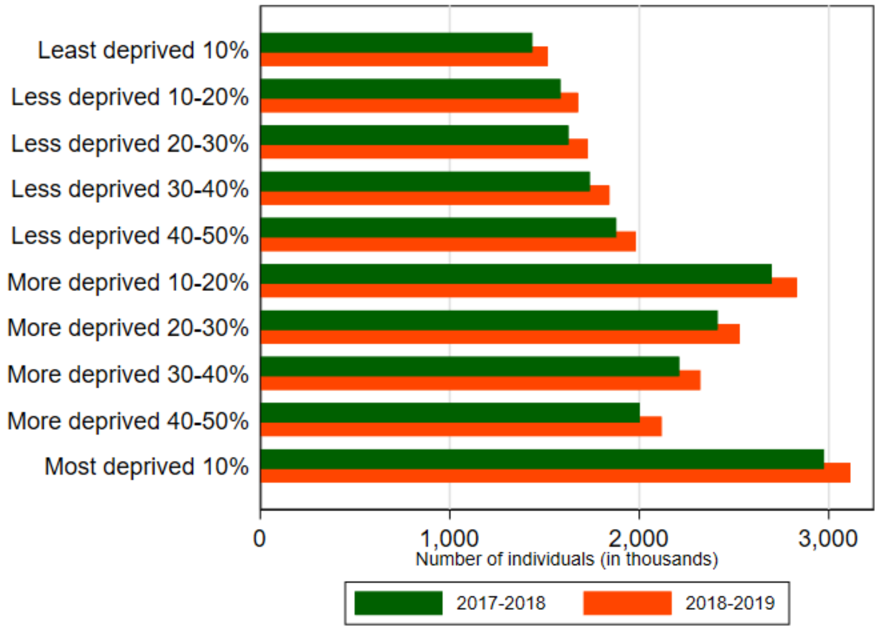
[14] See more about health disparities in *"Closing the gap in a generation: health equity through action on the social determinants of health. Final report of the Commission on Social Determinants of Health. 2008"*.

[15] Currie (2009) documents the extensive evidence on the links between parental circumstances and child health, as well as the subsequent link between a child's early-life health and their eventual educational and labour market outcomes.

[16] Key data on young people reported by Hagell (2019), in their *"Key data on young people"* report, brings together robust and representative information to get a full impression of young people in the United Kingdom.

[17] Studies from Inchley, Currie, et al. (2005) and Viner, Ozer, et al. (2012) report evidence on the effects of social determinants on health in adolescence, and present evidence that the health of adolescents and young adults is affected by social factors at personal, family, community, and national levels.

FIGURE 1.4: Accident and Emergency attendances by Index of Multiple Deprivation (IMD) decile output for England 2017-18 and 2018-19 (Hospital Episodes Statistics)



Notes: Activity in English NHS Hospitals and English NHS commissioned activity in the independent sector. Planned A&E attendances are excluded. Null observations 451,914 (2017/18) and 455,702 (2018-19). *Source:* Figure created using data from NHS Digital and NHS England.

Chapter 4 focuses on socioeconomic inequalities in health and health care utilisation in England, particularly regarding inequalities relative to needs that may be considered unfair. While health inequalities arising from differences in choices or factors for which individuals are deemed responsible are often tolerated, inequalities arising from factors that are beyond an individual's responsibility (e.g., place of birth or family background) are defined as unfair (Woodward and Kawachi (2000); Fleurbaey and Schokkaert (2009)). This chapter identifies the main factors contributing to these inequalities using an Inequality of Opportunity framework emphasising the role of individual responsibility in defining a "fair" distribution of outcomes, i.e., inequality stemming from circumstances beyond personal responsibility such as socioeconomic background (e.g., Fleurbaey and Schokkaert (2009); Ramos and Van De Gaer (2016); Roemer and Trannoy (2016)). Shapley-Shorrocks decomposition techniques are employed to explore the relative contribution of childhood circumstances in inequality of opportunity of adolescent health and health care utilisation.

There are fewer data relating specifically to adolescence rather than adult age groups. Chapter 4 uses survey data from a cohort longitudinal study (Next Steps) that follows the lives of 16,000 people in England born in 1989-90 – the so-called millennial generation. This survey data has recently been linked to hospital administrative records and is used in this chapter to examine socioeconomic inequalities in health and health care utilisation among adolescents. In doing so, the chapter highlights that there are links between adolescent disadvantage and specific adolescent health outcomes. Erreygers' corrected concentration index is used to measure income-related and small-area deprivation level inequalities in psychological distress and disability/long-term illness among adolescents in England.

Notably, individuals from the millennial generation – which accounts for the dominant generation of the post-financial crisis era – have seen how the Great Recession has shaped their life choices, future earnings and entry to adulthood. This recession and the COVID-19 pandemic are casting a long shadow, including fewer jobs available, decreased savings, and difficulty buying homes given ever rising prices. In parallel, job losses, illness and increased economic pressure have limited the life chances of millions of children and young people.[18] Moreover, subsequent changes to welfare policy and cuts to support services have pushed thousands more families below the poverty threshold (UNICEF, 2021). Thus, a debate about whether and how social inequalities are evolving among millennials can inform decisions made by policymakers regarding more than 14 million millennials in the United Kingdom. In Chapter 4, An interrupted time-series analysis is implemented to examine the evolution of health care utilisation in the emergency and outpatient care during the years of Great Recession and subsequent austerity policies.

1.3 Summary of thesis chapters

The next chapter of this thesis (Chapter 2) studies the causal effect of retirement on health and whether the health effects of retirement change in the presence of economic shocks. The literature identifies the importance of macroeconomic effects on health outcomes. Yet, it is known relatively little about the health effects of retirement after an economic shock. This chapter uses data from the English Longitudinal Ageing Study (ELSA) to explore whether the health effects of retirement are affected by the Great Recession. Econometric models such as inverse probability weighting regression adjustment and difference-in-differences approach combined with matching are employed in this analysis. Findings suggest that, on average, retirement may lead to a deterioration in health; however, retiring just after the Great Recession, in some cases, had positive results on mental and physical health.

Chapter 3 studies the long-term health effect of parental unemployment on their children's life outcomes. This chapter aims to shed light on the long-term effect of experiencing parental unemployment during different childhood stages on child health formation. This analysis uses data drawn from the British Household Panel Study and the UK Household Longitudinal Study, linking detailed parental information with their children. Results from both the correlated random effects and the generalised estimating equation models reveal that experiencing parental unemployment during specific childhood stages has a negative effect on the children's likelihood of suffering from physical and mental ill-health later in life. Children in low-socioeconomic families are likely more affected, and higher frequencies of parental unemployment spells appear to be a potential mechanism driving this relationship. These findings indicate that intergenerational impacts of parental unemployment could be a significant cost of recessions. It also adds evidence to better understand the total societal cost of job loss.

The fourth chapter explores associations between adolescent health and socioeconomic deprivation at income and small-area levels in England. This study employs administrative data drawn from the Health Episode Statistics (HES) linked to Next Steps, a longitudinal survey including a cohort of millennial adolescents born in 1990. This analysis measures

[18] The UNICEF (2021) report *"Preventing a lost decade"* highlights how urgent it is to act to reverse the devastating impact of the current economic downturn and coronavirus crisis on children and young people.

income-related and small-area deprivation level inequalities in psychological distress and disability/long-term illness. We also study income-related inequalities in access to health care among adolescents. This chapter employs Erreygers' corrected concentration index and Shapley-Shorrocks decomposition techniques to explore the relative contribution of childhood circumstances in inequality of opportunity of adolescent health and health care utilisation. An interrupted time-series (ITS) analysis is implemented to examine the evolution of health care utilisation in the emergency and outpatient care during the years of Great Recession and subsequent austerity policies. Results suggest that small area deprivation and income both yield inequalities in health among adolescents, favouring the better-off. There are also pro-rich inequalities in the utilisation of specific outpatient hospital services (e.g., orthodontic and mental health services), while pro-poor disparities are found in the use of emergency services. Results also suggest that the number of appointments for outpatient hospital services slightly increased after the Great Recession, whereas the number of yearly visits to accident and emergency decreased due to austerity. These findings shed light on the main drivers of health inequalities during a critical stage of human development and may have relevant policy implications.

Finally, Chapter 5 discusses the main findings, conclusions, contributions, and limitations of this thesis. First, it summarises how the empirical analyses in this thesis provide improved evidence on the effects of economic shocks on health and health inequalities. Then, it builds on these conclusions to review the policy implications of the findings. Finally, it outlines the limitations and outstanding questions that arise from the analyses and discuss potential directions for future research. It is worth noting that this thesis does not have a chapter dedicated to an overall review of the literature. Instead, each chapter has its own literature review. References for each chapter are combined and placed at the end of the dissertation.

2 Health, Retirement and Economic Shocks

This paper explores the effects of retirement on both physical and mental ill-health, and whether these change in the presence of economic shocks. Inverse probability weighting regression adjustment is used to examine the mechanisms influencing the relationship between retirement and health and a difference-in-differences approach combined with matching to investigate whether the health effects of retirement are affected by the Great Recession. Models are estimated on data from the English Longitudinal Study of Ageing (ELSA) and find that in general retirement leads to a deterioration in both mental and physical health. However, retiring shortly after the Great Recession appears to improve mental and physical health in the short-term, although only among individuals working in the most affected regions. Overall, results indicate that the health effects of retirement could be influenced by the presence of economic shocks. This might have implications for policies aimed at retaining older workers in the labour market, especially during periods of economic shocks.

Keywords: retirement; health; Great Recession; ELSA
JEL Classification: *J14; J26; I10*

2.1 Introduction

There is a large and growing body of evidence on the health effects of retirement (e.g., Bonsang and Klein (2012); Eibich (2015); Fitzpatrick and Moore (2018)). However, findings are still mixed and previous papers have rarely focused on the mechanisms governing this relationship or whether the effects of retirement on health could significantly change in the presence of economic shocks, a potentially increasing phenomenon. More specifically, Belloni, Meschi, and Pasini (2016) appear to be the only study explicitly attempting to estimate the impact of retirement on health while accounting for the presence of an economic shock by exploiting the Great Recession. They find that retiring immediately after an economic shock improves mental health, although only among blue-collar men living in the most severely affected regions. Also, while this paper suggests a positive effect of retirement on mental health within a specific population sub-group, it does not appear to investigate the different causal pathways linking retirement to changes in (mental) health nor to explore corresponding effects on physical health. Furthermore, Belloni, Meschi, and Pasini (2016) make use of data from several European countries but do not investigate such effects in the UK. Another recent paper by Carrino, Glaser, and Avendano (2020) employs a UK pension reform increasing women's State Pension age and finds that raising the State Pension age might lead to a higher probability of developing depression among women, especially those in lower occupational grades. The authors suggest that this effect might be driven by a prolonged exposure to high strain jobs. Although this paper does not explicitly focus on the role played by economic shocks, it is of interest as it employs UK data covering the period when the country was affected by the Great Recession. Overall, and despite their policy relevance, the direction of the impact of retirement on health as well as the specific factors influencing such effects have not been established conclusively.

In addition, the literature on the impact of economics shocks on health also presents varying and inconclusive results (e.g., Di Tella, MacCulloch, and Oswald (2001); Modrek, Stuckler, et al. (2013); Karanikolos, Mladovsky, et al. (2013)). Ruhm (2000)'s seminal work on the effects of macroeconomic conditions on health shows that in the US mortality appears to be procyclical and this is confirmed by other studies using data from different countries, including Spain (Granados, 2005); Germany (Neumayer, 2004); France (Buchmueller, Jusot, Grignon, et al., 2007); Canada (Ariizumi and Schirle, 2012); and Mexico (Gonzalez and Quast, 2011). However, a more recent strand of the literature finds that mortality is either countercyclical or unaffected by macroeconomic shocks (Ruhm, 2015). For instance, Tekin, McClellan, and Minyard (2013) find no evidence that the recent Great Recession had a significant influence on health or health-behaviours.

The main objective of this paper is to examine the effects of retirement on both physical and mental health by: I) focusing on the mechanisms driving the relationship between retirement and health, and II) exploring whether the health effects of retirement may vary in the presence of a severe economic shock. Accordingly, we use rich panel data drawn from eight waves (2002-2018) of the English Longitudinal Study of Ageing (ELSA) and explore the effects of retirement on a wide range of physical and mental health conditions. Specifically, using inverse probability weighting regression adjustment, we allow for the identification of both the effects of retirement on health and the potential mechanisms affecting such relationship (Cattaneo, 2010). In addition, a kernel propensity score matching difference-in-differences approach is used to identify whether the health effects of retirement were affected by the Great Recession (e.g., Heckman, Ichimura, and Todd (1998); Blundell and Costa Dias

(2000)). In this case, the combined use of matching with difference-in-differences allows construction of more comparable treatment and control groups and production of more accurate estimates on the role played by the Great Recession (Stuart, King, et al., 2011).

Results suggest that in general retirement has a statistically significant effect on several measures of health: it appears to have a negative impact upon mental health, especially among women, while increasing the probabilities of having a stroke and being diagnosed with pulmonary disease, particularly among men and blue-collar workers. Furthermore, retirement seems to increase the likelihood of reporting lower levels of self-reported health and having health limitations (i.e., difficulties with mobility). As for potential mechanisms, results from inverse probability weighting regression adjustment models suggest that low levels of education; physical inactivity and living in deprived areas are among the key factors affecting changes in mental health following retirement. Also, key mediating factors driving the relationship between retirement and physical health are: age; gender; and broader environmental characteristics of the geographical areas where individuals reside (e.g., population density and deprivation levels).

However, we also find that the health effects of retirement may differ in the presence of economic shocks. When we explore the short-term health effects of retirement immediately after the Great Recession, it is found that retirement improves mental health and decreases the probability of suffering from angina and heart attacks. While mental health effects appear to be stronger among male individuals living in the most affected regions, improvements in physical health are mostly concentrated among women also residing in the most severely hit areas. Overall, these results suggest that the health effects of retirement might be affected if retirement occurs around the time of economic shocks.

This paper offers several contributions to the literature. First, we extend the literature on the health effects of retirement by exploring the potential mechanisms driving the relationship between retirement and changes in physical and mental health. While the association between retirement and health is well-documented, there is sparse evidence on the mechanisms and mediating factors driving it. Second, new evidence is provided on the impact of retirement on health shortly after the Great Recession, a recent economic shock. This is especially relevant in policy terms as most OECD countries are currently experiencing rapid trends of population ageing (OECD, 2019) with increasing larger proportions of individuals near retirement age coupled with a succession of economic shocks, such as the Great Recession and the one induced by the ongoing COVID-19 pandemic. Given this, it is important to provide evidence to policy makers around the main drivers of retirement choices during periods of economic (and health related) shocks, which will inevitably reoccur. Third, whereas most previous studies looking at the health effects of the Great Recession employed data from other European countries, we focus on England, one of the most seriously affected economies during this period. Fourth, the difference-in-differences approach combined with matching allows estimating both short- and long-term impacts of retirement on health following the Great Recession, allowing the provision of new knowledge which we can learn from for the future.

2.2 Background

2.2.1 Literature

Empirical studies on the causal impact of retirement on health often present conflicting results. This might be due to differences in the methods and data used as well as the varying institutional incentives to retire across different countries. More specifically, studies using an instrumental variable (IV) approach (often exploiting statutory retirement age) tend to find positive impacts of retirement on health (e.g., Bound and Waidmann (2007); Neuman (2008); Bonsang and Klein (2012)), whereas studies employing panel data methods tend to find negative effects (e.g., Dave, Rashad, and Spasojevic (2006); Bamia, Trichopoulou, and Trichopoulos (2007)). Relevant to this study, Behncke (2012) employs nonparametric matching and instrumental variable approaches on three waves of ELSA and finds that retirement increases the risk of being diagnosed with chronic conditions and the probability of reporting lower levels of self-assessed health. Conversely, Gorry, Gorry, and Slavov (2018) use eligibility to social security as an instrument for retirement on US data from the Health and Retirement Study and find that retirement improves self-reported general health, mental health, and life satisfaction. Moreover, results from Coe and Zamarro (2011), obtained exploiting country-specific early and full retirement ages as instruments for retirement and data from SHARE, suggest no significant effects of retirement on health. Finally, Eibich (2015) and Rose (2020) use a Regression Discontinuity Design (RDD) based on financial incentives in the German and English pension systems, respectively. Both studies find that retirement improves subjective general health status. Studies evaluating the effects of changes to the State Pension age on health also report mixed results. Recently, Carrino, Glaser, and Avendano (2020) use data from Understanding Society between 2009-2016 and find that that raising the state pension age leads to a decline in mental health among women in lower occupational groups.[1]

Estimates on the impact of labour market status on health during economic shocks are also inconsistent (Browning and Heinesen (2012); Avdic, De New, and Kamhöfer (2021)). A strand of studies finds that economic shocks can negatively affect health outcomes by increasing the stress associated with job loss and reducing monetary and non-monetary benefits (e.g., by reducing the availability of flexible-time, periods of leave, mentoring and childcare related programs), and that these effects vary by age, gender and occupational status (e.g., Eliason and Storrie (2009); Sullivan and Von Wachter (2009); Jofre-Bonet, Serra-Sastre, and Vandoros (2018); Black, Jackson, and Johnston (2022)). The literature has so far paid less attention to the impact of economic shocks on the health of older individuals. Yet, Stevens, Miller, et al. (2015) find that the largest part of the procyclical variation in mortality appears to be driven by people living in nursing homes, a group with a very low attachment to the labour market. McInerney and Mellor (2012) estimate that during economic shocks the mental health of older individuals appears to deteriorate and that such individuals are also less likely to engage in healthy behaviours. Ruhm and Black (2002) also find that older individuals tend to engage less in potentially risky behaviours during periods of recession. Overall, this may further suggest that the health effects of retirement vary by age and occupational status but also that the mechanisms linking economic shocks and health among older individuals are not entirely understood.

[1] Other studies evaluating the effects of lowering the State Pension age report either negative (Bloemen, Hochguertel, and Zweerink, 2017) or no effects on mortality (Hernaes, Markussen, et al., 2013).

2.2.2 Mechanisms linking economic shocks, retirement and health

Little is known about the specific mechanisms driving the impact of retirement on health, especially during economic shocks. Standard models of health investment (e.g., Grossman (1972); Grossman (2000)) suggest that while the depreciation rate on an individual's health stock increases with age, individuals would still invest in their own health. More specifically, individuals may still invest in their health capital post-retirement, even though this will no longer increase their labour productivity or earnings, as "healthy time" also enters the utility function directly as a consumption good (Dave, Rashad, and Spasojevic, 2006). According to this interpretation, the direction of the effect of retirement on health is ambiguous and would also depend on the marginal value of time after retirement. As a result, the identification of direction and size of the impact of retirement on health remains open empirical questions.

Several studies argue that changes in labour status could have an impact on an individual's health through health-behaviours or increased psychological distress due to income and wealth shocks. Yet, there is conflicting evidence on such influences. For instance, Eibich (2015) reports that increased sleep duration, as well as more frequent physical exercise, seem to positively affect health after retirement. Also, retirees are more likely to quit smoking (Insler, 2014) and to experience lower levels of stress (Midanik, Soghikian, et al., 1995). Other studies suggest little, or even negative effects of retirement on social interactions (Sugisawa, Sugisawa, et al., 1997); alcohol consumption (Zins, Guéguen, et al., 2011); healthy eating and physical activity (Nooyens, Visscher, et al., 2005); and cognitive ability and health care utilisation (Rose, 2020). In addition, retirement has also been considered a stressful "life event" per se (Minkler, 1981). Stress can affect health-behaviours such as smoking, drinking, sleeping, eating, and exercising (Brannon, Feist, and Updegraff, 2013) as well as mental health by increasing depression or anxiety, and this may ultimately have an impact on physical health (Scheier and Bridges, 1995). Eibich (2015) also suggests that individuals who retire could experience an improvement in mental health, as they might be relieved from occupational stress. As such, we could also expect that retiring during or immediately after an economic shock could also result in improved mental health due to a reduction in job strain during a particularly stressful time for workers. However, this has not been comprehensively tested on empirical data.

2.3 Data

2.3.1 Data set and definition of retirement

Data from the English Longitudinal Study of Ageing (ELSA) are used, including rich individual-level health and socioeconomic information on a representative sample of the English population aged 50 or above between 2002-2017. ELSA currently includes eight waves through two-yearly interviews combined with biomarkers collected during home visits by nurses every four years (i.e., at Waves 2, 4, and 6). The dataset covers extensive information on both mental and physical health as well as detailed socioeconomic variables on employment, wealth and pensions. Importantly, the main health variables are also complemented by information on participants' previous health conditions drawn from the Health Survey of England (HSE) between 1998-2001 (note that the original ELSA starting sample is drawn from the HSE).[2]

[2] ELSA is sampled from the Health Survey for England (HSE). More specifically, sample members recruited for wave 1 of ELSA (2002/2003) were individuals who previously took part in one of the

We focus on a sample of individuals who are employed during the first wave (2002-2003). Specifically, the initial sample includes employees or self-employed who were in *"work"* or in *"paid work during the last month"* in the first wave. We exclude those individuals that despite being *"in paid work"* also describe themselves as *"retired"*; *"looking-after home or family"*; *"semi-retired"*; *"unemployed"* or *"disabled"*.[3] This results in a sample of 1,830 individuals who were employed in Wave 1. We focus on retirement between consecutive waves and define retirement when, conditional on being employed in the previous wave, individuals report being *"retired"* and/or *"not in work during the last month"* in the subsequent wave. Voluntary first exits from the labour market are considered (i.e., we consider retirement as an "absorbing state"), removing individuals transitioning into unemployment. Accordingly, the retirement variable is a binary indicator taking value 1 if the individual retires between waves, 0 otherwise (if the individual is still working between consecutive waves). A balanced sample of individuals who are present in all waves is used.

Macroeconomic conditions are measured using the annual Unemployment Rate (UR) within each Government Office Region (GOR), the highest tier of the sub-national geographical division of England. The Office of National Statistics (ONS) reports each GOR's UR in 3 months intervals that we use to compute yearly URs.[4] Although we are aware that this might be subject to measurement errors and could underestimate real unemployment rates during periods of economic shocks, this is the most accurate and consistent measure currently available.[5]

2.3.2 Health outcomes and other key variables

A wide range of self-reported and diagnosed chronic health conditions included in ELSA are used, exploiting information on the timing of the diagnosis to define newly diagnosed conditions after retirement to ease concerns around reverse causality. Specifically, the following newly diagnosed conditions: *heart attack and angina*; *stroke*; *asthma*; *musculoskeletal (osteoporosis or arthritis)*; *pulmonary diseases* and *psychiatric diseases*.[6] Finally, self-reported general health status variables are included (e.g., *self-assessed health*, *life-satisfaction* and *loneliness*), and biomarkers collected during nurse visits (e.g., *blood pressure* and *cholesterol levels*).

The main measure of mental health is based on the 8-item version of the Centre for Epidemiological Studies Depression Scale (CES-D) (Radloff, 1977). This is a well-established and psychometrically validated measure of depression obtained using information on mental health symptoms experienced by respondents (e.g., Irwin (1999)). The 8-item version includes information on whether individuals in the previous week *"felt depressed"*; *"felt that everything was an effort"*; *"had a restless sleep"*; *"were not happy"*; *"felt lonely"*; *"felt sad"*; *"could*

previous three HSE (i.e., 1998, 1999, 2001) and were aged at least 50 or over at the time of the wave 1 ELSA interview (Steptoe, Breeze, et al., 2012).

[3] We exclude 785 respondents reporting that they are both *"in work"* and *"retired"*.

[4] Data are available at `https://www.nomisweb.co.uk`.

[5] We merge data from ELSA with ONS's UR using the GOR variable to obtain unemployment rate across regions over time. In 2017, the unemployment rate in some regions was still above their pre-2008 levels, reflecting the severity of the economic crisis. The broad time horizon of the data ensures variation in business cycle conditions across regions. This can be seen in Figure A.1 (see Appendix A.1) plotting the percentage point changes in unemployment rates for each regional unit analysed during the sample period—calculated as the difference between the maximum and the minimum unemployment rate for each region in the sample period.

[6] Specifically, we use information on whether the respondent has been diagnosed with depression or anxiety by a physician. However, this variable might still underestimate the prevalence of such conditions as some individuals may not report them during face-to-face interviews.

not get going"; and *"did not enjoy life"*. Following the literature (Cable, Chandola, et al., 2017), we generate a dummy variable for depression taking value 1 if an individual reports 4 or more symptoms (0 otherwise).

The regressions also account for a wide range of further individual-level sociodemographic characteristics. These include: age; gender; marital status (married/cohabiting); having children living in the household; being born in the UK; and education levels using the International Standard Classification of Education (ISCED). In addition, geographical-level variables are included, such as dummies identifying the nine Government office regions (GOR); quintiles based on a multiple deprivation index and quintiles of population density by postcodes. Pension related-characteristics such as: type of pension scheme (e.g., defined benefit vs defined contribution);[7] total pension wealth; and age equal or above the State Pension Age (SPA) are also used. Health behaviours, including being a current smoker; drinking over the limit; never engaging in vigorous or moderate activities more than once a week; using any medications; and having health insurance are included in the analyses. Finally, the models include (pre-ELSA) health status variables drawn from the HES interview, such as self-assessed health and having limited long-standing conditions. These are collected before the first wave of ELSA and thus may help defining baseline (initial) health status (i.e., before individuals turned 50 years old).

2.3.3 Descriptive statistics

Table 2.1 shows descriptive statistics for selected variables for different subsamples defined by occupational status, i.e., employed versus retired. The third column reports standard t-tests to explore statistically significant differences between means of observed variables in the two groups of individuals.[8] Overall, retirees present lower levels of health status before they retire. In particular, they report higher number of (pre-ELSA) long-standing conditions as identified by the variables collected in the HSE. Moreover, retired individuals are, on average, three years older than individuals who are still employed. Retired individuals are also more likely to be aged above the state pension age compared to employees and they are less likely to have their pensions in defined contribution schemes. With respect to health habits, retired individuals are more prone to engage in moderate physical activity, and less likely to drink alcohol more than once a week.

[7] A defined contribution pension scheme is based on how much has been contributed to the pension pot and the growth of that money over time. A defined benefit plan is always set up by an employer and offers a set benefit each year after retirement. See more about this here: `https://www.gov.uk/pension-types`.

[8] We have also performed standard t-tests adjusted by age.

TABLE 2.1: Descriptive statistics by employment status

Variables	Means				Test for Mean Differences*
	Employed		Retired		
	Mean	*SD*	*Mean*	*SD*	
Health status at HSE interview					
More than 1 long-standing illness	0.405	0.491	0.433	0.496	**
Fair or poor self-assessed health	0.132	0.339	0.123	0.328	
Socio-demographics					
Female	0.476	0.499	0.519	0.500	
Age	61.36	5.310	64.74	5.421	
Aged 50-60	0.487	0.500	0.211	0.408	***
Aged 61-70	0.452	0.498	0.662	0.473	***
Aged 71-80	0.057	0.233	0.117	0.322	***
Aged 81+	0.003	0.055	0.010	0.099	***
Married/Cohabitee	0.727	0.445	0.710	0.454	
Child lives in household	0.294	0.456	0.174	0.380	*
Birth in the UK	0.942	0.233	0.939	0.239	
Education					
never went or not yet finished	0.007	0.081	0.007	0.084	
went to school until 14 or below	0.015	0.123	0.024	0.154	**
O levels	0.450	0.498	0.455	0.498	
A levels	0.126	0.332	0.115	0.320	
Higher education below degree	0.161	0.367	0.165	0.371	
Degree	0.241	0.428	0.233	0.423	
Regional Characteristics					
Government office region (GOR)					
North East	0.049	0.216	0.046	0.212	
North West	0.109	0.311	0.101	0.301	
Yorkshire and the Humber	0.103	0.305	0.112	0.315	
East Midlands	0.116	0.321	0.103	0.304	
West Midlands	0.106	0.308	0.105	0.307	
East of England	0.152	0.359	0.160	0.367	
London	0.077	0.267	0.077	0.268	
South East	0.181	0.385	0.183	0.387	
South West	0.107	0.309	0.110	0.313	
Population Density for Postcode Sectors					
First quintile (least dense)	0.195	0.396	0.206	0.404	
Second quintile	0.246	0.431	0.239	0.427	
Third quintile	0.231	0.421	0.223	0.416	
Fourth quintile	0.178	0.383	0.195	0.396	
Fifth quintile (most dense)	0.141	0.348	0.128	0.334	
Index of Multiple Deprivation Score 2004					
First quintile (least deprived)	0.287	0.452	0.302	0.459	
Second quintile	0.273	0.446	0.255	0.436	
Third quintile	0.198	0.399	0.201	0.401	
Fourth quintile	0.159	0.366	0.167	0.373	
Fifth quintile (most deprived)	0.083	0.275	0.076	0.264	
Pension characteristics and financial variables					
Aged equal or above the State Pension Age (SPA)	0.327	0.469	0.616	0.486	***
Has a defined benefit pension scheme	0.232	0.436	0.236	0.425	
Has a defined contribution pension scheme	0.255	0.436	0.214	0.478	***
Total pension wealth/10000	18.08	16.38	17.72	15.26	
Health behaviours					
Current smoker	0.709	0.454	0.713	0.453	
Drinks over the limit per week	0.623	0.485	0.587	0.493	**
Whether taking medication - excluding contraceptives only	0.445	0.496	0.491	0.500	***
Never engages vigorous or moderate act more than once a week	0.254	0.436	0.235	0.424	*
Private health insurance	0.213	0.409	0.115	0.319	***
Observations	6,257		1,812		

Notes: T-test of equality of means between retired and employed. Significance levels: ***p≺0.01;**p≺0.05;*p≺0.1. Last column tests for mean differences in aged adjusted variables, where variables are balanced on age, age squared and four age dummies. * Results for the t-test adjusted by age reinforced the results.

2.4 Empirical Strategy

2.4.1 Inverse probability weighting regression adjustment

Inverse Probability Weighting Regression Adjustment (IPWRA) is used to identify the health effects of retirement and explore the mechanisms governing the relationship between retirement and health (Imbens and Wooldridge (2009); Cattaneo (2010); Hsu, Huber, and Lai (2019)). IPWRA is a quasi-experimental approach providing measurements of unobserved potential outcomes and involving a two-stage estimation, including a treatment model (first stage) and an outcome model (second stage).[9] The first stage allows estimating selection into treatment (retirement) conditional on observables, and the computation of inverse probability weights. The second stage employs the estimated inverse probability weights produced during the first stage to: I) estimate weighted linear regression models of the outcomes (mental and physical health variables) for retired vs non-retired individuals and II) compute means of the treatment-specific predicted outcomes from the linear weighted regression outcomes models. The difference between these predicted outcomes provides the average treatment effect of interest, i.e., the effect of retirement on health. In addition, the estimates produced by the second stage outcome models allow investigating specific mechanisms and mediating factors affecting the relationship between retirement and health.

We focus on the effects of retirement on health by looking only at first exits from the labour market, i.e., we exclude those individuals who re-entered into the labour market after an initial exit. Thus, individuals are defined as treated if their transition from work into retirement between consecutive waves is observed. Similarly, individuals who are still working are included in the control group.

The first stage (treatment model) involves the estimation of a probit model for the treatment (retirement) including a wide range of observed covariates:

$$p(X) = P(D = 1|X) = \phi(\gamma + \eta X_i) \tag{2.1}$$

where ϕ is the cumulative standard normal distribution function, D is the corresponding treatment dummy variable and X_i is a vector of covariates including broader individual and regional characteristics. Covariates include gender (female); age; married/cohabiting; the presence of dependent children; being born outside UK; ISCED educational classification (never went to school or not yet finished; went to school until 14 or below; O level equivalent; A level equivalent; post-secondary non-tertiary and short-cycle tertiary[10]; university degree or equivalent); dummies for the nine English regions (GOR) (base category: South West); eight wave dummies (base category: wave 1, 2002/03); four dummies of quintiles of population density using the Quintile Population Density for Postcode Sectors (base category: most densely populated quintile); four dummies of deprivation area using the Quintile Index of Multiple Deprivation Score 2004 (base category: most deprived); and age equal or above the state pension age (SPA); defined contribution pension; defined benefit pension;

[9] We make use of the Stata command *teffects ipwra* (StataCorp, 2017). *teffects ipwra* estimates the average treatment effect, the average treatment effect on the treated, and the potential-outcome means from observational data by inverse-probability-weighted regression adjustment (Cattaneo, 2010).

[10] Post-secondary non-tertiary education refers to programmes providing learning experiences that build on secondary education and prepare for labour market entry and/or tertiary education. In contrast, the short-cycle tertiary education are those programmes that are typically occupational-specific and prepare for labour market entry.

pension (private plus public) wealth/10000; reporting bad general health in the HSE; reporting having a long-standing illness in the HSE; being a current smoker; drinking over the limit; never engaging in vigorous or moderate activities more than once a week; using any medications; and having a private health insurance.[11]

Model (1) predicts the conditional probability of retirement for each observation in the data, $p(retirement) = \hat{p}(X_i)$. This allows generating inverse probability weights so that each individual's weight which is equal to the inverse of the probability of the actual treatment they received. That is,

$$w_i = 1/\hat{p}(X_i) \text{ } if \text{ } D = 1$$

are used to weight observations in the treatment group, thus weights will be large when the probability of retiring is small. Similarly,

$$w_i = 1/(1 - \hat{p}(X_i)) \text{ } if \text{ } D = 0$$

weight observations in the control group, therefore weights will be large when the probability of being employed (not retiring) is small. Effectively, this assigns larger weights to treated individuals (retirees) with similar observables to untreated individuals (employees), thus building counterfactuals that are as comparable as possible to treated individuals.

The second stage includes the estimation of linear weighted regressions (outcomes models) including on the right-hand side the same set of observed variables used in the first stage for the treatment model. Separate linear weighted regression models are estimated for individuals who retire and those who are still employed. This enables the exploration of the potential mechanisms influencing the relationship between retirement and health. Importantly, in these models, observations are weighted using the inverse probability weights, w_i, generated from the predicted conditional probabilities of retiring during the first stage. The difference between the potential outcomes provides an estimate of the average treatment effect of retiring on physical and mental health:

$$\tau_{ATE} = N^1 \sum_{i=1}^{N} (E[Y_i|X_i, D = 1] - E[[Y_i|X_i, D = 1]) \tag{2.2}$$

Note that this estimator is based on the assumptions of conditional independence (CIA), $(Y_1, Y_0 \perp D|p(X))$, and common support, $0 < Pr(D = 1|X) < 1$, hold. According to the CIA, all variables affecting both the treatment and the outcomes of interest can be observed. This implies that conditional on the observables, the treatment is independent of potential outcomes. The common support assumption ensures that there is sufficient overlap in the observed characteristics of treated and untreated individuals to find adequate matches. Tests around these assumptions can be found in the Appendix A.2. In addition, we also test the robustness of the results in the presence of selection on unobservables. Finally, IPWRA estimators also present a doubly-robust property, implying that estimates will be consistent even if one of the two models are not correctly specified (Cattaneo, 2010). Although we are not exploiting the panel nature of the data explicitly, standard errors are clustered at individual level to account for the fact that we are employing a pooled cross-section with repeated observations at individual-level.

[11] In order to account for a potential (selection) bias due to missing data, an additional missing data category is created for each variable. This also helps preserving the number of observations.

2.4.2 Kernel propensity score matching difference-in-differences

A kernel propensity score matching difference-in-differences approach (KPSM-DD) is used to identify whether the Great Recession (GR) influenced the impact of retirement on health (Heckman, Ichimura, and Todd, 1997). This method involves a two-stage difference-in-differences estimation that I) computes Kernel-based propensity score matching weights using a treatment model to pre-process the data and build more comparable treatment and control groups; and II) estimate a difference-in-differences (DD) specification to identify the impact of retirement on health after the GR using the re-weighted and improved treatment and control groups.

The Great Recession hit the UK between the second quarter of 2008 and the second quarter of 2009, leading to higher unemployment and worsening labour market conditions (Bell and Blanchflower, 2010). Accordingly, the years between 2004-2007 are used as the pre-recession period and the years between 2010-11 as the post-recession period. Following the previous literature exploring the effects of the GR (e.g., Pye, Taylor, et al. (2016); Thompson, Ophem, and Wagemakers (2019)), the years 2008-09 are excluded to allow the recession enough time to influence the relationship between retirement and health (i.e., it is assumed that the health effects of retirement would not be instantaneously affected by the GR). Accordingly, since we want to investigate whether the GR affected the impact of retirement on health, the difference-in-differences estimate focuses on the effect of retiring during the post-recession years (2010-11).

In practice, the first stage of the KPSM-DD approach simply translates into the estimation of a probit model for the treatment (retirement), including the same set of covariates used for the IPWRA's treatment model (see Equation 2.1). This stage predicts the conditional probability of retiring for each observation in the data, $p(retirement) = \hat{p}(X_i))$, and produces corresponding weights for each individual. Thus, individuals in the treatment group (retirees) receive a weight of 1, while individuals in other groups receive a weight that is defined by the probability of them being in the treatment group (retirees) relative to the probability of them being in the group they actually belong to. The weighting strategy used here weights the four groups (treatment groups pre- and post-recession and control groups pre- and post-recession) to be as similar as possible based on a set of key observable characteristics. This can be thought of as weighting each of the four corresponding cells to reflect the covariate distribution in the treatment group during the pre-recession period, thus removing biases due to systematic differences in the observables between the four groups.

The baseline DD specification is:

$$Y_{it} = \alpha + \beta_1 POST_t + \beta_2 TREAT_i + \beta_3 POST_t * TREAT_i + Year_t + Region_i + X_{it} + e_{it} \quad (2.3)$$

The dependent variable, Y_{it}, is the set of mental and physical health variables reported by individual i on a year t. $POST_t$ is a dummy variable that equals 1 for the post-recession period (2010-11), and 0 for the pre-recession period (2004-07). $TREAT_i$ is a dummy variable that equals 1 if the respondent retires between waves. The parameter of interest is β_3 corresponding to the interaction between binary variables identifying the treatment group ($TREAT_i$) and the post-recession period ($POST_t$), respectively. This specification controls for the same set of explanatory variables previously used for the IPWRA treatment model and also includes regional ($Region_i$) and years ($Year_t$) fixed effects.[12] In addition, we separately run Equation 2.3 using as the post-recession period variable ($POST_t$) the years between 2010-2017 to provide an average estimate on the health effects of retiring after the economic recession for a longer time period. Also in this case, standard errors are clustered at individual level.

2.5 Results

Determinants of retirement

Table 2.2 reports the probit estimates corresponding to the first stage (treatment model) of the inverse probability weighted regression adjustment (IPWRA) estimator.[13] The table shows that women have a higher probability of retiring compared to men while increasing age appears to be positively associated with retirement (with some evidence of a non-linear relationship between retirement and age provided by the statistically significant second-order polynomial of the variable age). Individuals with dependent children in their household are also less likely to retire. Living in Yorkshire and the Humber, quintile of most densely populated area, and the variable identifying the post Great Recession years (2010-13) present positive and statistically significant estimates and are thus linked to higher probabilities of retiring. As expected, being above the state pension age increases the probability of retiring. Furthermore, having a defined contribution pension scheme decreases the likelihood of retiring, while having a defined benefit pension scheme appears to have the opposite effect. Finally, the probability of retiring also increases for individuals who are physical inactive.

[12] We explore the common trend assumption by comparing trends in health outcomes during the years prior to the Great Recession (2004-2007) using the post-matching sample. See Figure A.6 in the Appendix A.2. Note that trends using the pre-matching sample for all the health outcomes are available upon request.

[13] In the Appendix A.2 we report a series of tests exploring the common support assumption and the improved covariate balance after matching, see figures A.3-A.5 and Table A.1.

TABLE 2.2: IPWRA: Probit estimates for retirement (treatment model)

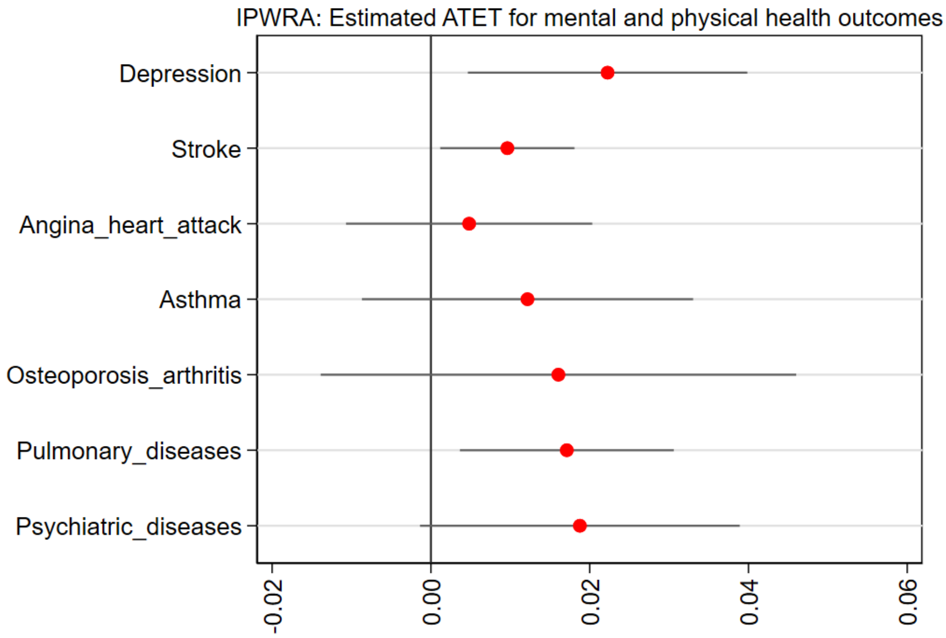
Variables	*Coeff.*	*Std. Err.*
Female	0.119***	0.041
Age	0.395***	0.059
Squared Age	-0.003***	0.001
Married or Cohabiting	0.020	0.041
Children lives in household	-0.251***	0.045
Country of birth in UK	0.091	0.082
Never went or not yet finished	0.137	0.193
Went to school until 14 or below	-0.038	0.139
O level	-0.039	0.051
A level	-0.047	0.067
Higher ed below degree	0.057	0.060
South East	-0.031	0.071
London	0.027	0.099
East England	0.041	0.073
West Midlands	0.013	0.079
East Midlands	0.022	0.078
Yorkshire and The Humber	0.180**	0.080
North West	0.022	0.082
North East	0.128	0.102
Wave 2004/05	0.158*	0.087
Wave 2006/07	-0.032	0.086
Wave 2008/09	0.102	0.083
Wave 2010/11	0.177**	0.082
Wave 2012/13	0.230***	0.083
Wave 2014/15	0.082	0.086
1st Population Density Group (Least dense)	0.261	0.224
2nd Population Density Group	0.139*	0.078
3rd Population Density Group	0.132*	0.075
4th Population Density Group (2nd most dense)	0.217**	0.074
1st Quintile Index of Multiple Deprivation Score 2004 (least deprived)	0.097	0.082
2nd Quintile Index of Multiple Deprivation Score 2004	0.020	0.080
3rd Quintile Index of Multiple Deprivation Score 2004	0.016	0.081
4th Quintile Index of Multiple Deprivation Score 2004 (2nd most deprived)	0.082	0.081
Aged equal or above the State Pension Age (SPA)	0.265***	0.052
Has a defined benefit pension scheme	0.124**	0.052
Has a defined contribution pension scheme	-0.099**	0.049
Total pension wealth/10000	0.001	0.001
Current smoker	-0.018	0.061
Drinks over the limit per week	-0.016	0.039
Never engages vigorous or moderate act more than once a week	0.200**	0.076
Whether taking medication - excluding contraceptives only	0.062	0.041
Private health insurance	-0.380***	0.055
Fair or poor self-assessed health (HES)	0.046	0.058
Has limiting long-standing illness (HES)	-0.056	0.037
Constant	-15.11***	2.001
Number of observations	6,666	

Notes: Standard errors in parentheses. ***p≺0.01;**p≺0.05;*p≺0.1. This table reports results of the two-stage estimation of the inverse probability weighting regression adjustment (IPWRA) specification. In particular, this table reports results of the first-stage probit model on the determinants of being retirement compared to being still employed (treatment model). All models include incrementally pseudo-region and time fixed effects and the full battery individual-level observed characteristics.

Health effects of retirement

Figure 2.1 presents the average treatment effects on the treated (ATET) obtained in the second stage of the IPWRA estimation (as the difference between the predicted values of the outcome models). This provides an estimate of the effect of retiring on health.[14]

FIGURE 2.1: IPWRA: Estimated ATET for mental and physical health outcomes using the full sample



Notes: Clustered standard errors by individual level in parentheses. This table reports results of the two-stage estimation of the inverse probability weighting regression adjustment (IPWRA) specification. In particular, this table reports results of the second-stage linear model on the effect of retirement on physical and mental health (outcome model) using the full samples. Number of observations for the full sample analysis is 6,666.

Here, it is observed that overall retirement significantly increases the probability of experiencing physical and mental ill-health. More specifically, retirement increases the likelihood of becoming depressed by 2.2 percentage points (pp). Furthermore, retirement significantly increases the risks of being diagnosed with severe pulmonary diseases (1.7 pp), psychiatric diseases (1.8 pp), and having a stroke (0.9 pp). Table 2.3 further explores heterogeneity of the health effects of retirement by gender and type of occupation (blue- vs white-collar). Estimates appear to be larger among women (except for pulmonary diseases) and blue-collar workers. Specifically, women and blue-collar workers present increased probabilities of becoming depressed after retirement (2.6 pp and 2.9 pp, respectively). In addition, women show higher probabilities of having psychiatric diseases (3.6 pp) and men are at higher risk of pulmonary diseases (2.5 pp).

[14] Additionally, we performed hypothesis testing on all the outcomes. This is because as the number of hypothesis tested increases, the proportion of type I errors (false positives) might increase as well. We thus apply an adjustment for multiple comparisons using a conservative approach based on Bonferroni-Holm (Holm, 1979), and compare the p-values generated by individual hypotheses with adjusted critical p-values.

TABLE 2.3: IPWRA: Estimated ATET for mental and physical health outcomes by sub-samples

Outcome variables	**Women: ATET**	**Men: ATET**	**Blue-collar: ATET**	**White-collar: ATET**
Depression (CES-D)	0.026**	0.016	0.029**	0.017
	(0.014)	(0.010)	(0.015)	(0.010)
Stroke	0.013**	0.005	0.015**	0.006
	(0.005)	(0.006)	(0.008)	(0.004)
Angina or heart attack	0.002	0.010	0.011	-0.002
	(0.009)	(0.011)	(0.012)	(0.008)
Asthma	0.010	0.015	0.019	0.003
	(0.015)	(0.013)	(0.015)	(0.013)
Osteoporosis or arthritis	0.015	0.014	0.033	0.002
	(0.020)	(0.021)	(0.024)	(0.018)
Pulmonary diseases	0.009	0.025**	0.025**	0.013
	(0.009)	(0.009)	(0.011)	(0.008)
Psychiatric diseases	0.036**	-0.003	0.009	0.016
	(0.014)	(0.013)	(0.016)	(0.012)
Region and Time FE	*Yes*	*Yes*	*Yes*	*Yes*
Individual characteristics	*Yes*	*Yes*	*Yes*	*Yes*
Observations	3,384	3,282	2,362	4,304

Note: Clustered standard errors by individual level in parentheses. ***p≺0.01;**p≺0.05;*p≺0.1. This table reports results of the two-stage estimation of the inverse probability weighting regression adjustment (IPWRA) specification. In particular, this table reports results of the second-stage linear model on the effect of retirement on physical and mental health (outcome model) by sub-samples. All models include incrementally pseudo-region and time fixed effects and the full battery individual-level observed characteristics. In this table, we are performing 7 x 5 = 35 hypothesis test, and therefore, we need to make adjustment for multiples comparisons. P-values adjusted for multiple hypothesis tests using the Bonferroni-Holm (Holm, 1979) method.

Selection on unobservables

Since IPWRA does not explicitly account for individual-level unobserved heterogeneity, we test the sensitivity of the results to selection on unobservables (Altonji, Elder, and Taber (2005); Oster (2019)). Specifically, we employ the test proposed by Oster (2019) which allows producing consistent estimates of bias-adjusted treatment effects using different values of the relative degree of selection on observed and unobserved variables (δ) and for varying R-squared values. After imposing an equal amount of selection on unobservables and observables (i.e., δ=1, a level considered to be an upper bound for the relative degree of selection on unobservables), we find that the effects of interest are virtually unchanged in size and statistical significance. This appears to imply that the findings are robust to large degrees of selection on unobservables.[15]

[15] The tests also show that, depending on the outcome considered, the relative degree of selection on unobservables vs observables would need to be between 3.635 and 29.329 to drive the estimates to zero. This further suggests that only implausibly large degrees of selection on unobservables would affect the results. Note that in the test we use the rule of thumb proposed in Oster (2019) and set the upper bound of the R-squared (R-max) equal to 1.3 times the actual R-squared obtained from the corresponding regressions. Full estimates are available upon request.

Mechanisms linking retirement to health

Tables 2.4 and 2.5 report the full set of results produced by the second stage (outcome models) of the IPWRA estimation. These are reported by treatment and control groups (individuals who retired between waves vs those who are still in the labour market). These allow exploring the mechanisms influencing the relationship between retirement and health. In this case, we focus on those health outcomes that were previously found to be significantly affected by retirement according to the ATET, i.e., depression; stroke; pulmonary and psychiatric diseases. To unveil the potential mechanisms, we compare estimated effects of key variables between the two groups and identify those factors that appear to be driving the changes in physical and mental health after retirement among those who retired.

TABLE 2.4: Second-stage of the IPWRA (outcome model): Control group (employed)

RA: Outcome model for control group (employed)	**Depression**		**Stroke**		**Pulmonary diseases**		**Psychiatric diseases**	
	Coeff.	*Std Err*	*Coeff.*	*Std Err*	*Coeff.*	*Std Err*	*Coeff*	*Std Err*
Female	0.021**	0.009	-0.006	0.006	-0.018	0.007	0.014	0.012
Age	-0.007	0.017	-0.009	0.012	0.020	0.014	-0.003	0.015
Squared Age	0.001	0.001	0.001	0.001	-0.001	0.001	-0.001	0.001
Married or Cohabiting	-0.033**	0.012	0.010*	0.005	0.011	0.008	-0.012	0.013
Children lives in household	-0.016	0.009	-0.001	0.006	-0.002	0.009	0.015	0.013
Country of birth in UK	0.007	0.021	0.006	0.018	-0.000	0.018	-0.099***	0.016
Never went or not yet finished	-0.032	0.032	-0.027*	0.010	-0.048***	0.013	-0.128***	0.028
Went to school until 14 or below	-0.003	0.043	0.015	0.026	0.096***	0.035	-0.070**	0.032
O level	0.010	0.012	-0.008	0.006	0.047***	0.007	-0.033**	0.016
A level	0.015	0.016	0.007	0.011	0.015	0.010	-0.106***	0.018
Higher education below degree	-0.007	0.014	-0.001	0.010	0.007	0.008	-0.013	0.021
South East	-0.004	0.017	-0.012	0.012	0.012	0.011	-0.037	0.024
London	0.068**	0.029	-0.021*	0.012	0.085***	0.011	-0.047	0.032
East England	0.005	0.017	-0.025**	0.011	0.053***	0.022	-0.002	0.025
West Midlands	0.018	0.019	-0.018	0.013	0.003	0.010	0.004	0.028
East Midlands	0.029	0.020	-0.026**	0.012	0.051***	0.017	-0.025	0.026
Yorkshire and The Humber	0.028	0.023	-0.015	0.013	0.001	0.011	-0.060**	0.026
North West	0.020	0.020	-0.030**	0.012	0.021	0.013	-0.005	0.029
North East	-0.013	0.021	0.015	0.020	0.031	0.022	-0.087***	0.029
Wave 2004/05	0.014	0.022	-0.031*	0.016	-0.009	0.018	-0.068***	0.026
Wave 2006/07	0.004	0.021	-0.028*	0.015	-0.011	0.017	-0.052**	0.024
Wave 2008/09	0.010	0.021	-0.016	0.016	-0.006	0.016	-0.027	0.026
Wave 2010/11	0.023	0.022	-0.011	0.016	-0.006	0.016	-0.027	0.025
Wave 2012/13	-0.014	0.020	-0.022	0.015	-0.001	0.017	-0.018	0.026
Wave 2014/15	-0.016	0.020	-0.029**	0.014	-0.010	0.018	0.001	0.028
1st Quintile Population Density (Least dense)	0.014	0.059	-0.007	0.010	0.014	0.018	-0.064	0.046
2nd Quintile Population Density	-0.005	0.021	0.017	0.010	0.020	0.014	-0.018	0.025
3rd Quintile Population Density	0.019	0.021	0.009	0.009	0.043***	0.015	-0.025	0.023
4th Quintile Population Density	-0.014	0.020	0.001	0.008	0.016	0.012	-0.015	0.023
5th Quintile Population Density (Most dense)	-0.008	0.021	0.005	0.010	0.071***	0.013	-0.031	0.022
1st Quintile Index of Multiple Deprivation Score 2004 (Least deprived)	-0.002	0.019	0.003	0.008	0.005	0.020	0 .001	0.022
2nd Quintile Index of Multiple Deprivation Score 2004	0.022	0.020	0.008	0.009	0.021	0.020	0.027	0.022
3rd Quintile Index of Multiple Deprivation Score 2004	-0.013	0.019	0.034***	0.010	0.004	0.019	0.028	0.020
4th Quintile Index of Multiple Deprivation Score 2004 (Most deprived)	0.008	0.019	0.010	0.007	-0.001	0.018	0 .089***	0.022
Individual aged equal or above the State Pension Age (SPA)	0.001	0.015	-0.011*	0.006	0.011	0.011	0.033	0.017
Has a defined benefit pension scheme	0.014	0.017	-0.001	0.008	-0.017	0.011	-0.012	0.022
Has a defined contribution pension scheme	0.001	0.013	0.001	0.007	0.009	0.015	-0.009	0.025
Total pension wealth/10000	-0.001**	0.001	-0.001	0.001	-0.001	0.015	0.004	0.001
Current smoker	-0.003	0.015	0.004	0.008	0.034**	0.016	-0.045***	0.015
Drinks over the limit per week	-0.033***	0.009	-0.009	0.005	-0.012*	0.007	-0.001	0.011
Never engages vigorous or moderate act more than once a week	0.084	0.028	0.005	0.013	0.049**	0.024	-0.004	0.025
Whether taking medication - excluding contraceptives only	-0.007	0.011	0.014	0.005	0.032***	0.008	0.056***	0.012
Has private health insurance, whether in your own name or through	-0.011	0.011	-0.001	0.006	0.001	0.009	-0.005	0.015
Fair or poor self-assessed health (HES)	0.132***	0.021	0.015	0.011	0.010	0.013	0.127***	0.023
Has limiting long-standing illness (HES)	-0.002	0.010	-0.006	0.005	0.004	0.009	0.026**	0.012
Constant	0.609	0.566	0.330	0.396	-0.686	0.462	0.515	0.518
Number of observations	6,666		6,666		6,666		6,666	

Note: Clustered standard errors by individual level. ***p≺0.01;**p≺0.05;*p≺0.1.

As for mental health, having no formal education degree (i.e., having no formal degree or having some early childhood/primary education); leading a sedentary life (i.e., never engaging in vigorous/moderate activities more than once a week); and living in the least deprived areas, appear to be all statistically significant factors in the relationship between retirement and depression (Table 2.5). More specifically, having no formal education and a sedentary lifestyle seem to increase the probability of being depressed by 9.8 and 5.2 pp, respectively. This might imply that less educated and physically inactive individuals are less able to cope with the changes brought by retirement. Also, living in the least deprived areas of England, according to the multiple deprivation index, seems to have a protective effect on depression after retirement (7 pp). This could suggest that a higher quality environment, including access to a wide range of services, may positively impact upon mental health after retirement. Also, while gender (women) and marital status (married/cohabiting) appear to affect the probability of depression among those who retired, this is also true for individuals who are still in the labour market as well (Table 2.5). However, gender seems to significantly increase the probability of developing psychiatric conditions (column 4 of Table 2.5) only among those who retired (6 pp).

An inspection of the main factors influencing poor physical health among those who retired appears to suggest that age, having a health condition requiring medications and broader environmental conditions could also play a role. For instance, suffering a stroke after retirement appears to be associated with being currently under medication (2.1 pp) and living in densely populated areas (3.4 pp). While the former variable might be simply suggest a general state of ill-health or the presence of a health condition, the latter could be a proxy for a worse/low quality general environment. Finally, factors driving the probability of being diagnosed with pulmonary diseases after retirement are age and living in specific areas, namely the North East of England (compared to living in the South West of England), an historically economically deprived region.

As expected, baseline health conditions (those reported as part of the Health Survey of England before the start of ELSA), seem to influence most health outcomes. In particular, reporting fair or poor general health and having a long-standing condition before turning 50 years old are associated with increased probabilities of mental ill-health among both individuals who retired and those still in the labour market.

TABLE 2.5: Second-stage of the IPWRA (outcome model): Treatment group (retirement)

RA: Outcome model for treatment group (retirement)	Depression		Stroke		Pulmonary diseases		Psychiatric diseases	
	Coeff.	*Std Err*	*Coeff.*	*Std Err*	*Coeff.*	*Std Err*	*Coeff*	*Std Err*
Female	0.043**	0.017	0.003	0.010	-0.026**	0.013	0.060***	0.018
Age	-0.046	0.029	-0.008	0.015	0.046***	0.015	-0.009	0.022
Squared Age	0.003	0.001	0.001	0.001	-0.001***	0.001	0.001	0.001
Married or Cohabiting	-0.054***	0.018	0.003	0.010	-0.005	0.014	-0.020	0.020
Children lives in household	0.001	0.021	-0.007	0.010	-0.013	0.016	-0.013	0.024
Country of birth in UK	0.004	0.038	-0.020	0.013	-0.013	0.027	-0.164**	0.030
Never went or not yet finished	0.098***	0.027	-0.033*	0.017	-0.050**	0.022	-0.164***	0.037
Went to school until 14 or below	0.020	0.060	0.056	0.050	0.060	0.053	-0.060	0.050
O level	0.011	0.019	-0.006	0.010	0.039**	0.016	-0.038	0.025
A level	-0.003	0.025	0.020	0.018	0.035*	0.022	-0.101	0.020
Higher education below degree	0.017	0.023	-0.006	0.012	0.032*	0.018	-0.012	0.030
South East	-0.022	0.027	-0.019	0.017	0.028	0.022	-0.022	0.035
London	0.074	0.047	0.003	0.024	0.050	0.031	-0.077	0.043
East England	0.028	0.030	-0.013	0.018	0.069*	0.024	-0.043	0.035
West Midlands	0.014	0.032	0.001	0.021	0.035	0.024	-0.025*	0.039
East Midlands	0.023	0.034	0.007	0.022	0.021	0.023	-0.034	0.041
Yorkshire and The Humber	-0.013	0.031	-0.029	0.018	0.030	0.023	-0.041	0.038
North West	-0.023	0.032	-0.009	0.021	0.035	0.024	0.007	0.043
North East	-0.036	0.039	-0.045	0.036	0.083***	0.040	-0.112	0.043
Wave 2004/05	-0.031	0.035	-0.012	0.019	-0.003	0.028	-0.040**	0.034
Wave 2006/07	-0.016	0.036	0.004	0.021	-0.009	0.028	-0.064	0.036
Wave 2008/09	-0.024	0.034	-0.005	0.018	-0.002	0.028	-0.038*	0.034
Wave 2010/11	-0.023	0.033	-0.001	0.019	0.010	0.028	-0.020	0.034
Wave 2012/13	-0.035	0.031	0.007	0.021	0.004	0.027	0.032	0.035
Wave 2014/15	-0.022	0.034	0.006	0.022	0.024	0.029	-0.005	0.036
1st Quintile Population Density (Least dense)	0.065	0.124	-0.004	0.017	-0.081**	0.035	0.099	0.111
2nd Quintile Population Density	0.017	0.037	0.040*	0.015	0.026	0.029	0.025	0.037
3rd Quintile Population Density	0.006	0.035	0.033*	0.015	0.002	0.026	-0.016	0.034
4th Quintile Population Density	0.005	0.035	0.017	0.016	-0.008	0.025	0 .033	0.035
5th Quintile Population Density (Most dense)	0.003	0.035	0.034**	0.016	0.008	0.027	0.014	0.033
1st Quintile Index of Multiple Deprivation Score 2004 (Least deprived)	-0.070**	0.042	-0.025	0.021	-0.008	0.033	-0.068*	0.041
2nd Quintile Index of Multiple Deprivation Score 2004	-0.071*	0.042	-0.016	0.022	-0.019	0.032	-0.065	0.041
3rd Quintile Index of Multiple Deprivation Score 2004	0.052	0.042	0.010	0.023	-0.005	0.032	0.038	0.041
4th Quintile Index of Multiple Deprivation Score 2004 (Most deprived)	0.074*	0.042	-0.024	0.021	-0.014	0.032	0.029	0.042
Individual aged equal or above the State Pension Age (SPA)	-0.101	0.021	-0.007	0.010	0.009	0.016	-0.012	0.026
Has a defined benefit pension scheme	-0.025	0.017	-0.014	0.004	-0.015	0.015	-0.020	0.023
Has a defined contribution pension scheme	-0.018	0.021	-0.012	0.009	-0.019	0.016	-0.044**	0.021
Total pension wealth/10000	-0.001*	0.001	-0.001	0.001	-0.001	0.001	-0.001	0.001
Current smoker	0.029	0.029	0.005	0.015	0.031	0.025	-0.005	0.029
Drinks over the limit per week	-0.030**	0.015	-0.011	0.009	-0.017	0.013	0.023	0.019
Never engages vigorous or moderate act more than once a week	0.052***	0.046	0.032	0.024	0.043	0.034	0.029	0.038
Whether taking medication - excluding contraceptives only	0.018	0.017	0.021**	0.009	0.031**	0.013	0.050**	0.019
Has private health insurance, whether in your own name or through	-0.027	0.022	-0.003	0.012	-0.006	0.018	0.001	0.027
Fair or poor self-assessed health (HES)	0.108***	0.033	0.005	0.015	-0.010	0.019	0.136***	0.035
Has limiting long-standing illness (HES)	-0.021	0.017	0.002	0.009	-0.009	0.014	0.052***	0.019
Constant	1.94**	0.986	0.264	0.512	-1.52***	0.533	0.861	0.779
Number of observations	6,666		6,666		6,666		6,666	

Note: Clustered standard errors by individual level. ***p≺0.01;**p≺0.05;*p≺0.1.

Health effects of retirement following the Great Recession

Table 2.6 shows estimates produced using the KPSM-DD estimator for both mental and physical health outcomes. Column 1 shows that retiring immediately after the Great Recession decreases the probabilities of depression (3.9 pp) and being diagnosed with angina/having a heart attack (3.3 pp). The heterogeneity analysis by gender, areas and type of occupation (blue vs white-collar workers) also reveals that the positive effects on depression are larger among men and those living in severely hit regions.[16] In contrast, the decrease in the probability of being diagnosed with physical health conditions is mostly concentrated among women, also living in severely affected regions.

TABLE 2.6: KPSM-DD estimates for mental and physical health outcomes: short-term impacts

Outcome variables	**Full sample**	**Living in a severely hit region**	**Blue-collar worker**	**Male**	**Male living in a severely hit region**	**Blue-collar male worker living in a severely hit region**	**Female**	**Female living in a severely hit region**	**Blue-collar female worker living in a severely hit region**
Depression	-0.039**	-0.086**	-0.009	-0.077***	-0.090***	-0.044	-0.023	-0.033	0.084
(CES-D)	(0.022)	(0.038)	(0.039)	(0.026)	(0.041)	(0.075)	(0.035)	(0.062)	(0.238)
Stroke	-0.012	-0.017	-0.005	0.016	0.037	0.090	-0.047***	-0.084***	-0.431***
	(0.010)	(0.020)	(0.017)	(0.012)	(0.026)	(0.044)	(0.014)	(0.029)	(0.108)
Angina or heart	-0.033*	-0.014	0.066	-0.002	0.063	0.068	-0.046**	-0.053	0.091
attack	(0.019)	(0.035)	(0.037)	(0.031)	(0.059)	(0.100)	(0.021)	(0.033)	(0.175)
Asthma	0.052	0.023	0.021	0.025	0.034	-0.026	0.073	0.022	-0.003
	(0.024)	(0.041)	(0.044)	(0.031)	(0.053)	(0.086)	(0.037)	(0.061)	(0.220)
Osteoporosis or	-0.011	0.094	0.018	0.031	0.056	0.019	-0.007	-0.073	-0.249
arthritis	(0.034)	(0.060)	(0.059)	(0.044)	(0.079)	(0.157)	(0.051)	(0.087)	(0.243)
Pulmonary	0.017	0.001	0.073	0.012	0.026	0.096	0.025	0.012	-0.020
diseases	(0.016)	(0.029)	(0.035)	(0.024)	(0.040)	(0.086)	(0.022)	(0.040)	(0.163)
Psychiatric	-0.007	0.023	0.022	-0.014	0.002	-0.034	0.052	0.134	-0.062
diseases	(0.023)	(0.040)	(0.036)	(0.014)	(0.045)	(0.053)	(0.036)	(0.060)	(0.818)
Region and Time FE	*Yes*	*Yes*	*Yes*	*Yes*	Yes	*Yes*	*Yes*	*Yes*	*Yes*
Individual characteristics	*Yes*	*Yes*	*Yes*	*Yes*	Yes	*Yes*	*Yes*	*Yes*	*Yes*
Observations	4,403	1,573	1,487	2,203	758	302	1,688	751	112

Note: Clustered standard errors by individual level in parentheses. ***p≺0.01;**p≺0.05;*p≺0.1. Severely hit region takes value 1 if the individual lives in a region with unemployment rate higher or equal to the mean during the studied period. P-values adjusted for multiple hypothesis tests using the Bonferroni-Holm (Holm, 1979) method. Kernel-based Propensity Score Matching to generate weights of the treated group using probit model.

Table 2.7 provides estimates of the health effects of retiring after an economic shock using a longer time window post-recession. Interestingly, all the estimated effects are not statistically significant in this case (see Column 1), suggesting the absence of overall long-term health effects of retiring following an economic shock. However, after stratifying the sample by occupation type, the results indicate that blue-collar women living in more badly hit regions are still experiencing decreases in the probability of being diagnosed with a series of physical health conditions. While the magnitude of such effects appears substantial and it is reasonable to believe this group of individuals might have experienced improvements

[16] We define living in a severely hit region as a dummy variable that takes value 1 if the region experiences an increase in the unemployment rate above the mean during the sample period, and 0 otherwise. Therefore, GOR are classified in two categories those above the mean are "high" unemployment areas, and those below the mean are "low" unemployment areas.

in health, we should be cautious in placing emphasis to these results because of the corresponding small sample size.[17]

TABLE 2.7: KPSM-DD estimates for mental and physical health outcomes: long-term impacts

Outcome variables	**Full sample**	**Living in a severely hit region**	**Blue-collar worker**	**Male**	**Male living in a severely hit region**	**Blue-collar male worker living in a severely hit region**	**Female**	**Female living in a severely hit region**	**Blue-collar female worker living in a severely hit region**
Depression	-0.013	-0.032	-0.007	-0.026	-0.060	-0.030	-0.003	-0.044	0.189
(CES-D)	(0.017)	(0.031)	(0.030)	(0.020)	(0.037)	(0.079)	(0.026)	(0.050)	(0.132)
Stroke	0.005	-0.006	0.003	0.020	0.018	0.070	-0.013	-0.031	-0.245***
	(0.004)	(0.017)	(0.015)	(0.011)	(0.025)	(0.049)	(0.011)	(0.023)	(0.102)
Angina or heart	-0.017	-0.009	0.031	-0.002	-0.008	0.016	-0.025	-0.049	0.071
attack	(0.015)	(0.028)	(0.028)	(0.024)	(0.048)	(0.083)	(0.016)	(0.033)	(0.093)
Asthma	0.020	-0.023	-0.007	-0.014	-0.021	-0.034	0.020	-0.046	-0.012
	(0.019)	(0.034)	(0.032)	(0.024)	(0.045)	(0.072)	(0.029)	(0.050)	(0.126)
Osteoporosis or	-0.018	-0.029	-0.067	0.032	0.062	-0.019	-0.028	-0.015	-0.384***
arthritis	(0.027)	(0.056)	(0.047)	(0.039)	(0.079)	(0.032)	(0.040)	(0.076)	(0.063)
Pulmonary	0.023	0.038	0.040	0.014	0.025	0.065	0.021	0.011	-0.477***
diseases	(0.014)	(0.024)	(0.026)	(0.019)	(0.036)	(0.075)	(0.018)	(0.037)	(0.096)
Psychiatric	0.004	-0.084	-0.025	-0.031	-0.008	0.051	-0.067	-0.091	-0.020
diseases	(0.019)	(0.096)	(0.022)	(0.028)	(0.015)	(0.024)	(0.009)	(0.018)	(0.084)
Region and Time FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Individual characteristics	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	6,666	2,112	1,999	3,014	1,072	424	2,882	1,016	400

Note: Clustered standard errors by individual level in parentheses. ***p≺0.01;**p≺0.05;*p≺0.1. Severely hit region takes value 1 if the individual lives in a region with unemployment rate higher or equal to the mean during the studied period. P-values adjusted for multiple hypothesis tests using the Bonferroni-Holm (Holm, 1979) method. Kernel-based Propensity Score Matching to generate weights of the treated group using probit model.

Robustness checks: further health outcomes and biomarkers

As a robustness check, results based on further health outcomes are presented, including biomarkers. Specifically, this additional set of variables is divided into three main groups: self-reported health, long-standing illnesses, and biomarkers. In the first group, a binary variable for poor self-reported health is included, which takes taking value 1 if an individual report *"bad"* or *"very bad"* general health, and 0 otherwise. Further binary variables for life satisfaction (taking value 1 if an individual agrees that *"in most ways his life is close to his ideal"*) and loneliness (taking value 1 if the respondent feels *"isolated from others"*) are included. Within the second group of variables, a binary indicator is added for "difficulties with mobility" (taking value 1 in case of any difficulties with mobility).[18] Finally, we employ biomarkers such as a binary indicator of (pre-) obesity using information on Body Mass Index (BMI) based on WHO guidelines (BMI $\geq$25); and variables for high waist circumference;

[17] In addition, Figure A.6 in the Appendix A.2 appears to show slightly converging pre-treatment trends in treatment and control groups for the outcome osteoporosis/arthritis.

[18] This variable is an index we built using information from 10 binary variables about mobility, including the following questions: difficulty walking 100 yards; difficulty sitting 2 hours; difficulty getting up from chair after sitting long periods; difficulty climbing several flights stairs without resting; difficulty climbing one flight stairs without resting; difficulty stooping, kneeling or crouching; difficulty reaching or extending arms above shoulder level; difficulty pulling or pushing large objects; difficulty lifting or carrying weights over 10 pounds; and difficulty picking up 5p coin from a table.

high systolic and diastolic blood pressure; high cholesterol level; high triglyceride level; and high-sensitivity C-reactive protein level. These health indicators are sensitive to lifestyle changes and are all reliable predictors of cardiovascular-related diseases.

Columns 1-3 of Table 2.8 report ATET of the effects of retirement on health obtained using IPWRA for the full sample as well as broken down by gender and region. Here, retirement increases the probability of reporting poor SAH and having difficulties with mobility by 1.5 pp and 4.7 pp, respectively. The magnitude of these effects appears to be larger among men. In addition, a reduction in diastolic blood pressure can be observed also among men (4.3 pp).

TABLE 2.8: Robustness checks: effects of retirement on further health outcomes and biomarkers

Outcome variables	**Full sample: ATET**	**Women: ATET**	**Men: ATET**	**Full sample: KPSM-DiD**	**Female living in a severely hit region KPSM-DiD**	**Male living in a severely hit region KPSM-DiD**
Poor self-assessed health	0.015***	0.011*	0.020**	-0.006*	0.010	0.037
	(0.004)	(0.005)	(0.006)	(0.008)	(0.018)	(0.023)
Life satisfaction (close to ideal)	0.001	-0.006	0.008	-0.003	0.048	0.008
	(0.007)	(0.011)	(0.010)	(0.015)	(0.044)	(0.027)
Loneliness (lack of companionship)	0.006	0.014	0.004	0.004	0.078	-0.024
	(0.014)	(0.020)	(0.018)	(0.027)	(0.075)	(0.068)
Difficulties with mobility	0.047***	0.031	0.063***	-0.047**	-0.138**	0.130
	(0.013)	(0.019)	(0.015)	(0.024)	(0.065)	(0.035)
BMI (obese)	-0.004	-0.025	0.026	0.046	-0.071	0.129
	(0.014)	(0.020)	(0.020)	(0.025)	(0.068)	(0.118)
High Waist circumference (>102	-0.005	-0.009	-0.003	-0.014	-0.039	-0.002
cm for men and >88 cm for women)	(0.015)	(0.021)	(0.020)	(0.028)	(0.072)	(0.072)
High systolic Blood Pressure	-0.017	-0.006	-0.017	0.013	-0.456	0.082
(>140mmHG)	(0.011)	(0.027)	(0.031)	(0.066)	(0.085)	(0.114)
High diastolic Blood Pressure	-0.017	0.005	-0.043***	-0.001	0.043	0.124
(>90mmHG)	(0.021)	(0.014)	(0.015)	(0.069)	(0.065)	(0.073)
High cholesterol level	0.014	0.012	0.019	0.005	-0.006	-0.087
(>6.2mmol/l)	(0.021)	(0.032)	(0.028)	(0.069)	(0.261)	(0.131)
High triglyceride level	0.027	0.030	0.017	0.020	0.114	0.172
(>2.26 mmol/l)	(0.017)	(0.022)	(0.027)	(0.057)	(0.094)	(0.094)
High-sensitivity C-reactive protein	0.012	0.002	0.026	0.012	-0.096	-0.028
level (>3mg/l)	(0.018)	(0.025)	(0.027)	(0.054)	(0.100)	(0.131)
Region and Time FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Individual characteristics	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	6,666	2,455	2,526	4,403	1,003	1,059

Note: Clustered standard errors by individual level in parentheses. ***p≺0.01;**p≺0.05;*p≺0.1. P-values adjusted for multiple hypothesis tests using the Bonferroni-Holm (Holm, 1979) method. Estimated average treatment effects on the treated (ATET) using an Inverse probability weighting regression adjustment estimator (Columns (1)-(3)), and kernel propensity score marching difference-in-difference (KPSM-DD) estimator for effects in short-term (Columns (4)-(6)) for mental and physical health outcomes by different subsamples.

Columns 4-6 of Table 2.8 include results from the KPSM-DD estimation on the impact of retirement on health following the Great Recession. Results show that retirement immediately after an economic shock appears to significantly decreases the likelihood of reporting poor self-assessed health. Also, retiring immediately after an economic shock decreases the risk of having difficulties with mobility by 13.8 pp among women who live in severely hit regions.

Finally, the validity of the main findings is explored by repeating the estimation of the baseline IPWRA and KPSM-DD models while excluding the self-employed from the control group. This is because the initial control group includes all individuals, employees and self-employed, who were still in the labour market. However, the literature appears to suggest (e.g., Parker and Rougier (2007); Zwier, Damman, and Van Den Heuvel (2020)) that the health effects of retirement might be systematically different for the self-employed, as they could potentially have more flexible working conditions and a higher degree of independence on their working schedule. In this case, results appear to be very similar across alternative definitions of control groups.[19]

2.6 Discussion and conclusions

This paper contributes to the literature on the effects of retirement on health by exploring the potential mechanisms driving this relationship and examining whether the health effects of retirement might be affected by economic shocks. Inverse probability weighting regression adjustment and a difference-in-differences approach combined with matching are used on rich longitudinal data from ELSA. The former specification is used to examine the mechanisms linking retirement to changes in both physical and mental health, while the latter exploits the Great Recession to identify short- versus long-term impacts of retirement on health after a severe economic shock. Understanding the different pathways linking economic shocks, retirement and health among older individuals is crucial for devising targeted policies to ensure the wellbeing of an increasingly larger proportion of the population and strengthen resilience of individuals most at risk from future, inevitable shocks.

The results suggest that, overall, retirement appears to impact negatively on mental and physical health. Specifically, we find that retirement increases the risk of depression, stroke, pulmonary and psychiatric diseases. This is broadly in line with previous relevant studies (e.g., Dave, Rashad, and Spasojevic (2006); Bamia, Trichopoulou, and Trichopoulos (2007); Behncke (2012)). In addition, results presented here might offer an insight into the potential mechanisms driving the health effects of retirement. According to the analysis, the key factors affecting the relationship between retirement and health are: age; gender; physical inactivity; low levels of education as well as broader socioeconomic and environmental conditions of the area where the individual lives (e.g., North/South of England; density levels; deprivation quintiles). Importantly, only a small fraction of these factors, such as physical inactivity, seems to be easily modifiable via post-retirement policies, whereas the remaining factors would be only affected by more fundamental policy changes concerning education, housing, and area level socioeconomic status. Hence, a potentially important policy implication could be that the negative health effects of retirement should be mostly addressed by structural policies implemented well before retirement.

Interestingly, when economic shocks are accounted for, the picture appears to change. We find that that retiring after the Great Recession improves mental health and decreases the probability of suffering from angina and heart attacks, with some differences by gender. These results confirm evidence reported by Belloni, Meschi, and Pasini (2016) on mental health and might provide support to the view that leaving the labour market shortly after an economic shock with rapidly deteriorating working conditions, could improve mental health by reducing work-related stress, at least in the short-term. In addition, we also find

[19] Results are available upon request.

that physical conditions concerning cardiovascular and heart diseases might improve. Since these conditions are strongly associated with chronic stress, this could also lend some further support to the hypothesis that leaving the labour market after an economic shock could improve health via reduced stress. This would be also in line with recent UK evidence suggesting a negative impact on mental health among women caused by the prolonged exposure to high strain jobs due to the raising of the State Pension age (Carrino, Glaser, and Avendano, 2020). This is of course also dependent on the ability to retire and further research on the longer-term impact on the labour market of losing those who retire earlier than planned, especially high skilled workers and those who can afford an early exit, might of be useful.

It should be noted that a potential limitation of the analysis of the mechanisms influencing the health effects of retirement is that regression adjustment inverse probability weighting relies on selection on observables. Yet, we employ rich data from ELSA, one of the most comprehensive longitudinal datasets currently available, to investigate the relationship between health and labour market status within a population of older individuals in England. In addition, the estimates are robust to large degrees of selection on unobservables as well as confirmed by a series of further robustness checks.

This is one of the first papers providing a systematic exploration of the mediating factors and mechanisms influencing the health effects of retirement by focusing on both mental and physical health. Building resilience into policies impacting upon vulnerable and at risk populations, as well as into the labour market itself, well in advance of increasing numbers of potentially severe shocks may pay health and economic dividends.

3 The Long-Term Health Effects of Parental Unemployment

While the effects of unemployment on the health of the unemployed is well-documented, its long-term spillover effects on the health of their relatives, especially children, remain poorly understood. This research focuses on the effects of parental unemployment spells experienced during early, mid and late childhood on the long-term children's mental and physical health. The analysis exploits data drawn from the British Household Panel Survey (BHPS) and the UK Household Longitudinal Study (UKHLS), linking detailed parental socioeconomic information with their children. This paper employs a Correlated Random Effects (CRE) probit model that allows accounting for unobserved heterogeneity as well as a non-linear Generalized Estimating Equations (GEE) random effects estimator accounting in addition for the dependency structure of the data. Results indicate that experiencing parental unemployment during early and late childhood has a negative effect on the children's likelihood of suffering from long-standing illnesses later in life, while experiencing parental unemployment during middle childhood affects the young adult's mental health negatively. Moreover, experiencing parental unemployment during late childhood increases the probability of both reporting poor or fair self-assessed health and the likelihood of consuming prescribed medicines in early adulthood. However, there seems to be a considerable effect heterogeneity by family socioeconomic status and parent's gender, whereas frequencies of parental unemployment spells appear to be a potential mechanism affecting overall results. These results may help policymakers shaping appropriate policy responses to mitigate the psychological and physical burden derived from parental unemployment, especially among already disadvantaged households.

Keywords: parental unemployment; early life conditions; long-term health effects
JEL Classification: *I10; I15; J11*

3.1 Introduction

In 2019 in the UK, around 27% of children live in households where at least one adult did not work, and 14% of children lived in households where all adults were unemployed.[1] Children are then likely to face parental unemployment during childhood, especially during periods of economic recessions.[2] An extensive body of research has focused on the negative health effects unemployment causes among the unemployed (Clark, Frijters, and Shields (2008); Bloemen, Hochguertel, and Zweerink (2018); Gathmann, Huttunen, et al. (2021)) due to the direct negative consequences job loss has on future employment and earnings (Couch and Placzek (2010); Hilger (2016)). Unemployed individuals are also more likely to suffer negative health effects, and experience an increased likelihood of divorce (Eliason and Storrie (2009); Eliason (2012)). Since these factors are likely to affect family environment, it is reasonable to expect that parental unemployment may have spillovers effects on other household members, including children (Henkel (2011); Doiron and Mendolia (2012)). Though a large literature has documented the long-run effects of parental unemployment on children's education and labour outcomes in adulthood (Oreopoulos, Stabile, et al. (2008); Page, Stevens, and Lindo (2009); Currie, Stabile, et al. (2010); Eliason (2012)), less is known about whether growing up in families exposed to spells of parental unemployment may have long-term effects on children's health.

The main objective of this paper is thus to explore the longer-term health effects of experiencing parental unemployment during different childhood stages (i.e., between 0–5, 6–10 and 11–15 years old). Given that parental unemployment causes changes in family income, parental time use, and the physical and mental wellbeing of the parents (Charles and Stephens (2004); Huttunen, Møen, and Salvanes (2011)), it is likely to alter household dynamics in which children grow up. Hence, understanding the role of parental unemployment in shaping child human capital and health is essential when considering the full societal cost of unemployment. Moreover, the severity of the recent economic shocks has generated renewed interest among researchers in the consequences of parental unemployment spells on the children of unemployed workers (Andrew, Cattan, et al., 2020).

Few articles have studied the effects of parental unemployment on children's health in the UK, presenting conflicting results. For instance, Ermisch, Francesconi, and Pevalin (2004) use a sample of young adults from the British Household Panel Survey (BHPS) to examine whether less education and work inactivity in early adulthood are associated with either a single-parent family or a family with jobless parents during childhood. Findings show that parental unemployment during childhood increases the likelihood of experiencing psychological distress later in life. In contrast, Powdthavee and Vernoit (2013) use the BHPS's youth sample and estimate whether adolescents' overall happiness is related to parental unemployment. The authors conclude that parental unemployment has null or even a positive influence on child overall happiness. While this previous literature identifies an effect of parental unemployment experienced as a child on health, underlying mechanisms influencing parental unemployment with longer-term health outcomes have been relatively under-studied (Ruiz-Valenzuela, 2021).

[1] Source from Annual population Survey household datasets.

[2] See Figure B.1 in Appendix B for the distribution (%) of children (aged 0-14) by the employment status of adults in the household, 1999-2015 in UK. By region, the North East of England records 20.3% of workless households, while the South East has 10.2% of workless households (OECD, 2020).

Detailed data from the BHPS and the UK Household Longitudinal Study (UKHLS) are used to examine the effects of experiencing parental unemployment during childhood on children future health. The paper employs a correlated random effects probit model estimated via a pooled maximum-likelihood estimator, and a non-linear generalized estimating equation (Wooldridge, 2019) to account for unobserved heterogeneity and the dependency structure of the data. The latter accounts in addition for higher-level structure of the data, such as family or region where a child lives during childhood. Findings show that experiencing parental unemployment during middle (6-10) and late (11-15) childhood increases the likelihood of reporting poor self-assessed health in adulthood. Moreover, results indicate that experiencing parental unemployment during early (0-5) and late childhood has a negative effect on the children likelihood of suffering from long-standing illnesses later in life, while experiencing parental unemployment during middle childhood may affect their mental health in long-run.

This paper also explores heterogenous effects by family socioeconomic status (family financial resources and highest parental education attainment) and (parents' and children's) gender. Results show that experiencing parental unemployment in less-educated families has larger adverse effects on child health later in life. Studying the effect of maternal and paternal unemployment spells separately shows that paternal unemployment is more strongly negatively associated to children future health than maternal unemployment. Further exploring possible mechanisms, findings indicate that those higher frequencies of parental unemployment spells appear to be more harmful, and its effects may last well into adulthood. It also appears that parental unemployment is more negatively associated when children grow older (25-33) rather than when they are young adults (18-24).

This study offers several contributions to the literature. First, this study provides a comprehensive analysis of the long-term consequences of parental unemployment on their children's physical and mental health. This paper aims to build on and complements earlier studies of the consequences of parental unemployment, typically focused on short-term health outcomes, by providing evidence on the relevance of childhood environment for long-term health. Second, it focuses on a broad set of childhood circumstances that matter for the children's human capital and health formation which the literature is very scarce. Therefore, this research contributes to the growing literature on how family environment matters in long-term health. In particular, exploring heterogeneity effects of parental unemployment during childhood along several dimensions (including socioeconomic groups of families). Finally, this paper analyses the potential mechanisms underlying effects of parental unemployment on children future health by, for instance, frequencies of parental unemployed spells and different timings during young adulthood when parental unemployment effects arise.

3.2 Previous literature

During the last decade, a large body of research has documented the critical role of childhood experiences (such as parental unemployment) have on shaping human development over the life cycle (Conti, Heckman, and Urzua, 2010), presenting mixed results. For instance, Kind and Haisken DeNew (2012), using data from the German Socio-Economic Panel (SOEP), find that father's unemployment experienced during childhood decreases life satisfaction among their (male) children grow older (17-25). Bubonya, Cobb-Clark, and Wooden

(2017) also find that parental unemployment worsens female children's mental health in Australia. By contrast, Mörk, Sjögren, and Svaleryd (2020) use rich Swedish administrative data and find no effects of parental job loss on childhood health, suggesting that welfare institutions successfully ensure low-income family disposable income.

Moreover, little is known on whether and how parental unemployment experienced at different stages of childhood may have longer-run health effects. Nikolova and Nikolaev (2021) employ data from the German SOEP and find that young adults who experienced parental unemployment during early and late childhood are more likely to report lower levels of life satisfaction. Also, previous studies have been limited in assessing heterogenous effects due to the lack of sufficient data across socioeconomic subgroups. As an exemption, Schaller and Zerpa (2019),[3] using survey data from the US, find that paternal job loss is harmful to children's health, particularly among those children in low-economic status families. In addition to that, this paper analyses whether the effect of parental unemployment is concentrated on disadvantaged households (measured in terms of income, education, or wealth), and it further assess whether already disadvantaged families suffer more.

Few papers have explored the long run effects of parental unemployment using data from the UK, and most previous evidence focuses on short-run effects (Joshi and Verropoulou, 2000). Ermisch, Francesconi, and Pevalin (2004), using a sample of British young adults with retrospective information on family characteristics, examine how parental joblessness during childhood affects a range of outcomes (such as educational attainment and economic inactivity) in the long-term. The authors find that experiencing parental unemployment is negatively associated with lower educational attainment and higher risk of non-labour activity as young adults. Powdthavee (2014) exploits the BHPS Youth Survey to examine how childhood experiences mediate the relationship between unemployment and life satisfaction for adults aged between 16-29 years. The author finds that father's unemployment during late childhood is related to a significant drop in life satisfaction later in life. Therefore, these previous articles appear to have either only used a small sample of children on their late childhood, or they have not explored the more longer-term health effects of parental unemployment on both mental and physical health outcomes. This paper aims to add to this previous literature exploiting variation in the time when parental unemployment occurs.

3.3 Mechanisms

3.3.1 Intra-household resource allocation and child health formation

This section discusses how parental unemployment may affect children's cognitive development and heath formation through parental changes in intra-household resource allocation. By introducing a health production function,[4] it shows that parents can undermine or enhance their children's health along different dimensions as consequences of an income shock that may persist well into adulthood.

[3] Schaller and Zerpa (2019)'s measures of child health are reported by parents (usually the mother), and as such changes in these measures may result from changes in the mother's own mental state rather than changes in the child's health.

[4] The proposed health production function and intra-household resources allocation is based on Rosenzweig and Schultz (1983); Currie (2009); Mörk, Sjögren, and Svaleryd (2014); Chiappori and Meghir (2014); and Yi, Heckman, et al. (2015) articles.

A simple production function for a child's health ($\theta_{i,\tau}$) is formed by (Yi, Heckman, et al., 2015): household consumption of market goods (h_{τ}); parental care, including parental time and human capital ($I_{i,\tau}$); publicly provided goods and care (e.g., preventive health care programs and health investments in schools); child previous health condition (e.g., prenatal endowment such as birthweight, $w^{H}_{i,\tau}$; or any health shock experienced during childhood, $e_{i,\tau}$); genetic endowment (e.g., gender and ethnicity, $\zeta_{i,\tau}$); and other cognitive and non-cognitive child skills, $w^{C}_{i,\tau}$. Hence, a health production function for a child i in family τ can be described as follows:

$$\theta_{i,\tau} = H(h_{\tau}, I_{i,\tau}, w^{H}_{i,\tau}, e_{i,\tau}, \zeta_{i,\tau}, w^{C}_{i,\tau})$$

Parents are assumed to value child outcomes, but they also care about their own consumption and leisure. Parental preferences are represented by the utility function:

$$U^{P} = U(c, l, q_{i})$$

where c is parental consumption, l is parental leisure time and q_i is the overall quality of life for child i. While all children have the same quality function, they may have different health status due to differences in initial endowments, early family shocks and parental investment in their human capital. The parents' budget constraint can be written as:

$$p_{I}(\textstyle\sum_{i} I_{i}) + c + wl = Y + w$$

where p_I is the price of human capital investment; wl and Y are parents' wage multiplied by time available and non-labour overall income, respectively. The price of parental consumption (c) is normalised to one. Thus, short-term impacts of parental unemployment on cognitive achievement and health outcomes may translate into longer-term effects (i.e., on the longer-term health outcomes). However, the impact of parental unemployment on longer-term health outcomes could be less clear, and it might mask important differences across subgroups of population. In this context, the need to test this empirically arises.

3.3.2 Previous evidence on the mechanisms underlying effects

Theoretically, the effect of parental unemployment on overall children's human capital accumulation and longer-term health outcomes can be either positive or negative. On one hand, parental unemployment can affect children's future psychological wellbeing, particularly through diminishing families' ability to invest in the resources needed to promote their achievements (e.g., high-quality education and physical exercise) (Kalil and Ziol-Guest, 2008). Moreover, parental unemployment could be associated with social stigma affecting social interaction (Schneider, Richard, et al., 2000), and ultimately increasing the risk of experiencing loneliness, anxiety, depression or self-blame (Rubin, Coplan, and Bowker, 2009). Parental unemployment can also be seen as a family "stressful" event potentially leading to a deterioration of parental (mental) health or an increase in the prevalence of parental risky behaviours, such as smoking (Gathmann, Huttunen, et al., 2021). Hence, parental unemployment may create a challenging family environment affecting children's cognitive and academic performance negatively (Oreopoulos, Stabile, et al. (2008); Pinger (2015)).

On the other hand, jobless parents could also potentially allocate more time to childcare tasks (Knabe, Rätzel, et al., 2010), and this might positively affect children's human capital development and health formation. For instance, unemployed parents may spend more time on childcare, which may increase the amount of health care received by the child (e.g., doctor visits). Additionally, children might spend less time in preschool or afterschool activities, reducing their exposure to illness or their chances of incurring injuries (Schaller and Zerpa, 2019) – although day-care plays an essential part in developing social skills and human capital. Moreover, children of unemployed parents may become more motivated to stay in school longer and do well to avoid their parents' misfortune. Finally, welfare institutions (such as the presence of unemployment insurance, the organization of schools, healthcare organizations, and so on) can successfully insure families against negative income shocks caused by parental unemployment (Mörk, Sjögren, and Svaleryd, 2020). However, welfare institutions might be less able to protect low-income families when parental unemployment occurs in multiple times. This paper further analyses whether experiencing different frequencies of parental unemployment spells during childhood may influence more negatively children health later in life.

Previous empirical studies also suggest that parental unemployment might have different effects depending on the family socioeconomic status (Schaller and Zerpa, 2019), as well as parental and child biological characteristics (Nikolova and Nikolaev, 2021). For instance, Forret, Sullivan, and Mainiero (2010) show that men with children tend to perceive periods of unemployment more negatively compared to women, while Bubonya, Cobb-Clark, and Wooden (2017) find that the negative effects of parental unemployment are concentrated among female adolescents. Nonetheless, little is known whether children from (disadvantaged) households with lower income or less educated parents are more affected by parental unemployment using data from UK.

3.4 Data

This paper combines data from fifteen waves of the BHPS (Taylor, Brice, et al., 1993) and one wave of the UKHLS (Fumagalli, Knies, and Buck, 2017). In particular, I collect self-reported information on children's individual and family circumstances during their entire childhood from the years between 1993 and 2008 in BHPS and match this information to one wave of UKHLS (2011-2013), obtaining their current health status at one point of their young adulthood.[5] The BHPS initially includes around 5,500 households and 10,300 individuals. Each adult member of the sampled households was interviewed. If they left the original household to form a new household, all adult members of this new household were also interviewed. The British Household Panel Survey ended in 2009 when participants were asked to join the UKHLS, obtaining a longitudinal survey following individuals over their entire childhood and young adulthood.

Several features make the BHPS and UKHLS suitable to this empirical analysis. First, thanks to the rich longitudinal information following parents and their children for about three decades, measures of parental and household characteristics over the entire childhood can be observed. Second, all children aged between 11-15 years in originally sampled households are interviewed first in the youth questionnaire and when they reach 16 years old, they also answer the main adult questionnaire (and they are eventually followed across all waves when/if they form a new household). This provides a wide range of health variables later in

[5] The decision of just including one period in the future rather than more than one is due to obtaining a sample of young people (between 18 and 33 years old) in a similar stage of their life. Including one wave more of the UKHLS will increase this age range to 45 years old, making it very difficult to compare them.

life and adolescents' characteristics. Finally, all information regarding their parents' socioeconomic situation comes from their own responses rather than from the children's retrospective responses and this may ease concerns around reporting errors. Similarly, longer-term measures of child health are reported by survey respondents (rather than mothers/fathers), and as such it captures changes in the child's actual health instead of changes in the mother's (mental) state.

To estimate the long-term health effects of parental unemployment, mothers and fathers are first linked using the partner identifier in the BHPS. Each child is matched to their biological or adoptive/stepparents, interviewed in at least one wave, using the purposely built mother and father identifiers. Mothers and fathers can be cohabiting or married but they need to be living in the same household. Then, parents' responses about family and work histories are used to determine the measures of parental unemployment and childhood characteristics. This ensures a sample of young adults that fulfil the following conditions: (i) they are born between 1978 and 1993; (ii) they do not have any serious long-standing disability at 16 years of age and onwards; (iii) they are living with their biological, adoptive or stepparents during their childhood (from 0 to 15); and (iv) they have paternal and maternal labour market information over the childhood period (i.e., both parents are present in the data). Parental ages range between 18 and 62 for mothers and 18 to 65 for fathers to capture the working-age population.[6]

The first condition ensures a relatively homogenous group of young adults, who went through a relatively similar educational system, and allows for a sufficiently large number of birth cohorts. The second condition removes those parents whose labour market status depends on children's health. The third condition ensures that information on the parents (e.g., age, education, health behaviours, labour market status) and family circumstances can be observed during childhood. The last condition allows full information on both the father's and mother's employment status (reported by themselves) that are in working-age during entire childhood. Parental unemployment at a given age (between birth and 15 years) is defined as either parent not being in paid work for at least 1 month (following Ermisch, Francesconi, and Pevalin (2004)).[7] Hence, when both mothers and fathers have paid work (or mothers are continuously out of the workforce due to family care) are considered as employed parents (and these include also employees and self-employment). Mothers out of the workforce due to family care reasons are considered as employed (following Nikolova and Nikolaev (2021)).[8] Being out of the labour force might affects children quite differently than parental employment, and therefore, inactive women are excluded from the analyses as a robustness check (Nikolova and Nikolaev, 2021). Three separate parental unemployment groups are defined, depending on when (i.e., the specific period) the children experience parental unemployment during their childhood, i.e., between 0–5, 6–10 and 11–15 years old. Note that

[6] During the years when the parental information is collected, the statutory pension age for women was 62 years old and 65 for men.

[7] One could potentially use the *"Employment History"* files in the BHPS to construct the parental unemployment variable using the *"reason for stopping previous job"* information. However, this variable has around 40% of missing observations across BHPS waves, and it would dramatically drop the number of observations in the analysis.

[8] Mothers out of the labour force to care for a sick child or mothers staying at home taking care of (healthy) children can be considered as an employee (Nikolova and Nikolaev, 2021). In the UK, carers can get £67.60 a week if they care for someone at least 35 hours a week and they get certain benefits. Moreover, mothers can get time off for family and dependants care (spouse, partner, child, grandchild or someone who depends on you for care) and still get paid. Doing this also helps to ending up with more observations, although the incidence of maternal unemployment considerable decreases.

either parent can experience unemployment in these groups. This results in an unbalanced panel of 15,656 observations (1,675 children) in total.[9]

Importantly, condition three excludes from the analysis those households with single parents. Yet, results obtained from the analysis can be considered a downward estimated coefficient of those estimates from single parents' analysis.

3.4.1 Health outcomes and key covariates

The primary health outcome variables are self-reported mental and physical health, as well as the number of prescribed medicines reported in young adulthood. For physical health, a dichotomic self-assessed health variable is used. This variable takes value 1 whether the respondent reports poor health status, and 0 whether the respondent reports excellent, very good or good general health. For mental health, the General Health Questionnaire (GHQ-12) is a well-established, psychometrically validated and widely used screening tool for the detection of psychiatric disorders (psychiatric morbidity) in the general population (Goldberg, 1988). The GHQ-12 questionnaire includes 12 questions aimed at detecting symptoms of anxiety, depression or insomnia.[10] The GHQ score is then used with a cut-off of 4 and higher to create a binary variable coded as 1 reflecting a clinically significant level of distress (psychiatric morbidity; (Imo, 2017)), and 0 otherwise.

Moreover, a long-standing illness or disability variable is included in the analysis.[11] This variable takes value 1 whether the respondent reports to have any long-standing physical or mental impairment, illness or disability that troubles them for at least 12 months, and 0 otherwise. Therefore, this variable can be considered either psychological or physical, and it is important to take it as an outcome as a more specific measure of general health. Finally, the number of prescribed medicines is taken (coded as 1 if the individual consumed 1 or more prescribed medicines and 0 otherwise) as an outcome variable. This variable includes any type of prescribed medicines, and the information is collected during a nurse health assessment, and therefore, it might be less prone to measurement errors.[12]

A range of children, parental and household characteristics are included in the analyses. These include the following variables: age and age squared of children when they become adult; educational attainment of children when they become adult; children's migration background; mother's and father's education as well as parental age when child was born. Additional variables such as household monthly income; number of siblings; household size; and frequencies of parental unemployment spells during respective childhood ages are used. Control variables for annual regional unemployment rates during childhood; year of birth dummies (which capture commonly shared experiences such as economic shocks and

[9] 1,675 children with information on both their mother's and father's occupational status observed at least in one BHPS' wave and complete details of their young adult health in wave 3 of UKHLS.

[10] This measure converts valid answers to 12 questions into a single scale measure by recoding 1 and 2 values on individual variables to 0, and 3 and 4 values to 1, and then summing, giving a scale running from 0 (the least distressed) to 12 (the most distressed).

[11] This is based on the following question: *"Do you have any long-standing physical or mental impairment, illness or disability? By 'long-standing' I mean anything that has troubled you over a period of at least 12 months or that is likely to trouble you over a period of at least 12 months"*.

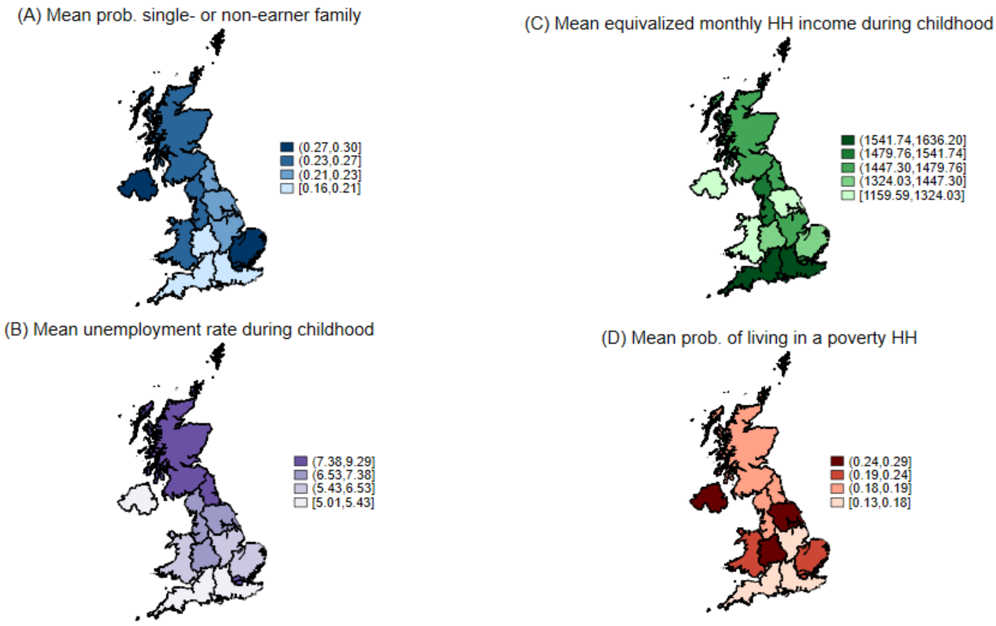
[12] Generally, the nurse coded prescription medications while the respondent was resting before the blood pressure readings. The nurse asked, *"Are you taking any other medicines, pills, ointments or injections prescribed for you by a doctor?"*. The nurse was instructed to ask to see the containers for the medicines.

technological progress), as well as dummies identifying region of residence during childhood are also used. In the robustness checks, further controls on mother's and father's smoking behaviour during childhood, and parental and children personality traits are included.[13] Finally, to avoid bias from dropping observation due to missing data, for all the control variables included in the analyses that have missing information, an additional missing data indicator is used helping to preserve the number of observations.[14]

3.4.2 Descriptive statistics

Figures 3.1-3.3, jointly with Tables B.1-B.3 in Appendix B, show descriptive statistics of all variables employed in the analysis. Figure 3.1 illustrates the mean distribution of some household socioeconomic characteristics experienced during childhood by region (Government Office Regions, GOR). Figures 3.2-3.3 show the, on average, probability of reporting poor self-reported general health; suffering mental ill-health; and having long-standing illness across different parental occupational status and childhood stages (Figure 3.2) and children ages when they become adults (Figure 3.3).

FIGURE 3.1: Mean of household socioeconomic characteristics experienced during childhood by region (GOR)



Notes: Panel (A) shows the mean probability of living in a single- or non-earner family during childhood by regions; Panel (B) shows the mean of unemployment rate experienced during childhood by regions; Panel (C) shows the mean of the regional equivalised monthly household during childhood; Panel (D) mean of the probability of living in a household which income is under the poverty threshold. GOR= Government Office Regions; HH= household; childhood compress the following years 1993-2008; own maps based on drawn and combined data from BHPS and UKHLS.

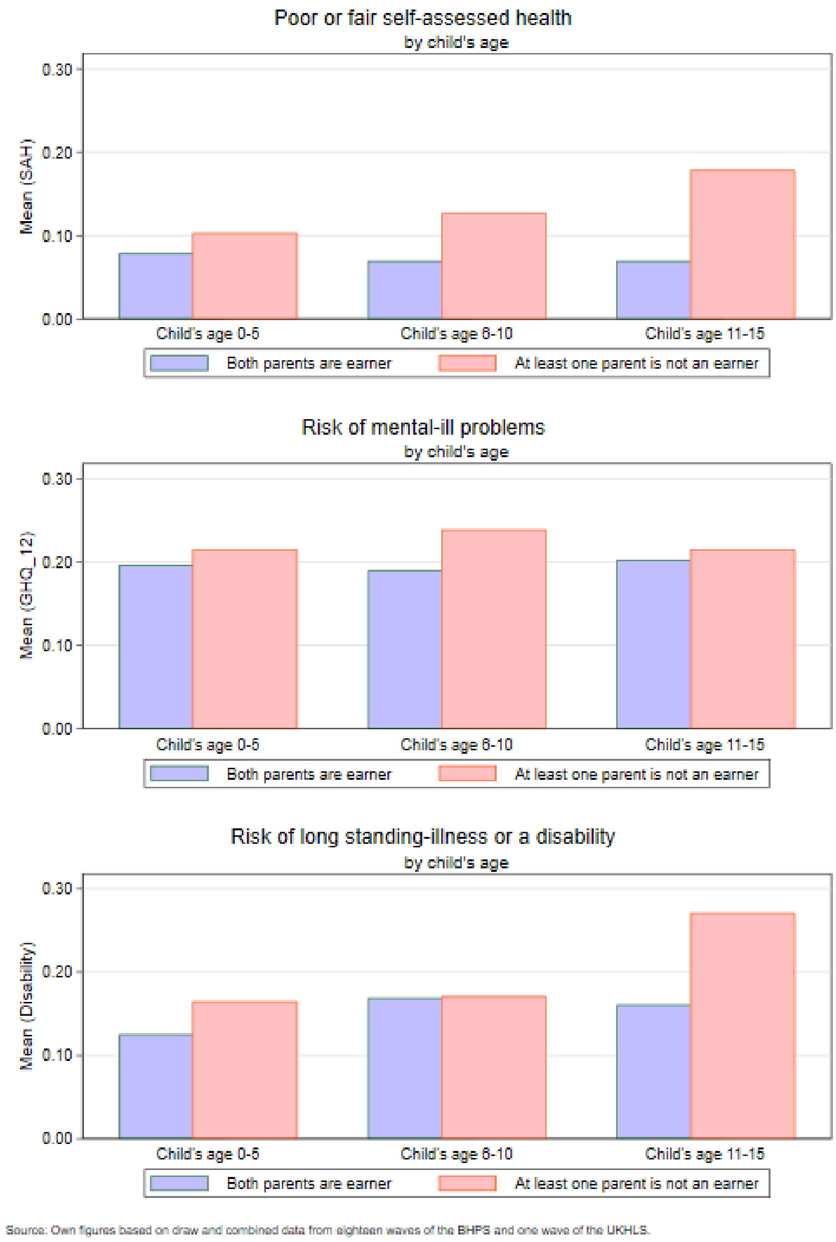
Figure 3.1 displays some disparities by regions with respect to experiencing worse household income levels and unemployment rates during childhood. In particular, on average,

[13] Parental "*Big-5*" personality traits are collected during BHPS wave 15 (2005) and children "*Big-5*" personality traits are collected during wave 3 (2011-2013).

[14] Specifically, this category has been included just in the following control variables: adult child's migration background (856 observations – 5.47%); adult child's highest education achieved (139 obs. – 0.89%); and father's and mother's highest education achieved (397 (2.54%) and 161 (1.03%) missing observations, respectively).

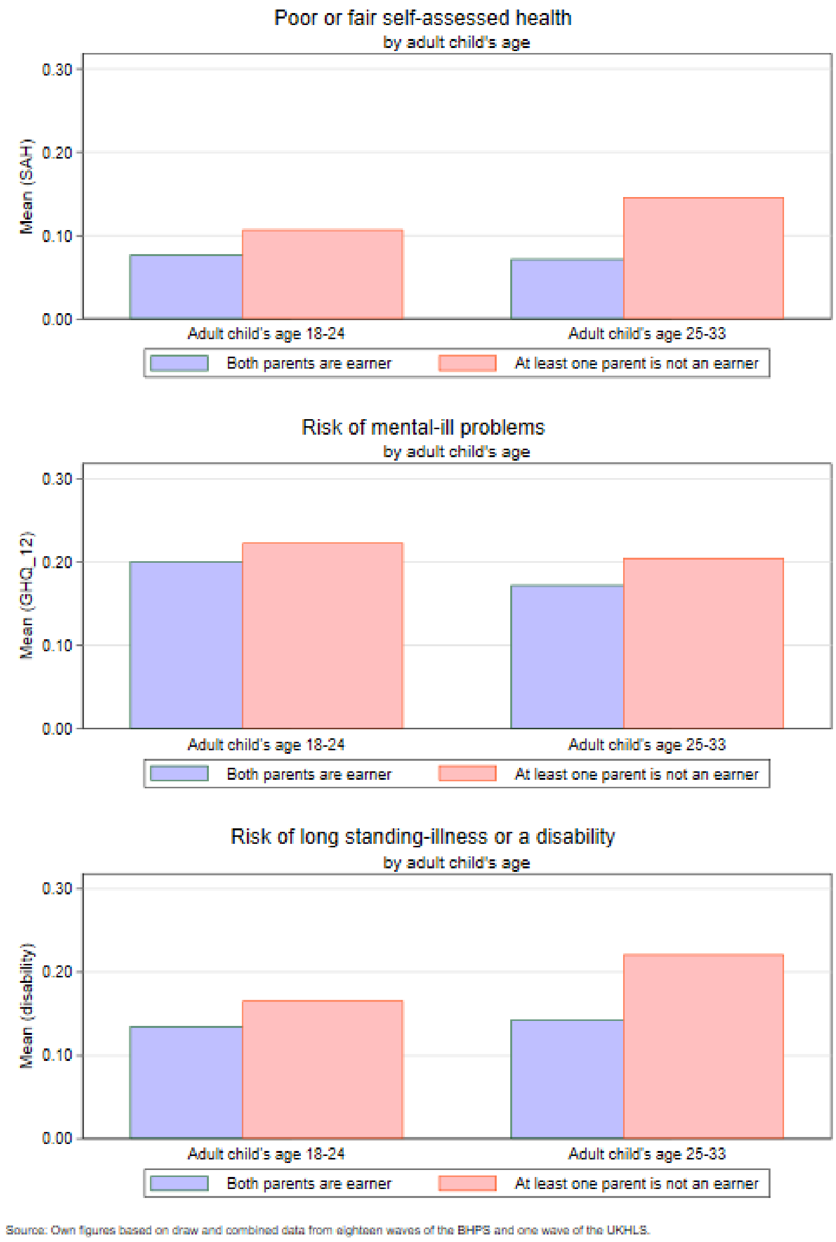
children living in London and northern regions of England, Scotland and North Ireland, have higher chances of living in a single- or non-earner family, with a lower household income, to experience higher regional level of unemployment, and to live in households below the poverty threshold during their childhood. In Figures 3.2, one can see that the average for reporting poor health status and having long-standing illness varies considerably across different childhood stages, and this gap is largest for the oldest children in the sample (aged 11-15). This might suggest that experiencing parental unemployment in late childhood lowers overall general health status or leads to higher risk of suffering from disabilities for children when they become adults. In contrast, the risk of a worse mental ill-health is largest among those adults who had experienced parental unemployment at ages 6-10 years old. Figure 3.3 shows the association between parental unemployment and different timings of long-term health effects. In Figure 3.3, one can see that the average gap between experiencing parental unemployment and having both parents employed during childhood for the following health outcomes: level of general health, risk of suffering mental ill-problems, and long-standing disabilities is largest among adults at ages 25-33. This may suggest that the effects of parental unemployment might become apparent once individuals are older (i.e., between 25-33).

FIGURE 3.2: Average young adult's risk of mental-ill problems and long-standing illness across different childhood parental employment status and child's ages



Source: Figure created using drawn and combined data from eighteen waves of the BHPS and one wave of the UKHLS.

FIGURE 3.3: Average young adult's risk of mental-ill problems and long-standing illness across different childhood parental employment status and young adult's ages



Source: Figure created using drawn and combined data from eighteen waves of the BHPS and one wave of the UKHLS.

Tables B.1-B.3 in Appendix B show differences in socioeconomic characteristics between children whose both parents are employed versus those with at least one unemployed parent during early (0-5 years), mid- (6-10 years) and late- (11-15 years) childhood. For instance, experiencing parental unemployment at any stages of their childhood leads to lower levels of educational attainment later in life compared to those individuals whose parents were employed during childhood. There appear to be further differences especially around household and regional characteristics. For instance, individuals who experience parental unemployment during childhood report lower monthly household income and more people living in their household compared to their counterparts.

3.5 Empirical Strategy

In order to model the time-invariant nature of most of the variables used in the analysis, a Correlated Random Effects (CRE) probit is specified, which is estimated by a pooled maximum-likelihood estimator (Wooldridge, 2019). This allows the possibility of specifying correlated random effects in the absence of a panel data estimation, such a fixed effects (within-child) estimator. Therefore, CRE appears appropriate as it not only allows modelling the binary nature of the dependent variables, but also accounts for individual-level time-invariant unobserved heterogeneity.

Specifically, it is assumed that the binary outcome variables are linked to the latent health status y^*_{ij} of respondent i of a family j, such that $y_{ij} = 1[y^*_{ij} > 0]$. The latent variable specification with unobserved heterogeneity is:

$$y^*_{ij} = \phi U^P_{ij} + \gamma X^{C,F,R}_{ij} + \alpha_i + u_{ij} \tag{3.1}$$

with $i = 1, \ldots, N$ and $j = 1, \ldots, J$. U^P_{ij} is a binary indicator for parental unemployment (at ages 0-5, 6-10, 11-15), which takes the value 1 if at least one of the parents did not have a paid job during the previous week, and 0 otherwise (i.e., both mother and father have paid occupations). X_{ij} is a vector including children (C), family (F) and regional (R) covariates, including father's and mother's socio-demographic characteristics, as explained above. Equation (1) also includes normally distributed time-constant individual (children) effects accounting for unobserved heterogeneity (α_i) and an idiosyncratic error term (u_{ij}). Both α_i and u_{ij} are assumed not to be correlated with the independent variables nor with each other.

Given that parental unemployment occurred in childhood, while all outcome variables are measured in adulthood, reverse causality might not be a concern in this case. Indeed, the main identification issue is that the effect of parental unemployment on wellbeing later in life may be biased due to unobservable or unmeasurable factors (i.e., the unobserved heterogeneity (α_i) error term is correlated with parental unemployment). Therefore, to enhance the specification of unobserved heterogeneity α_i for a panel dataset, a specification strategy suggested by Wooldridge (2019) is used. The key assumptions are that all covariates are strictly exogenous conditional on α_i and selection bias does not arise. The CRE approach allows correlations between X_{it} and α_i via the average over the sample period of all time-varying explanatory variables ($\bar{X}_i$). This is effectively equivalent to the approach proposed by Mundlak's (1978) where the individual effect is specified as:

$$\alpha_i = \varphi + \xi \bar{X}_i + c_i \tag{3.2}$$

where c_i is purely random error term with $c_i | \bar{X}_i \approx N(0, \sigma^2_c)$. A pooled Maximum Likelihood Estimation (MLE) is implemented to obtain average partial effects (APEs), which impose no restriction on the serial correlation of the idiosyncratic error. Plugging Equation (2) into Equation (1) leads to a CRE model. If the conditional distribution of α_i is correctly specified, unobserved heterogeneity is captured by time averages and random elements, and all parameters can be consistently estimated:

$$y^*_{ij} = \phi U^P_{it} + \gamma X^{C,F,R}_{it} + \xi \bar{X}_i + c_i + u_i \tag{3.3}$$

Standard errors are clustered at individual level for more precise inference. To test for selection bias, Equation (3) has been estimated separately, including a selection indicator (s_{it}) that specifies the missing data for all the variables across time and individual (i.e., observing a data point in any time period cannot be systematically related to the idiosyncratic errors, u_{ij}). If these parameter estimates ($\hat{s_{it}}$) are not statistically significant, this would mean that selection bias does not occur in the main specification.

Pooled MLE of CRE probit restricts ($D(c_i|X_i)$) but does not impose any assumption on the dependency structure of the data. However, one can argue that the long-term health effects of parental unemployment on children can be clustered within further groups (e.g., families, regions), and ignoring the dependence structure of the data might have the potential to affect the estimates. Generalized estimating equations (GEE) random effects estimators (Liang and Zeger, 1986) are multivariate least squares estimators that are capable of accounting for serial correlation,[15] and thus, to potentially obtain more efficient estimates.[16] A non-linear GEE is estimated by a quasi-maximum likelihood estimation (QMLE) framework, and it is supposed to produce more efficient conditional mean parameters via a covariance matrix accounting for the dependency structure of the data (i.e., accounting for higher-levels structure of the data). Parameter estimates from GEE are consistent even when the variance and covariance structure is misspecified under mild regularity conditions.[17] A non-linear GEE with the probit response function that includes the time-averages of all time-varying explanatory variables ($\bar{X}_l$) is thus employed.

In practice, a non-linear GEE estimator is obtained by a two-step procedure, where the first step is to estimate the working correlation matrix of each group (g) using a partial QMLE, and the second-step specifies the following GEE estimator.

Precisely, the first-step estimation is the pooled Bernoulli quasi-MLE (QMLE), which is obtained by maximizing the pooled Probit log-likelihood. The log likelihood function for each observation is:

$$l_i(\beta) = y_i log\Phi(x_i\beta) + (1 - y_i)log[(1 - \Phi(x_g\beta)] \tag{3.4}$$

Let $\bar{u_i} = y_g - \Phi(x_g\beta)), i = 1, 2, \ldots, n$ be the residuals from the partial QMLE estimation.

The second-step GEE estimator for β is as follows:

$$\hat{\beta}_{GEE} = argmin_B \sum_g (y_g - \Phi(x_g\beta))^T \hat{W}_g^{-1}(y_g - \Phi(x_g\beta)) \tag{3.5}$$

where $y_g - \Phi(x_g\beta)$ is the residuals from the partial QMLE estimation produced in the firs-step and $\hat{W}_g$ is the specified correlation structure. Importantly, $\hat{\beta}_{GEE}$ follows a normal distribution and is consistent even for a misspecified data correlation structure ($\hat{W}_g$).[18] Combined

[15] Ignoring dependence in the estimation of parameters will result in wrong inferences if the variances are calculated in the way that independence is assumed.

[16] Mixed effect models or hierarchical models (Raudenbush and Bryk, 2002) are another way to handle for this. Estimates of this approach are available upon request.

[17] Mild regularity conditions are, for instance, the second or third derivative of the density function exist and is continuous, or derivative pass under integral sign, and information is positive.

[18] The following *Stata* command has been used *xtgee* with *fam(binomial)*, *link(probit)* and *corr(independent)* to estimate the GEE random effects estimators.

cross-sectional adult interview weight is used in all the regression, and robust standard errors are provided.

3.6 Results

3.6.1 Physical and mental health effects

Tables 3.1-3.3 present the average partial effects (APE) obtained from the CRE probit models estimated by pooled MLE and the non-linear GEE random effects estimators. In separate models, physical and mental health variables, as well as consumption of prescribed medicines at ages 18-33 are regressed on parental unemployment spells experienced at different stages during childhood (i.e., when the child was between 0-5, 6-10, 11-15 years old). Column (1) and (3) refer to the APE for Equation (3), and column (2) and (4) refer to the APE for Equation (5). All models control for confounders such as growing up during periods of economic recessions, and characteristics of the families, parents, and children. Models whose estimates are reported in columns (3) and (4) further include family monthly income during childhood, the completed child's educational attainment, and several other household and regional characteristics such as household size, number of siblings and regional unemployment rates. The coefficient estimates reported in columns (3) and (4) are obtained using the preferred specification from Equation (3) and Equation (5), which include the additional set of covariates.

TABLE 3.1: Estimates of the long-run effect of parental unemployment on self-assessed health status (SAH)

Average partial effects		Self-assessed health status (SAH)			
Parental unemployment	N	(1) CRE probit estimated by MLE	(2) GEE random effects	(3) CRE probit estimated by MLE with additional covariates	(4) GEE random effects with additional covariates
Child's age 0-5	7,797	0.034 (0.026)	0.032 (0.025)	0.020 (0.014)	0.020 (0.014)
Child's age 6-10	3,241	0.055*** (0.020)	0.058** (0.022)	0.032** (0.015)	0.044** (0.017)
Child's age 11-15	2,880	0.065*** (0.019)	0.065*** (0.021)	0.035** (0.017)	0.039** (0.018)
Exogenous control variables		*Yes*	*Yes*	*Yes*	*Yes*
Socio-economic control variables		*Yes*	*Yes*	*Yes*	*Yes*
Additional control variables		*No*	*No*	*Yes*	*Yes*

Note: CRE= Correlated random effects; GEE= Generalized estimating equation. Robust standard errors in parentheses, clustered at the child's level. The table shows the coefficient estimates of three different regressions whereby the focal independent variables are parental unemployment at the respective child's ages. The focal independent variables are coded as 1 if either parent is not in a paid work and 0 if both parents are in a paid work during respective ages. The dependent variable is a binary variable that takes 1 whether the individual reports fair or poor self-assessed health status and 0 otherwise. Models from columns 1 and 2 include controls for the annual cumulative regional unemployment rate at the respective ages, year of birth, adult child age, gender, child's migration background, the region of birth, mother's and father's education, mother's and father's age at which the child is born, survey year and region of residence. Models from columns 3 and 4 include addition controls for household income at the respective childhood ages, the adult's child education attainment, household size at the respective childhood ages, the number of siblings during respective childhood ages, the size of home during respective childhood ages, and the number of parental unemployment spells during the respective childhood ages. ***p≺0.01;**p≺0.05;*p≺0.1.

Table 3.1 shows the results for the effect of experiencing parental unemployment during childhood on reporting poor/fair general health status later in life. Specifically, experiencing parental unemployment at ages 6-10 and 11-15 increases on average the likelihood of reporting poorest levels of general health by around 3.2-4.4 and 3.5-3.9 percentage points, respectively, compared to parental employment experienced at these ages. The estimated ranges depend on whether the correlation structure of the data is accounting for (i.e., estimates reported are from columns (3) and (4) using Equation (3) and Equation (5) that include the additional set of covariates). As a possible explanation for the negative consequences associated with experiencing parental unemployment at middle and late childhood is that these children might be more aware of the consequences that unemployment might have on the family's income. If so, they might feel more pressured to take responsibilities (Arbeit, 2013). Similar findings are reported by Ermisch, Francesconi, and Pevalin (2004) and Nikolova and Nikolaev (2021), suggesting that parental unemployment at older childhood ages is negatively associated with overall wellbeing later in life.

TABLE 3.2: Estimates of the long-run effect of parental unemployment on self-reported mental health

Average partial effects		GHQ-12: General Health Questionnaire-12			
Parental unemployment	N	(1) CRE probit estimated by MLE	(2) GEE random effects	(3) CRE probit estimated by MLE with additional covariates	(4) GEE random effects with additional covariates
Child's age 0-5	7,140	0.015 (0.025)	0.016 (0.026)	0.013 (0.023)	0.016 (0.024)
Child's age 6-10	3,600	0.059** (0.024)	0.049** (0.020)	0.083*** (0.026)	0.074*** (0.025)
Child's age 11-15	2,448	-0.003 (0.031)	-0.022 (0.033)	-0.001 (0.023)	-0.024 (0.031)
Exogenous control variables		*Yes*	*Yes*	*Yes*	*Yes*
Socio-economic control variables		*Yes*	*Yes*	*Yes*	*Yes*
Additional control variables		*No*	*No*	*Yes*	*Yes*

Note: CRE= Correlated random effects; GEE= Generalized estimating equation. Robust standard errors in parentheses, clustered at the child's level. The table shows the coefficient estimates of three different regressions whereby the focal independent variables are parental unemployment at the respective child's ages. The focal independent variables are coded as 1 if either parent is not in a paid work and 0 if both parents are in a paid work during respective ages. The dependent variable is the GQH-12 index with a cut-off of 4 and higher reflecting psychiatric morbidity (binary). Models from columns 1 and 2 include controls for the annual cumulative regional unemployment rate at the respective ages, year of birth, adult child age, gender, child's migration background, the region of birth, mother's and father's education, mother's and father's age at which the child is born, survey year and region of residence. Models from columns 3 and 4 include addition controls for household income at the respective childhood ages, the adult's child education attainment, household size at the respective childhood ages, the number of siblings during respective childhood ages, the size of home during respective childhood ages, and the number of parental unemployment spells during the respective childhood ages. ***p≺0.01;**p≺0.05;*p≺0.1.

The results from Table 3.2 demonstrate that parental unemployment during middle childhood (6-10) may increase the on average risk of suffering mental ill-health later in life by around 7.6-6.8 percentage points. However, the estimates at ages 0-5 and 11-15 are not statistically significant. One might consider that children aged 6-10 are older enough to start developing abstract thinking (i.e., the ability to think about hypothetical situations), which can make them more aware of social stigma associated with parental unemployment (Gauvain and Cole, 2005). Importantly, these findings are in line with those from Schaller and Zerpa (2019) showing that paternal unemployment experienced at ages 6-12 (primary and middle school) increases the likelihood of reporting bad mental health outcomes later in life.

Nonetheless, further analyses on the potential channels through which parental unemployment experienced at ages 6-10 may affect adult mental ill-health are presented in Section 3.6.3.

TABLE 3.3: Estimates of the long-run effect of parental unemployment on self-reported physical health

Average partial effects		Long-standing illness or disability			
Parental unemployment	N	(1) CRE probit estimated by MLE	(2) GEE random effects	(3) CRE probit estimated by MLE with additional covariates	(4) GEE random effects with additional covariates
Child's age 0-5	8,143	0.059*** (0.018)	0.052*** (0.018)	0.044** (0.018)	0.039** (0.017)
Child's age 6-10	4,187	0.052 (0.084)	0.051 (0.083)	0.010 (0.023)	0.010 (0.024)
Child's age 11-15	2,941	0.083*** (0.027)	0.083*** (0.030)	0.080*** (0.027)	0.080*** (0.029)
Exogenous control variables		*Yes*	*Yes*	*Yes*	*Yes*
Socio-economic control variables		*Yes*	*Yes*	*Yes*	*Yes*
Additional control variables		*No*	*No*	*Yes*	*Yes*

Notes: CRE= Correlated random effects; GEE= Generalized estimating equation. Robust standard errors in parentheses, clustered at the child's level. The table shows the coefficient estimates of three different regressions whereby the focal independent variables are parental unemployment at the respective child's ages. The focal independent variables are coded as 1 if either parent is not in a paid work and 0 if both parents are in a paid work during respective ages. The dependent variable is coded as 1 if the adult child reports to have a long-standing illness or disability and 0 otherwise. Models from columns 1 and 2 include controls for the annual cumulative regional unemployment rate at the respective ages, year of birth, adult child age, gender, child's migration background, the region of birth, mother's and father's education, mother's and father's age at which the child is born, survey year and region of residence. Models from columns 3 and 4 include addition controls for household income at the respective childhood ages, the adult's child education attainment, household size at the respective childhood ages, the number of siblings during respective childhood ages, the size of home during respective childhood ages, and the number of parental unemployment spells during the respective childhood ages. ***p≺0.01;**p≺0.05;*p≺0.1.

Table 3.3 reports that parental unemployment during early and late childhood negatively affects adult physical health. Yet, experiencing parental unemployment during middle childhood (6-10) does not seem to have long-term physical health effects. Specifically, parental unemployment experienced at ages 0-5 increases the likelihood of suffering from long-standing illnesses or disability by around 3.9-4.4 percentage points. Similarly, parental unemployment experienced at ages 11-15 may have long-term effects the likelihood of suffering from long-standing illnesses by around 8 percentage points. Possible explanation for the negative consequences of parental unemployment experienced at an early age (0-5) could be that stressful events at an early stage in life might provoke long-term (psychological) trauma via on overall human capital accumulation (Nikolova and Nikolaev, 2021). The magnitudes of these estimates present evidence consistent with this perspective as the negative effects of parental unemployment on the risk of suffering from long-illness or disabilities later in life appear to be larger for those who were 11-15 than those who were 0-5 when the parental unemployment spell occurs.

TABLE 3.4: Estimates of the long-run effect of parental unemployment on consumption of prescribed medicines

Average partial effects		Prescribed medicines			
Parental unemployment	N	(1) CRE probit estimated by MLE	(2) GEE random effects	(3) CRE probit estimated by MLE with additional covariates	(4) GEE random effects with additional covariates
Child's age 0-5	2,791	0.009 (0.034)	0.009 (0.036)	0.011 (0.030)	0.010 (0.033)
Child's age 6-10	1,481	-0.008 (0.027)	-0.009 (0.046)	-0.011 (0.025)	-0.010 (0.035)
Child's age 11-15	1,383	0.109*** (0.041)	0.109** (0.044)	0.049*** (0.019)	0.048*** (0.021)
Exogenous control variables		*Yes*	*Yes*	*Yes*	*Yes*
Socio-economic control variables		*Yes*	*Yes*	*Yes*	*Yes*
Additional control variables		*No*	*No*	*Yes*	*Yes*

Notes: CRE= Correlated random effects; GEE= Generalized estimating equation. Robust standard errors in parentheses, clustered at the child's level. The table shows the coefficient estimates of three different regressions whereby the focal independent variables are parental unemployment at the respective child's ages. The focal independent variables are coded as 1 if either parent is not in a paid work and 0 if both parents are in a paid work during respective ages. The dependent variable is coded as 1 if the adult child reports to consume 1 or more than 1 prescribed medicine, and 0 otherwise. Models from columns 1 and 2 include controls for the annual cumulative regional unemployment rate at the respective ages, year of birth, adult child age, gender, child's migration background, the region of birth, mother's and father's education, mother's and father's age at which the child is born, survey year and region of residence. Models from columns 3 and 4 include addition controls for household income at the respective childhood ages, the adult's child education attainment, household size at the respective childhood ages, the number of siblings during respective childhood ages, the size of home during respective childhood ages, and the number of parental unemployment spells during the respective childhood ages. ***p≺0.01;**p≺0.05;*p≺0.1.

Table 3.4 illustrates the APE for the consumption of prescribed medicines. Results from Table 3.4 suggest that parental unemployment experienced in late childhood (11-15 ages) increases the likelihood of consumption of prescribed medicines by around 4.8-4.9 percentage points later in life. Prescribed medicines can be considered as a more objective health measure since one would take them only if a health condition is diagnosed by a medical doctor. However, it should be acknowledged that these diagnosed conditions might have little to do with that specific shock earlier in life, and thus, one needs to interpret this result with caution.

3.6.2 Heterogeneous effects

It is possible that the effects of parental unemployment identified previously are masking important heterogeneity in the treatment effects along several dimensions.[19] Before proceeding, it should be noted that the heterogeneity analysis is conducted by interacting parental unemployment across childhood stages separately with a set of family, parents, and children characteristics.[20]

First, Table 3.5 expands the baseline analyses to explore if the effects reported previously depend on whether the mother or the father (or both) is the unemployed parent. Results show that experiencing paternal unemployment has negative effects on reported physical

[19] Note that effects of heterogeneity for prescribed medicines are not reported due to lack data.

[20] Additionally, multiple hypothesis testing is performed on all regressions. This is because as the number of hypothesis testes increases, the proportion of type I errors (false positives) may increase as well. Thus, an adjustment for multiple comparisons using a conservative approach based on Bonferroni-Holm (Holm, 1979) is performed. Then, the p-values generated by individual hypothesis are compared with adjusted critical p-values.

and mental health. In particular, paternal unemployment spells experienced at ages 6-10 increases the likelihood that adult's self-reported health status is poor by around 5 percentage points. Importantly, comparing to those estimates from those experiencing both maternal and paternal unemployment at the same time, the magnitudes of the estimates are substantially larger. This effect is significant even after the multiple hypothesis testing (MHT) is performed. By contrast, maternal unemployment is no associated with worse longer-term mental and physical health effects. The differential effects between mother's and father's unemployment reported in Table 3.5 are perhaps not surprising considering the existing literature. Several studies have found that paternal unemployment is associated with detrimental health outcomes for children (Schaller and Zerpa, 2019), whereas results studying the effects of maternal unemployment on child health outcomes are mixed (Brand and Simon Thomas (2014); Bubonya, Cobb-Clark, and Wooden (2017)).

TABLE 3.5: Long-term health effects of parental unemployment during childhood by parent's gender

Average partial effects		Self-assessed health (SAH)		GHQ-12		Long-standing illness or disability	
By parents' gender	N	CRE probit estimated by MLE	GEE random effects	CRE probit estimated by MLE	GEE random effects	CRE probit estimated by MLE	GEE random effects
Father's unemployment but mother still in a paid work							
Child's age 0-5	6,924	0.030	0.030	0.007	0.008	-0.033	-0.032
		(0.020)	(0.020)	(0.033)	(0.032)	(0.024)	(0.025)
Child's age 6-10	3,367	0.051**	0.050**	0.041**	0.040***	-0.002	-0.002
		(0.022)	(0.024)	(0.015)	(0.066)	(0.027)	(0.029)
Child's age 11-15	2,169	0.036	0.036	0.018	0.017	0.122***	0.121***
		(0.027)	(0.030)	(0.045)	(0.048)	(0.036)	(0.041)
Mother's unemployment but father still in a paid work							
Child's age 0-5	6,924	-0.007	-0.006	0.012	0.011	0.022	0.022
		(0.014)	(0.016)	(0.029)	(0.031)	(0.022)	(0.023)
Child's age 6-10	3,367	0.036	0.026	0.097	0.096	0.030	0.030
		(0.024)	(0.025)	(0.087)	(0.088)	(0.026)	(0.027)
Child's age 11-15	2,169	0.003	0.002	-0.070*	-0.070*	0.013	0.012
		(0.022)	(0.016)	(0.037)	(0.041)	(0.030)	(0.031)
Both parents unemployed							
Child's age 0-5	6,924	0.047*	0.046*	0.090	0.089	0.103***	0.102***
		(0.027)	(0.026)	(0.059)	(0.061)	(0.032)	(0.033)
Child's age 6-10	3,367	0.027	0.027	0.122**	0.121**	0.005	0.004
		(0.031)	(0.038)	(0.053)	(0.060)	(0.051)	(0.058)
Child's age 11-15	2,169	0.055**	0.054**	0.058	0.057	0.077	0.076
		(0.018)	(0.019)	(0.057)	(0.059)	(0.056)	(0.058)
Exogenous control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Socio-economic control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Additional control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Note: CRE= Correlated random effects; GEE= Generalized estimating equation. Robust standard errors in parentheses, clustered at the child's level. The focal independent variables are interaction terms between whether the mother, the father or both are unemployed and child's ages. The depend health variables are reporting poor self-assessed health; suffering from mental ill-health; and risk of reporting one or more than one long-standing illnesses or disabilities. All models include controls for the annual cumulative regional unemployment rate at the respective ages, year of birth, adult child age, gender, child's migration background, the region of birth, mother's and father's education, mother's and father's age at which the child is born, survey year and region of residence. Additional controls for household income at the respective childhood ages, the adult's child education attainment, household size at the respective childhood ages, the number of siblings during respective childhood ages, the size of home during respective childhood ages, and the number of parental unemployment spells during the respective childhood ages. ***p≺0.01;**p≺0.05;*p≺0.1.

Second, Tables 3.6-3.7 test whether family socioeconomic status (SES) could partly compensate for the effect of parental unemployment on children future health. This aims to shed light on whether suffering parental unemployment in already disadvantaged household may exacerbate their lack of opportunities across the first stages in life (Oreopoulos, Stabile, et al. (2008); Page, Stevens, and Lindo (2009)). Tables 3.6-3.7 show results on the long-term health effects of parental unemployment may differ depending on the family's socioeconomic status, measured in terms of household overall income and highest parental educational status.[21] Findings from Table 3.6 suggest that experiencing parental unemployment

[21] Family earnings is defined using the net household income across a childhood, cross-sectional weight is used to produce population estimate of the median equivalised net household income based

in less-educated families has larger negative effects on children future mental and physical health. By contrast, experiencing parental unemployment in higher-educated families does not lead to worse self-assessed general health or higher risk of disabilities later in life, and they may even experience a reduction in the likelihood of suffering mental health problems later in life when parental unemployment occurs at ages 11-15.

TABLE 3.6: Long-term health effects of parental unemployment during childhood on by family's socioeconomic status (family education attainment)

Average partial effects		Self-assessed health (SAH)		GHQ-12		Long-standing illness or disability	
By family education	N	CRE probit estimated by MLE	GEE random effects	CRE probit estimated by MLE	GEE random effects	CRE probit estimated by MLE	GEE random effects
Highest-educated parent has attended college							
Child's age 0-5	8,174	0.015 (0.023)	0.014 (0.024)	0.035 (0.038)	0.034 (0.039)	0.015 (0.027)	0.015 (0.027)
Child's age 6-10	3,708	0.004 (0.025)	0.004 (0.024)	0.008 (0.036)	0.008 (0.037)	-0.003 (0.034)	-0.003 (0.037)
Child's age 11-15	2,848	0.033 (0.023)	0.033 (0.025)	-0.171*** (0.046)	-0.171*** (0.052)	0.028 (0.048)	0.027 (0.052)
Highest-educated parent has NOT attended college							
Child's age 0-5	8,174	0.023 (0.018)	0.022 (0.018)	0.006 (0.029)	0.006 (0.030)	0.047** (0.022)	0.047** (0.021)
Child's age 6-10	3,708	0.059** (0.020)	0.058** (0.022)	0.094*** (0.033)	0.094*** (0.036)	0.016 (0.027)	0.015 (0.026)
Child's age 11-15	2,848	0.024 (0.024)	0.024 (0.027)	0.024 (0.035)	0.023 (0.036)	0.097*** (0.033)	0.097*** (0.033)
Exogenous control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Socio-economic control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Additional control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Notes: CRE= Correlated random effects; GEE= Generalized estimating equation. Robust standard errors in parentheses, clustered at the child's level. The focal independent variables are interaction terms between whether the mother, the father or both are unemployed and child's ages. The dependent health variables are reporting poor or fair self-assessed health; suffering from mental ill-health; and risk of reporting one or more than one long-standing illnesses or disabilities. All models include controls for the annual cumulative regional unemployment rate at the respective ages, year of birth, adult child age, gender, child's migration background, the region of birth, mother's and father's education, mother's and father's age at which the child is born, survey year and region of residence. Additional controls for household income at the respective childhood ages, the adult's child education attainment, household size at the respective childhood ages, the number of siblings during respective childhood ages, the size of home during respective childhood ages, and the number of parental unemployment spells during the respective childhood ages. ***$p \prec 0.01$;**$p \prec 0.05$;*$p \prec 0.1$.

Similar results are reporting using overall household income as a proxy for family socioeconomic status (see Table 3.7). In particular, experiencing parental unemployment in families with an equivalised net annual income below 60 percent of the median household income (i.e., below poverty line) leads to a larger increase in the likelihood of reporting poor general health by 4.9-5.4 percentage points later in life. One possible explanation is that low-SES

on sample data. Then, a poverty variable that takes values 1 if the children live in a family whose equivalised net household income lies below 60% median household income, and 0 otherwise. Parent's education attainment is defined as the highest education achievement among both parents. A college-educated family takes values 1 for the children whose highest-educated parents has attended college, and 0 otherwise.

families have less resources to cope with the adversity associated with parental unemployment, and this might have a longer-term health effect on children. These findings are in line with previous literature showing that the long-run effects of parental unemployment tend to be concentrated among low-income families (Schaller and Zerpa, 2019). For instance, Page, Stevens, and Lindo (2009) find that worse effects of parental unemployment on children's labour market, education and health are concentrated at the bottom of the SES distribution.

TABLE 3.7: Long-term health effects of parental unemployment during childhood on by family's socioeconomic status (family earnings)

Average partial effects		Self-assessed health (SAH)		GHQ-12		Long-standing illness or disability	
By family earnings	N	CRE probit estimated by MLE	GEE random effects	CRE probit estimated by MLE	GEE random effects	CRE probit estimated by MLE	GEE random effects
Above poverty threshold							
Child's age 0-5	8,174	0.004 (0.014)	0.008 (0.015)	-0.003 (0.024)	-0.003 (0.025)	0.031 (0.031)	0.031 (0.031)
Child's age 6-10	3,708	0.023 (0.015)	0.023 (0.015)	0.068 (0.067)	0.068 (0.066)	-0.002 (0.021)	-0.002 (0.021)
Child's age 11-15	2,848	0.019 (0.021)	0.019 (0.021)	-0.039 (0.027)	-0.038 (0.029)	0.035 (0.034)	0.034 (0.035)
Below poverty threshold							
Child's age 0-5	8,174	0.032 (0.023)	0.032 (0.023)	0.039 (0.038)	0.038 (0.039)	0.031* (0.020)	0.031* (0.021)
Child's age 6-10	3,708	0.065*** (0.023)	0.064** (0.026)	0.054 (0.039)	0.053 (0.041)	0.033 (0.036)	0.033 (0.039)
Child's age 11-15	2,848	0.028 (0.029)	0.027 (0.030)	0.029 (0.054)	0.028 (0.057)	0.061** (0.027)	0.061** (0.030)
Exogenous control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Socio-economic control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Additional control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Note: CRE= Correlated random effects; GEE= Generalized estimating equation. Robust standard errors in parentheses, clustered at the child's level. The focal independent variables are interaction terms between families equivalised net household income is below the 60% of the median household income (below poverty) and child's ages parental unemployment is experienced. The dependent health variables are reporting poor or fair self-assessed health; suffering from mental ill-health; and risk of reporting one or more than one long-standing illnesses or disabilities. All models include controls for the annual cumulative regional unemployment rate at the respective ages, year of birth, adult child age, gender, child's migration background, the region of birth, mother's and father's education, mother's and father's age at which the child is born, survey year and region of residence. Additional controls for household income at the respective childhood ages, the adult's child education attainment, household size at the respective childhood ages, the number of siblings during respective childhood ages, the size of home during respective childhood ages, and the number of parental unemployment spells during the respective childhood ages. ***p≺0.01;**p≺0.05;*p≺0.1.

Finally, Table 3.8 explores whether boys or girls are deferentially affected by parental unemployment. Results suggest that parental unemployment at ages 0-5 and 11-15 increases the likelihood of suffering disabilities and lower levels of general health particularly among men. No statistically significant associations are found among women for their physical and general health outcomes. An explanation of these findings can be that boys, especially at an early age, tend to show lower levels of inhibition/control and regulatory abilities if compared to girls (Chang, Olson, et al., 2011). A further notable result that emerges from Table 3.8 is that parental unemployment experienced at ages 10-15 could also have negative consequences on the long-term mental health of women. However, this result is not statistically significant.

TABLE 3.8: Long-term health effects of parental unemployment during childhood by child's gender

Average partial effects		Self-assessed health (SAH)		GHQ-12		Long-standing illness or disability	
By child´s gender	N	CRE probit estimated by MLE	GEE random effects	CRE probit estimated by MLE	GEE random effects	CRE probit estimated by MLE	GEE random effects
Female							
Child's age 0-5	8,174	0.032 (0.020)	0.032 (0.021)	0.044 (0.033)	0.044 (0.037)	-0.002 (0.027)	-0.002 (0.028)
Child's age 6-10	3,708	-0.018 (0.025)	-0.017 (0.028)	0.011 (0.030)	0.011 (0.030)	-0.022 (0.028)	-0.022 (0.029)
Child's age 11-15	2,848	-0.036 (0.029)	-0.035 (0.033)	-0.008 (0.041)	-0.008 (0.044)	0.068* (0.038)	0.067* (0.039)
Male							
Child's age 0-5	8,174	0.002 (0.021)	0.002 (0.022)	0.004 (0.032)	0.003 (0.035)	0.064** (0.025)	0.065*** (0.026)
Child's age 6-10	3,708	0.086*** (0.023)	0.086*** (0.024)	0.141*** (0.039)	0.141*** (0.041)	0.042 (0.035)	0.041 (0.037)
Child's age 11-15	2,848	0.088*** (0.026)	0.088*** (0.028)	-0.044 (0.044)	-0.044 (0.045)	0.079** (0.040)	0.079* (0.045)
Exogenous control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Socio-economic control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Additional control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Note: Correlated random effects; GEE= Generalized estimating equation. Robust standard errors in parentheses, clustered at the child's level. The focal independent variables are interaction terms between child's gender and child's ages parental unemployment is experienced. The dependent health variables are reporting poor or fair self-assessed health; suffering from mental ill-health; and risk of reporting one or more than one long-standing illnesses or disabilities. All models include controls for the annual cumulative regional unemployment rate at the respective ages, year of birth, adult child age, gender, child's migration background, the region of birth, mother's and father's education, mother's and father's age at which the child is born, survey year and region of residence. Additional controls for household income at the respective childhood ages, the adult's child education attainment, household size at the respective childhood ages, the number of siblings during respective childhood ages, the size of home during respective childhood ages, and the number of parental unemployment spells during the respective childhood ages. ***p≺0.01;**p≺0.05;*p≺0.1.

3.6.3 Potential mechanisms underlying effects

This section tests empirically to what extent the mechanisms discussed above account for the findings. Specifically, results based on different I) frequencies of parental unemployment spells, and II) timings when the long-term effects arise are presented.

First, as previously noted, in columns (3)-(4) from Tables 3.1-3.3, additional covariates related to household characteristics are included (e.g., monthly family income during childhood stages, the children education attainment when they become adult, household size and number of siblings). Results show that when including these further set of covariates, both magnitudes and level of statistical significance tend to reduce. This suggests that household characteristics (such as, monthly family income, household size and number of siblings) appear to be one possible mechanism through which parental unemployment affects long-term physical and mental health.

Second, Table 3.9 tests whether experiencing higher frequencies of parental unemployment spells during childhood leads to larger negative long-term health effects. Results show that experiencing at least three parental unemployment spells during childhood leads to larger negative effects on adult's physical and mental health. By contrast, Table 3.9 suggests positive effects of experiencing parental unemployment at ages 6-10 on adult's mental health when this occurs less or equal than two times. These findings might suggest positive long-term health effects of lower frequencies of parental unemployment spells, which may indirectly imply that parents might have more time for childcare tasks (Mooi-Reci, Bakker, et al., 2019).

TABLE 3.9: Long-term health effects of parental unemployment during childhood by number of parental unemployment spells

Average partial effects		Self-assessed health (SAH)		GHQ-12		Long-standing illness or disability	
By frequencies of unemployment spells	N	CRE probit estimated by MLE	GEE random effects	CRE probit estimated by MLE	GEE random effects	CRE probit estimated by MLE	GEE random effects
Number of parental unemployment spells higher than 2							
Child's age 0-5	8,174	0.031* (0.018)	0.031* (0.018)	0.030 (0.031)	0.031 (0.032)	0.059*** (0.023)	0.059*** (0.019)
Child's age 6-10	3,708	0.059*** (0.020)	0.058*** (0.022)	0.099*** (0.033)	0.099*** (0.035)	0.002 (0.029)	0.001 (0.031)
Child's age 11-15	2,848	0.048** (0.023)	0.048* (0.026)	-0.024 (0.040)	-0.024 (0.041)	0.100*** (0.035)	0.100** (0.039)
Number of parental unemployment spells less or equal than 2							
Child's age 0-5	8,174	-0.020 (0.016)	-0.020 (0.017)	-0.028 (0.021)	-0.027 (0.021)	-0.032* (0.017)	-0.032* (0.018)
Child's age 6-10	3,708	-0.023 (0.026)	-0.022 (0.028)	-0.028 (0.028)	-0.028 (0.031)	-0.030 (0.024)	-0.030 (0.026)
Child's age 11-15	2,848	-0.036 (0.026)	-0.036 (0.031)	-0.014 (0.032)	-0.014 (0.034)	-0.003 (0.029)	-0.002 (0.031)
Exogenous control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Socio-economic control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Additional control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Note: CRE= Correlated random effects; GEE= Generalized estimating equation. Robust standard errors in parentheses, clustered at the child's level. The focal independent variables are interaction terms between frequencies of parental unemployment spells (equal or higher than 2) and child's ages parental unemployment is experienced. The dependent health variables are reporting poor or fair self-assessed health; suffering from mental ill-health; and risk of reporting one or more than one long-standing illnesses or disabilities. All models include controls for the annual cumulative regional unemployment rate at the respective ages, year of birth, adult child age, gender, child's migration background, the region of birth, mother's and father's education, mother's and father's age at which the child is born, survey year and region of residence. Additional controls for household income at the respective childhood ages, the adult's child education attainment, household size at the respective childhood ages, the number of siblings during respective childhood ages, the size of home during respective childhood ages, and the number of parental unemployment spells during the respective childhood ages. ***p≺0.01;**p≺0.05;*p≺0.1.

Finally, further examination on different timings concerning when long-term health effects are likely to occur is performed. In particular, the analysis here focuses on the long-term health effects of experiencing parental unemployment during childhood on different adulthood stages, such as "young adults" (ages 18–24) and "emerging adults" (ages 25–33). This follows previous literature considering different young adulthood stages (Arnett, 2011).[22] Findings in Table 3.10 show that the effects of experiencing parental unemployment during childhood manifests itself more clearly when children grow older (25-33) rather than when they are still "young adults". Therefore, baseline results may seem to be driven by "emerging adults" aged 25–33. As a possible explanation, one may think that societal (or even own) expectations for success develop with age, awakening childhood experiences (Nikolova and Nikolaev, 2021).

[22] Prolonged transition to adulthood experienced in developed countries requires different development stages across young adulthood ages.

TABLE 3.10: Long-term health effects of parental unemployment during childhood by adult child's age

Average partial effects		Self-assessed health (SAH)		GHQ-12		Long-standing illness or disability	
By adult child's age	N	CRE probit estimated by MLE	GEE random effects	CRE probit estimated by MLE	GEE random effects	CRE probit estimated by MLE	GEE random effects
Ages 18-24 (Young adults)							
Child's age 0-5	8,174	0.021 (0.014)	0.020 (0.014)	0.017 (0.023)	0.016 (0.024)	0.034 (0.024)	0.034 (0.026)
Child's age 6-10	3,708	0.027 (0.018)	0.027 (0.020)	0.059 (0.055)	0.059 (0.058)	-0.039 (0.046)	-0.039 (0.049)
Child's age 11-15	2,848	0.024 (0.034)	0.024 (0.035)	0.054 (0.052)	0.054 (0.053)	0.014 (0.013)	0.014 (0.015)
Ages 25 and older (Emerging adults)							
Child's age 0-5	8,174	0.018 (0.018)	0.017 (0.017)	0.026 (0.024)	0.026 (0.025)	0.039** (0.018)	0.039** (0.018)
Child's age 6-10	3,708	0.083** (0.036)	0.083** (0.037)	0.075** (0.028)	0.075** (0.029)	0.027 (0.025)	0.027 (0.026)
Child's age 11-15	2,848	0.027 (0.019)	0.028 (0.022)	-0.024 (0.029)	-0.024 (0.031)	0.081** (0.027)	0.080** (0.029)
Exogenous control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Socio-economic control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Additional control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Note: CRE= Correlated random effects; GEE= Generalized estimating equation. Robust standard errors in parentheses, clustered at the child's level. The focal independent variables are interaction terms between adult child's ages (young adults (18-24) or emerging adults (25-33) and child's ages parental unemployment is experienced. The dependent health variables are reporting poor or fair self-assessed health; suffering from mental ill-health; and risk of reporting one or more than one long-standing illnesses or disabilities. All models include controls for the annual cumulative regional unemployment rate at the respective ages, year of birth, adult child age, gender, child's migration background, the region of birth, mother's and father's education, mother's and father's age at which the child is born, survey year and region of residence. Additional controls for household income at the respective childhood ages, the adult's child education attainment, household size at the respective childhood ages, the number of siblings during respective childhood ages, the size of home during respective childhood ages, and the number of parental unemployment spells during the respective childhood ages. ***p≺0.01;**p≺0.05;*p≺0.1.

3.7 Robustness checks and limitations

This section checks both directly and indirectly the robustness of this paper's identification strategy. The direct check consists of estimating Equation (3) and Equation (5) using a slightly different definition of parental unemployment. In the baseline specification, mothers out of the workforce due to family care reasons are considering as employed. Nonetheless, one can argue that mothers out of the labour force might affect children quite differently than mothers actively looking for a job. Therefore, a new treatment variable is defined excluding from the sample those mothers who consider their labour force status as a family carer.[23] Results from Table 3.11 row (1) are very similar to those results from the baseline definition of parental unemployment and for the sake of maintaining high numbers of observations, family carer's mothers are included in the analysis.

[23] 3,809 (24.34%) observations are dropped from these mothers that their current labour force status is *"family care"*.

As a second check, control variables for maternal and paternal smoking behaviour are added.[24] In particular, dummy variables taking value one whether the individual is a current smoker (and 0 otherwise) for both mothers and fathers during the children's childhood are created.[25] Here, the goal is to indirectly test whether parental unhealthy behaviour during childhood might negatively influence long-term health for children. Results in Table 3.11 row (2) are very similar to those reported in Tables 3.1-3.3, suggesting that parental smoking behaviour during childhood may not be associated with negative long-term health effects.

Third, a test for the sensitivity of the findings by controlling for the *"Big-5"* parental personality traits is performed. There is general agreement among psychologists that five broad traits dimensions can describe the range of possible personalities (Wiggins, 1996). In particular, control variables for mothers' and fathers' personality traits of *extraversion*, *agreeableness*, *conscientiousness*, *neuroticism*, and *openness to experience* reported during childhood are included.[26] Note that these questions are only asked during wave 15 (year 2005) of the BHPS, and thus, parental personality traits are assumed to remain constant across childhood stages (Schofield, Conger, et al., 2012). Estimates from Table 3.11 row (3), which include the *"Big-5"* parental personality traits, do not deviate from the main baseline results.

Similarly, control variables for the child's own *"Big-5"* personality traits when they grow up in addition to the paternal personality traits are also included in the baseline regressions. Nonetheless, the results should be viewed with caution as it is unclear whether the child's personality traits when they become adult are themselves affected by parental unemployment, meaning the results would be biased due to selection. The sample sizes using children and parental *"Big-5"* personality traits checks reported in Table 3.11 are reduced due to missing information on these variables. As one can see, findings from Table 3.11 row (4) are very similar to those obtained using the main specification. As final checks, results from the selection bias test suggest that missing values does not influences the estimates. Finally, a multiple hypothesis testing correction (Bonferroni correction) test is performed in all the regressions to check whether statistically significant results are false positive due to the fact of performing multiple hypotheses, confirming these findings.

[24] Parental alcohol consumption is not included as control variable due to lack of enough information on mother's and father's alcohol consumption.

[25] A missing category is included in these smoking control variables, which represents the 7.67% (1,201) of the total observations for maternal smoker variable and the 10.79% (1,689) of the total observations for paternal smoker variable.

[26] Extraversion refers to individual differences in sociability, gregariousness, level of activity, and the experience of positive affect. Agreeableness refers to individual differences in altruistic behaviour, trust, warmth, and kindness. Conscientiousness refers to individual differences in self-control, task-orientation, and rule-abiding. Neuroticism refers to individual differences in the susceptibility to distress and the experience of negative emotions such as anxiety, anger, and depression. Finally, openness to experience refers to individual differences in the propensity for originality, creativity, and the acceptance of new ideas.

TABLE 3.11: Robustness checks

Average partial effects		Self-assessed health (SAH)		GHQ-12		Long-standing illness or disability		Prescribed medicines	
Robustness checks	N	CRE probit estimated by MLE	GEE random effects	CRE probit estimated by MLE	GEE random effects	CRE probit estimated by MLE	GEE random effects	CRE probit estimated by MLE	GEE random effects
Exclude mothers who report that their current labour status is family care									
Child's age 0-5	6,019	0.020	0.020	0.025	0.025	0.050**	0.050**	0.003	0.004
		(0.013)	(0.014)	(0.025)	(0.026)	(0.018)	(0.019)	(0.026)	(0.031)
Child's age 6-10	2,929	0.030**	0.030**	0.101***	0.101***	0.009	0.009	-0.041	-0.044
		(0.014)	(0.013)	(0.024)	(0.026)	(0.023)	(0.024)	(0.031)	(0.033)
Child's age 11-15	2,305	0.026**	0.025**	-0.049	-0.049	0.051**	0.051*	0.033**	0.034**
		(0.011)	(0.011)	(0.033)	(0.035)	(0.025)	(0.028)	(0.017)	(0.016)
Control for parental unhealthy behaviours (smoking)									
Child's age 0-5	7,669	0.019	0.019	0.018	0.018	0.043**	0.042**	0.006	0.007
		(0.014)	(0.014)	(0.023)	(0.023)	(0.018)	(0.018)	(0.028)	(0.032)
Child's age 6-10	3,708	0.043***	0.043**	0.073***	0.073***	0.008	0.007	-0.017	-0.016
		(0.015)	(0.0187	(0.024)	(0.026)	(0.023)	(0.022)	(0.015)	(0.017)
Child's age 11-15	2,848	0.033*	0.033*	-0.022	-0.021	0.037**	0.038*	0.079***	0.078**
		(0.018)	(0.019)	(0.029)	(0.021)	(0.025)	(0.027)	(0.024)	(0.035)
Control for parental personality traits ("*Big-5*")									
Child's age 0-5	6,920	0.031**	0.031**	0.017	0.017	0.045**	0.045**	0.005	0.005
		(0.013)	(0.014)	(0.024)	(0.025)	(0.020)	(0.021)	(0.041)	(0.043)
Child's age 6-10	3,221	0.050***	0.050***	0.082***	0.082***	0.013	0.012	-0.022	-0.021
		(0.014)	(0.015)	(0.024)	(0.025)	(0.023)	(0.025)	(0.023)	(0.025)
Child's age 11-15	2,317	0.038**	0.035*	-0.052	-0.052	0.069**	0.069**	0.041**	0.040**
		(0.014)	(0.019)	(0.033)	(0.038)	(0.027)	(0.031)	(0.015)	(0.014)
Control for parental and adult child's personality traits ("*Big-5*")									
Child's age 0-5	7,016	0.021	0.021	0.026	0.025	0.053***	0.053***	0.005	0.006
		(0.015)	(0.016)	(0.023)	(0.025)	(0.019)	(0.020)	(0.026)	(0.028)
Child's age 6-10	3,301	0.045**	0.045**	0.068***	0.068***	0.018	0.019	-0.014	-0.015
		(0.017)	(0.019)	(0.019)	(0.020)	(0.022)	(0.021)	(0.011)	(0.013)
Child's age 11-15	2,408	0.011	0.010	-0.032	-0.032	0.058**	0.058**	0.074***	0.073**
		(0.018)	(0.021)	(0.027)	(0.031)	(0.026)	(0.029)	(0.030)	(0.031)
Exogenous control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Socio-economic control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Additional control variables		*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Note: CRE= Correlated random effects; GEE= Generalized estimating equation. Robust standard errors in parentheses, clustered at the child's level. The dependent health variables are reporting poor or fair self-assessed health; suffering from mental ill-health; and risk of reporting one or more than one long-standing illnesses or disabilities; and consuming one or more prescribed medicines. All models include controls for the annual cumulative regional unemployment rate at the respective ages, year of birth, adult child age, gender, child's migration background, the region of birth, mother's and father's education, mother's and father's age at which the child is born, survey year and region of residence. Additional controls for household income at the respective childhood ages, the adult's child education attainment, household size at the respective childhood ages, the number of siblings during respective childhood ages, the size of home during respective childhood ages, and the number of parental unemployment spells during the respective childhood ages. The sample sizes are different for prescribed medicines regressions ***p≺0.01;**p≺0.05;*p≺0.1.

This paper also has a few shortcomings. This analysis relies on econometric specifications accounting for unobserved heterogeneity, selection bias and the possible dependency structure of the data while controlling for a wide range of confounding factors. Several studies have tried to overcome the endogeneity of parental unemployment by comparing children whose parents suffered involuntary unemployment coming from factory closures with children whose parents continued to be employed in stable factories. However, neither the BHPS nor UKHLS datasets contain relievable information on unemployment status due to business closures or dismissals. Still, the estimates reported in this paper are in line with the previous literature using different definitions of parental unemployment based on business closings and dismissals.[27] This paper opts to rely on different methodology by controlling for time-invariant unobserved characteristics using Mundlak's (individual fixed effects) approach. Also, an important challenge with subjective health outcomes, in general, is how to interpret the relative nature of subjective responses. For instance, categorical variables such as self-assessed health status transformed into dichotomous variables might be a source of bias.[28] Finally, future research using accumulative household income and duration of parental unemployment as possible mechanisms underlying long-term health effects of parental unemployment constitute an important question.

3.8 Discussion and conclusions

This paper examines the long-term health effects of parental unemployment experienced during childhood. More specifically, this research explores whether experiencing parental unemployment during childhood may affect individual's physical and mental health later on in life, as well as the potential mechanisms underlying such effects. This study finds that experiencing parental unemployment during specific stages of childhood may negatively affect health later on in life, although this may vary depending on family socioeconomic status and the gender of the parent who was unemployed.

Using linked data from two UK panel household surveys, findings show that experiencing parental unemployment during early (0-5) and late (11-15) childhood increases the likelihood of reporting long-standing illnesses in early adulthood (18-33). These results support findings of previous studies, including Ermisch, Francesconi, and Pevalin (2004) showing that parental unemployment experienced at an early age would lead to lower educational attainment, economic inactivity, and unhealthy behaviours later on in life. One potential explanation is that such early shocks in children's lives may lead to further subsequent disruptions in the social and family environment with potentially long-lasting effects (Nikolova and Nikolaev, 2021). In addition, experiencing parental unemployment between 11-15 years old may lead to a deterioration of their health status as children may feel more pressure to take responsibility at home after their parents become unemployed (Arbeit, 2013).

[27] The *"Employment History"* survey contains this information, but with a considerable amount of missing data. Nevertheless, this paper's scope is to analyse the effect of living in a household where either the mother or the father (or both) is non-earners during childhood on children health later in life.

[28] This paper addresses this testing for different definitions of "poorest" self-assessed health, reporting no differentials overall results.

Results also reveals that experiencing parental unemployment during middle childhood (6-10) increases the probability of suffering mental ill-health later in life. This result corroborates evidence from Schaller and Zerpa (2019), finding that paternal unemployment experienced at ages 6-12 (primary and middle school) increases the likelihood of reporting worse mental health during young adulthood. Moreover, results suggest that parental unemployment experienced in late childhood (11-15) increases the likelihood of consuming prescribed medicines during young adulthood.

Findings from the heterogeneity analyses clearly indicate that the effects of parental unemployment on their children's health depend on the socioeconomic status of the family of origin (as measured by families' income and parental education attainment). For instance, among families whose parents are less educated experiencing parental unemployment is associated with larger adverse effects on child mental and physical health later in life. These findings are in line with those reported by Oreopoulos, Stabile, et al. (2008) and Page, Stevens, and Lindo (2009), suggesting that the strongest effects of parental unemployment on children's labour market and educational outcomes in adulthood are found at the bottom of the income distribution. This may reflect the fact that the consequences of the income loss induced by parental unemployment are more severe among already disadvantaged families (Huttunen, Møen, and Salvanes, 2011).

This paper also shows differential results based on the gender of the parent who became unemployed during the main respondent's childhood. Specifically, paternal unemployment is associated with detrimental long-term health outcomes, maternal unemployment does not appear to be correlated with long-term changes in children's physical or mental health. A potential explanation is that the income losses induced by paternal unemployment might be larger (as shown in Pieters and Rawlings (2020)). Alternatively, mothers may see unemployment as an opportunity to invest time in their children's development, suggesting a potential role for social norms and traditional gender roles (Rege, Telle, and Votruba, 2011). Different results are also found by child gender based biological differences. In particular, findings suggest that parental unemployment at ages 0-5 and 11-15 increases the likelihood of suffering from disabilities and worse general health levels among adult men. This perhaps suggests that gender based biological characteristics may lead to differences in inhibitory control or regulatory abilities by gender (Chang, Olson, et al., 2011).

Further exploration of potential mechanisms shows that multiple spells of parental unemployment are strongly associated with worse long-term health outcomes for children, and their effects may last longer into adulthood. It also appears that negative effects of experiencing parental unemployment during childhood manifest themselves when children grow older (25-33) rather than when they are "young adults" (18-24). This may be because societal expectations for success may arise in older ages, awakening childhood experiences (Nikolova and Nikolaev, 2021). Nonetheless, these results need to be interpreted with caution since the limited number of respondents used in the analysis may lack its power.

This study may have some potential limitations. The analysis proposed here relies on econometric specifications accounting for unobserved heterogeneity, selection bias and the likely dependency structure of the data, while controlling for a wide range of confounding factors. This of course relies on having sufficient variation over the sample period among time-varying explanatory variables. Thanks to the rich longitudinal data used in this study, which collects information among same households' members for three decades, this method can be successfully employed. Yet, several studies have tried to overcome the potential endogeneity of parental unemployment in the relationship between parental unemployment and children health, by comparing children whose parents suffered involuntary unemployment coming from factory closures with children whose parents continued to be employed. One caveat to that approach though is that the timing of layoffs might not be entirely random. Unfortunately, neither the BHPS nor UKHLS include reliable information on factory closures and related dismissals. Hence, this study accounts for time-invariant unobserved heterogeneity via a Mundlak's approach (Mundlak, 1978). Another potential source of bias might stem from the use of subjective measures of health and the potential for systematic reporting bias. However, if reporting bias is time-invariant, the inclusion time-invariant unobservables might account for that as well.

This paper might also have some potentially useful implications for the design of public policies. Results suggest that policies targeted at containing unemployment, especially among parents of young children, might also help in reducing the incidence of mental ill-health among young adults. Unemployment is potentially associated with permanent decreases in earnings and an increased likelihood of future unemployment spells, and this appears to affect children's future health. Therefore, policy interventions targeted at young children can potentially provide life-long health benefits, and thus, it might lead to significant savings in the public finances (Almond, Currie, and Duque, 2018). Overall, understanding the long-term health effects of parental unemployment can help shape appropriate policy responses to tackle widening inequalities derived from parental unemployment, especially among economically disadvantaged households.

4 Decomposing Health Inequalities Among Adolescents: Did Austerity Increase Inequalities Among Millennials?

This paper explores associations between adolescent health and socioeconomic deprivation at income and small-area levels in England. We employ administrative data drawn from the Health Episode Statistics (HES) linked to Next Steps, a longitudinal survey including a cohort of millennial adolescents born in 1990. Using the Income Deprivation Affecting Children Index (IDACI) and the Index of Multiple Deprivation (IMD), we measure income-related and small-area deprivation level inequalities in psychological distress and disability/long-term illness. We also study income-related inequalities in access to health care among adolescents. We employ Erreygers' corrected concentration index (CCI) and Shapley-Shorrocks decomposition techniques to explore the relative contribution of a set of childhood circumstances in the adolescent's health and health care utilisation inequalities. An interrupted time-series (ITS) analysis is implemented to examine the evolution of health care utilisation in the emergency and outpatient care during the years of Great Recession and subsequent austerity policies. Results suggest that small area deprivation and income both yield inequalities in health among adolescents, favouring the better-off. There are also pro-rich inequalities in the utilisation of specific outpatient hospital services (e.g., orthodontic and mental health services), while pro-poor disparities are found in the use of emergency services. Results also suggest that the number of appointments for outpatient hospital services slightly increased after the Great Recession, whereas the number of yearly visits to accident and emergency episodes department decreased due to austerity. These findings shed light on the main drivers of health inequalities during a critical stage of human development and may have relevant policy implications.

Keywords: small area deprivation; income; health inequalities; health care use; millennials
JEL Classification: *D63; I10; I14*

4.1 Introduction

Adolescence is a critical stage of human development (Heckman and Mosso, 2014). This is because fundamental aspects of an individual's health and health-behaviours are formed during adolescence (Currie, Zanotti, et al. (2009); Currie and Alemán-Díaz (2015); Patton, Sawyer, et al. (2016)). Despite their relevance, less attention has been devoted so far to the determinants of health and health inequalities during adolescence and young adulthood, and this might be partly due to difficulties in measuring adolescents' socioeconomic status. Yet, mental health disorders (e.g., depression or anxiety) are among the leading causes of illness and disability amid adolescents (WHO, 2008), and those adolescents with mental-ill health are more than twice as likely to live in low-income households (Sadler, Vizard, et al., 2018). In addition, recent economic shocks, including the Great Recession, appear to have exacerbated adolescents' living conditions (Bell and Blanchflower, 2011), increasing the likelihood of experiencing harsh parenting and economic deprivation (Schneider, Waldfogel, and Brooks-Gunn, 2017).

Accordingly, the main objective of this paper is twofold. Firstly, explore the main drivers of socioeconomic inequalities among adolescents' health and access to care in England. Secondly, investigate whether the Great Recession and subsequent austerity policies affected such inequalities. Previous research has shown that health inequalities emerge and potentially even deteriorate during adolescence (Currie, Zanotti, et al., 2009). Moreover, disparities in health formed during adolescence are likely to persist into adulthood with long-term consequences on an individual's health (Sawyer, Afifi, et al., 2012). As a result, reducing health inequalities among adolescents has become a priority among policymakers (Patton, Sawyer, et al. (2016); Currie and Alemán-Díaz (2015)). However, there are difficulties in identifying health inequalities that may limit the current understanding of health disparities among this particular age group. Such challenges are conceptual, including the availability of appropriate measures of adolescents' socioeconomic status (SES; Hanson and Chen (2007)), and methodological such as the lack of large-scale data on parental and household characteristics (Wardle, Robb, and Johnson (2002); Molcho, Gabhainn, et al. (2007)). This paper aims at addressing these limitations by merging rich survey data that includes socioeconomic information on adolescents and their families, with rich hospital records. We focus on adolescents' psychological distress and disability/long-term illness at ages 15 and 17, given that adolescents with mental health conditions and disabilities are at greater risk of experiencing disparities in health and health care use.

Adolescent and young people's health are areas of concern in the UK (Jessiman, Powell, et al., 2021). Yet, few papers have studied socioeconomic inequalities in health and health care among adolescents in the UK. Rougeaux, Hope, et al. (2017) are the first to study how population-level inequalities in health developed during childhood for a cohort born in 2000–2002. They use data from the Millennium Cohort Study and show that the SES gradient among the overweight increased steadily during childhood. Zilanawala, Bécares, and Benner (2019) find that adverse socioemotional ill-health and lower cognitive development among adolescents are associated with ethnic minorities in the UK. However, inequalities in health care utilisation among adolescents have been overlooked. Just a few studies using survey datasets find evidence of pro-rich inequity in the overall use of medical specialist visits (Cookson, Propper, et al., 2016). To the best of our knowledge, no previous literature has merged data from a cohort study with hospital administrative records to explore the evolution of SES inequalities in the utilisation of health care services among adolescents in England.

The UK has the second-highest levels of economic inequality among countries with universal health care (Murtin, Mackenbach, et al., 2017). Inequalities in unplanned health care activity in the UK may also offer a proxy measure of the level of inequality in health outcomes in young people, and it might reflect the failure of other services to meet their needs. The 2008 Great recession and subsequent UK austerity policies have disproportionately impacted vulnerable individuals, especially those at the bottom of the income distribution (MacLeavy, 2011). The existing literature on the effects of economic recessions on health care inequalities among adolescents is scarce, although these shocks may potentially exacerbate such inequalities. This paper investigates trends in socioeconomic inequalities in England's healthcare utilisation following the 2008 Great recession and subsequent austerity policy. It describes areas of inequalities in accident and emergency hospital care and outpatient care utilisation for adolescents in England, particularly for mental health services, and how they have changed over time.

Inequalities in health are often considered undesirable to the extent that they are objectively unfair. While health inequalities arising from differences in choices or factors for which individuals are deemed responsible are often tolerated, inequalities arising from factors that are beyond an individual's responsibility (e.g., place of birth or family background) are defined as unfair (Woodward and Kawachi (2000); Fleurbaey and Schokkaert (2009)). The existing literature focuses on socioeconomic inequalities in health and disparities associated with differences in living conditions, health care access, and health-related lifestyle (e.g., Contoyannis and Jones (2004); Baum II and Ruhm (2009)). This paper identifies the main factors contributing to these inequalities using an Inequality of Opportunity (IOp) framework emphasising the role of individual responsibility in defining a "fair" distribution of outcomes, i.e., inequality stemming from circumstances beyond personal responsibility such as socioeconomic background (e.g., Fleurbaey and Schokkaert (2009); Fleurbaey and Peragine (2013); Ramos and Van De Gaer (2016); Roemer and Trannoy (2016)). In particular, this study adopts an ex-ante approach to IOp that focuses on inequality in the distribution of outcomes across social types, defined by their circumstances. The ex-ante approach suggests that all individuals have equal opportunities if (in expectation) no differences in outcomes emerge from having different circumstances. The expectation over outcomes within a circumstances type can be taken with a simple mean (utilitarian reward) or with some inequality aversion (Van De Gaer (1995); Ooghe, Schokkaert, et al. (2007)).

Corrected Concentration indices (CCIs) are used to quantify income-related and small area deprivation related inequalities in (mental and physical) health and health care utilisation. Regression-based Shapley-Shorrocks decomposition analyses are then implemented to explore the contribution of these variables underpinning the observed SES-related health and health care utilisation inequalities of opportunity. We mainly focus on "unavoidable" factors, which are beyond individuals' control (such as parental education and social class status), as well as adolescents' health behaviours and lifestyle. Finally, we implement an interrupted time-series analysis (Cauley and Im (1988); Bloom (2003)), which considers the seasonality of health care use and its general trends, to explore the evolution of health care utilisation among this cohort of adolescents and young adults during the Great Recession and the subsequent cuts in (public) health care expenditures.

We use linked data from the Hospital Episodes Statistics (HES) and survey data from a cohort of adolescents drawn from Next Steps (Calderwood and Sanchez, 2016). Next Steps is the only England-wide longitudinal cohort study of the millennial generation. The millennial generation is particularly interesting as they faced several challenges as they entered the job market (due to the Great Recession and higher than ever university fees and student loan debt). These data allow us not only to observe adolescent and household characteristics over time (including family circumstances, small area deprivation index, and adolescent lifestyles) but also to have information on health care utilisation across time. Findings suggest that small area deprivation and income both yield inequalities in health among adolescents, favouring the better-off. There are also pro-rich inequalities in the utilisation of specific outpatient hospital services (e.g., orthodontic and mental health services), while pro-poor disparities are found in the use of emergency services. The results also suggest that the number of appointments for outpatient hospital services slightly increased during the Great Recession, whereas the number of yearly visits to Accident & Emergency (A&E) departments decreased due to austerity.

This study contributes to the literature in several ways. This is the first study, to our knowledge, that systematically explores income-related inequalities by focusing on access to health care among adolescents in England. More specifically, this paper contributes to the identification of the key factors driving current trends of SES inequalities in psychological distress and disability/long-term illness among adolescents, using different SES measures, such as Income Deprivation Affecting Children Index (IDACI) and the Index of Multiple Deprivation (IMD). Second, to the best of our knowledge, this is the first attempt to quantify the contribution of "unavoidable" factors and adolescent's lifestyles to SES-related inequality of opportunity in adolescent health and health care utilisation. Third, this paper also investigates trends in these inequalities before and after an economic shock. The evidence produced by this paper on the relationship between health-inequalities and economic shocks may help policymakers design new and more targeted policies aimed at reducing health disparities at a critical stage of an individual's life cycle.

4.2 Background

4.2.1 Previous literature

Health inequalities among young children as well as adults are well-established and widely discussed (Currie, Zanotti, et al., 2009). However, little attention has been devoted to health inequalities in adolescence, and the few existing studies appear to produce mixed results (West and Sweeting, 2004). For instance, previous work suggests that socioeconomic differences in health emerge in early childhood and then decrease in early adolescence, only to re-emerge in adulthood (e.g., Noonan (2019)). Previous studies also find that health inequalities tend to systematically decrease or disappear during adolescence (West and Sweeting (2004); Reiss (2013)) due to the role of the education systems and related educational policies. Yet, Starfield, Riley, et al. (2002) find a socioeconomic gradient in wellbeing to be present at each stage of an individual's life cycle, including adolescence.

Although research on young people tends to focus on under-fives, there has been an increasing interest in adolescent health in recent years. Between 2002-2010, socioeconomic differences across multiple areas of children's mental and physical health have increased in England, with young people from the poorest socioeconomic groups more likely to be in worse health (Elgar, Pförtner, et al., 2015). This trend seems to be persistent and increasing in recent years, with children and young people in the UK having worse health outcomes compared to similar Western countries (Taylor-Robinson, Lai, et al. (2019); Jessiman, Powell, et al. (2021)). Children with low socioeconomic status are not only more likely than other children to have worse health but also to have significantly less access to routine medical care (Newacheck, Hughes, and Stoddard, 1996).

One can argue that these inequalities can be fair to the extent that they depend on adolescents' choices. Roemer (1998) distinguishes among factors associated with individual attainments: effort factors, for which individuals should be held partially responsible, and circumstances which are beyond individuals' control. A large strand of the literature emphasises the role of inequality of opportunity as a measure of total inequality that refers to those inequalities due to circumstances beyond individual control (Van De Gaer, 1995). In this study, we follow an ex-ante approach to measuring inequality of opportunity, which has been widely used in the inequality of opportunity in health literature (e.g., Davillas and Jones (2020), among others). The ex-ante approach to *IOp* is based on the principle that there is equality of opportunity if all individuals face the same opportunity set prior to their efforts and outcomes being realised (Fleurbaey and Schokkaert, 2009).

Previous studies also suggest that austerity has exacerbated existing health inequalities between deprived and affluent neighbourhoods (Schneider, Waldfogel, and Brooks-Gunn, 2017). The health inequalities effects of recessions may well therefore be experienced quite differently by otherwise similar individuals and communities due to national policy variation (Whitehead, Burström, and Diderichsen (2000); Burstrom, Whitehead, et al. (2010)) with more generous welfare systems protecting the health of the population and especially the most vulnerable (Bambra, Copeland, et al., 2013). In England, local government spending (excluding police, schools, and Housing Benefit) fell by nearly 30% in real terms between 2008 and 2015 (Hastings, Bailey, et al., 2013).[1] In terms of the geographies of local authority budget cuts, more deprived local authorities were more severely affected by the cuts (Beatty and Fothergill, 2014).

4.2.2 Social determinants of adolescents' health and health care

Young people experience substantial physical, psychological, and behavioural changes as they move from adolescence into adulthood (Casey, Duhoux, and Cohen, 2010). During this transition, key socioeconomic factors may uniquely affect their health trajectories with long-term consequences regarding health and health-inequalities (Gilman, Kawachi, et al., 2002). Adolescence plays a vital role in the development of social and emotional habits contributing to an individual's mental and physical wellbeing (e.g., healthy sleep patterns; exercising regularly; developing coping, problem-solving, and interpersonal skills). Poverty and low socioeconomic status affect various aspects of an adolescent's life, including access to education, family income, health status, and health care utilisation (Reiss, 2013).

Several important circumstances and physiological factors can affect adolescent health inequalities (Skalická, Van Lenthe, et al. (2009); Bartley (2016)). For instance, the environmental factors in which adolescents live (i.e., economic, social, environmental, and cultural conditions) may affect their health (Glymour, Avendano, and Kawachi, 2014). Indeed, being

[1] Local government budgets in this context excludes schools, police and housing benefits, which are items that are either no longer under local authority control or are demand-led.

exposed to material risk factors, such as poor housing, inadequate diet, harsh parenting, and severe socioeconomic problems, can exacerbate inequalities in health (Gibson, Petticrew, et al., 2011). Psychosocial factors can also contribute to adolescents' health including exposure to adversity, pressure to conform with peers and exploration of identity. Socioeconomic status is a strong predictor of individual health (Chetty, Stepner, et al. (2016); Currie and Schwandt (2016)). However, adolescents themselves have little economic power, since they are still at school and are generally not in the labour market. Therefore, the socioeconomic status of the father, mother or head of the household is often used as a proxy for adolescent socioeconomic status (Currie, Zanotti, et al., 2009).

Poverty levels in the area where individuals reside are also a relevant factor influencing health disparities. Adolescent opportunities can be affected by local school quality, health facilities, and the availability of jobs in the local labour market (Holford, 2020). For instance, adolescents who live in the most (income) deprived areas are more likely to be admitted to hospital compared to those living in more affluent areas. Importantly, changes in the economy may have potential implications for adolescent health and health-inequalities. While the previous literature suggests that recessions tend to decrease population health, the effects of recessions on health disparities may be mediated by welfare and health care systems protecting the health of the population, especially with regards to the most vulnerable (Bambra, Garthwaite, et al. (2015); Munford, Mott, et al. (2022)). Although the UK was not as affected as the Eurozone by the Great Recession, it still experienced one of the most wide-ranging austerity programmes in Europe (Reeves, McKee, et al., 2014), and this might have affected health care utilisation among adolescents.

4.3 Data

We use data from the longitudinal cohort study Next Steps (Calderwood and Sanchez, 2016), previously known as the Longitudinal Study of Young People in England (LSYPE). Next Steps follows the lives of a group of around 16,000 individuals born in England between 1989-1990. The study started in 2004 and annual interviews with study members were conducted between 2004 and 2010 (ages 14 to 20), together with interviews with parents during the first four waves. The study re-started in 2015 (individuals aged 25), which is the last available survey. This survey includes direct responses from the main parent (and limited information on a second parent when present) of the young participant allowing us to observe a rich set of parental and household characteristics.[2]

Non-response in the first wave was approximately 25% and around 10% in all subsequent waves. All results that we present in this paper are estimated using the final weights to account for the initial oversampling of disadvantaged schools and ethnic minority students, school non-compliance, the ethnic boost added to the sample at age 16, and attrition. To avoid dropping cases with missing or unknown information on background variables, we make use of the first available answers around parental class, parental education, and household tenure over the first four waves.

[2] "Main parent" refers to the parent most involved in the child's schooling and is almost exclusively the mother.

We also use the Secure Access version of Next Steps (University College London, 2022), which is linked to hospital administrative records from the UK Department of Health's Hospital Episode Statistics (HES) dataset.[3] HES is an administrative dataset including information on English NHS hospital utilisation. Specifically, HES includes all hospital admissions of NHS funded and privately funded patients across NHS providers. We employed this version of Next Steps as it combines administrative records on health care use with household and socioeconomic information collected in the survey. Specifically, we focus on data concerning the accident and emergency episodes as well as outpatient episodes (OP). These data cover encompass the number of diagnoses, types of therapies, treatment length, and waiting times.

A total of 4,895 participants agreed to health linkage out of 7,707 who took part in the survey at age 25 (Sweep 8), corresponding to a consent rate of 63.5%. A total of 4,679 Next Steps participants were successfully matched out of 4,895, corresponding to a successful linkage rate of 93.5%. Table C.1 in Appendix C.1. shows the number of successful matches to HES records following data linkage.[4]

4.3.1 Health and health care measures

For adolescent health measures, we use the General Health Questionnaire (GHQ-12), and variables capturing living with disability (classified according to the Disability Classification Equality Act 2010) or long-term illness. These variables are observed at ages 15 (wave 2) and 17 (wave 4).

We first employ the Likert-scaled GHQ-12, a widely used measure of psychological distress (Bowling (1991); Goldberg, Gater, et al. (1997)). This is a single continuous index, ranging from 0 (least distressed) to 12 (most distressed). This index allows us to treat GHQ-12 as a pseudo-continuous measure in the analysis (e.g., Davillas and Jones (2020)). We have also used a combined GHQ-12 index based on the *caseness* scoring as an additional outcome (e.g., Maheswaran, Kupek, and Petrou (2015)). The *caseness* scoring GHQ-12 is typically dichotomised to create an indicator for distress; in line with the literature (Maheswaran, Kupek, and Petrou, 2015), *caseness* GHQ-12≧4 is used as the threshold to define the binary variable. We then use the twelve dimensions of the GHQ as different outcomes in the analysis. Specifically, the twelve dimensions of GHQ are (see Appendix C.2): concentration; loss of sleep; playing a useful role; ability to make decisions; coping under strain; overcoming difficulties; enjoying activities; facing problems; feeling depressed or unhappy; confidence; feeling worthless; and general happiness. Responses to the twelve dimensions are answered on a four-category scale (*"not at all"*, *"no more than usual"*, *"rather more than usual"* and *"much more than usual"*). For each of the GHQ dimensions, the two categories indicating the most depressed states are coded as one, and the remaining two categories that reflect better mental health are coded as zero (the *caseness* scoring).[5] Second, we include in the analysis a long-standing illness/disability variable.[6] This variable takes a value of 1 when the respondent reports having any long-standing physical or mental impairment, illness or disability that troubles them for at least 12 months and 0 otherwise.

[3] This dataset was accessed through a secure lab via the UK Data Service.

[4] A cohort member was only matched when there was a record for them as a patient within the various dataset, hence the difference in the numbers of matched cases for type of dataset.

[5] Further details on the GHQ-12 are provided in Appendix C.2.

[6] This is based on the following sentence: *"whether young person has a disability/long term illness affecting or not school."*

We exploit the longitudinal information on participants' hospital records from Next Steps recorded in HES to identify health care use. In particular, we observe NHS A&E and oupatient utilisation between the years 2007-2017 and 2003-2017, respectively. We create the following outcome variables for the accident and emergency hospital analysis. First, the number of visits per patient and year; the duration (in minutes) between the patient's arrival and the start of their treatment; the duration (in minutes) between the patient's arrival and conclusion of their visit or treatment (whichever is later); the duration (in minutes) between the patient's arrival and the time the A&E visit has concluded, and the department is no longer responsible for the care of the patient.[7]

For outpatient hospital care utilisation, we use the following variables as outcomes: number of appointments per patient and fiscal year; and a variable indicating whether or not a patient attended an appointment.[8] We also included the utilisation of the following treatment specialities in outpatient care hospitals: Mental Health Service; Obstetrics, Sexual and Reproductive Health Services; and Orthodontic Health Service. The analysis provides evidence on socioeconomic inequality in health and health care use employing all the variables described here.[9]

4.3.2 Deprivation and background variables

We use indices of deprivation at income and small area-level as the ranking variables in the corrected concentration index analyses.[10] In particular, the index of deprivation at the income-level included in the study is the IDACI (Income Deprivation Affecting Children Index), a score measuring the proportion of children aged 0 to 16 living in income deprived families, including parents of these children out of work, and with low income (Communities & Local Government, 2015).[11] The IDACI score is ordered from least to most deprived families. In addition, we use the Index of Multiple Deprivation (IMD) to account for small-area deprivation (the official measure of relative deprivation for small areas in England). The IMD ranks Lower-Layer Super Output Areas (LSOA) based on seven domains of deprivation (income, employment, education, health, crime, barriers to housing, and living environment) from least to most deprived (Communities & Local Government, 2015).[12] IMD is measured at the neighbourhood level and linked to individual postcodes.

[7] More information around these variables can be found in *"Appendix C.3: Description of the variables."*

[8] If the patient did not attend a visit, this variable also indicates whether or not advanced warning was given. It takes values 1 if the appointment was cancelled by, or on behalf of, the patient; did not attend – no advance warning given; appointment cancelled or postponed by the Health Care Provider; and did not attend – patient arrived late and could not be seen. It takes 0 when the patient was seen, was attended on time or, if late, before the relevant care professional was ready to see the patient; or arrived late after the relevant care professional was ready to see the patient but was seen.

[9] More details on how these variables are included in *"Appendix C.4: Treatment Function code."*

[10] Both indices of deprivation, at income and small area-level, are used as continuous variables.

[11] Family is used here to indicate a "benefit unit", that is the claimant, any partner and any dependent children for whom Child Benefit is received. Income deprived families are defined as families that receive: Income Support; or income-based Jobseekers Allowance; or income-based Employment and Support Allowance; or Pension Credit (Guarantee); or Working Tax Credit or Child Tax Credit with an equivalised income (excluding housing benefits) below 60 per cent of the national median before housing costs.

[12] The IMD combines information from the seven domains to produce an overall relative measure of deprivation. The domains are combined using the following weights: Income Deprivation (22.5%); Employment Deprivation (22.5%); Education, Skills and Training Deprivation (13.5%); Health Deprivation and Disability (13.5%); Crime (9.3%); Barriers to Housing and Services (9.3%); and Living Environment Deprivation (9.3%).

Taking advantage of the rich household members' information provided by the cohort survey, we can decompose health and health care inequalities by family and individuals' circumstances. Following the recent literature on health inequality (Rosa Dias (2009); Rosa Dias (2010); Carrieri, Davillas, and Jones (2020); Davillas and Jones (2020)), we use a set of individual, household, and regional-level covariates that are typically associated with physical and mental wellbeing. These are factors related to adolescents' lifestyle and health behaviours; parental socioeconomic status; household characteristics; and regional differences. Moreover, to provide additional insights into the possible factors influencing adolescents' health inequalities, we use a broad list of pre-existing circumstances (i.e., recorded before the health outcome is observed) to capture elements between birth and adolescence years that might be of interest to the policy debate around socioeconomic inequalities. One of the aims of the paper is to explore the extent to which differences in health and health care utilisation are attributable to childhood circumstances and adolescents' lifestyles and behaviours and to quantify the relative roles of these circumstances on the total health inequality.[13]

We include several individual-level covariates, such as gender; ethnicity (non-white vs white); and young carer (whether the participant ever reported regularly providing unpaid care to anyone in the household). We also include individual-level pre-existing circumstances: nursery school (whether the participant attended a nursery school or pre-school class); birth weight; early birth; and whether the mother returns to work after delivery. For health-related lifestyles covariates, we include the following ones: social life indicator (whether the participant has been to or done in any social events during the last 4-weeks);[14] attitude at school;[15] bullying indicator (whether the participant experienced bullying at school); playing any instrument; reading (whether the participant has mentioned that reads for pleasure at least once per week); TV hours (hours that participants spend watching the TV); sport (whether the participant does sport at least once a week); cannabis (whether the participant ever tried cannabis); alcohol (whether the participant has ever had proper alcoholic drink); cigarettes (whether the participant has smoked cigarettes ever).

Parental socioeconomic status is defined using parental social class. This is measured using the National Statistics Socio-Economic Classification (NS-SEC), which is based on occupational types (Rose, Pevalin, et al., 2001). We also include parental education (educational attainment of the main parent); the age of the main parent; cohabitation status (whether the main parent's cohabitation status is single, separated, divorced, or widowed); and parental disability indicator (whether the participants' main parent has any disability limiting work). Following previous literature indicating the association between living standards and children's health, we included the following household characteristics: single household (whether a participant has lived in a single-parent family at least once during their childhood); household income (as a total annual benefit amount plus gross annual salary of the main parental and the second parent per capita); the number of siblings; tenure (whether the participants' house tenure is owned outright or via mortgage /bank loan); having internet; and living in a non-English spoken household.

[13] Here, we follow previous literature (Rosa Dias (2009); Rosa Dias (2010); Costa-Font, Hernández-Quevedo, and Jiménez-Rubio (2014); Carrieri, Davillas, and Jones (2020); Davillas and Jones (2020)) and data availability as a criterion for choosing which variables are included in this study.

[14] Indicator variable for whether the participant has gone to any of the following events during the last 4-weeks: *football match*; *party, dance or nightclub*; *pub or bar*; *cinema, theatre or concert*.

[15] This variable captures attitude toward school defined as the following: *"I work as hard as I can"*; *"schoolwork is worth doing"*; *"school is not a waste of time"*; *"the work I do in lessons is interesting"*.

To explore the regional differences in mental and physical health, nine dummies for the Government Office Regions (GORs) for England are included. GORs are the highest regional layer level for England and are used to explore regional health differences at the aggregate level. We also included a rural indicator variable defined as living in a non-urban area (≧10,000 population and less sparse). Further details about these variables can be found in *"Appendix C.3: Description of the variables."*

4.4 Empirical Strategy

4.4.1 Concentration index

Concentration indices (CI) measure inequality in one variable over the distribution of another variable (Kakwani, 1977). They are commonly used for the measurement of socioeconomic-related health inequality, and they are derived from the Gini coefficient.[16] Concentration indices can also be represented graphically using concentration curves that depict differences in the proportion share of, for example, access to health care across socioeconomic groups (see, for example, Figure 4.4). Therefore, the concentration index is twice the area between the concentration curve and the 45 degrees line that indicates no relationship between the two variables (Wagstaff, Paci, and Van Doorslaer, 1991).[17]

As a result, the CI uses two variables, a dependent variable (y, health and health care variables) and a ranking variable (in this case: ICADI or IMD). Thus, in calculating a concentration index, the ranking variable ranks individuals based upon their income (IDACI) or area (IMD) level of deprivation, with the poorest (highest index scores) at the top of the ranking distribution. The index then defines distinct levels of inequality based upon the proportion of individuals in ill-health (e.g., whether the adolescent is suffering from psychological distress or not) within the distribution of the ranking variable (IDACI or IMD). If the largest proportion of psychological distress is found among the poorest individuals, a positive value (>0) is computed (*"pro-poor"* inequality), while if the largest proportion of the psychological distress among adolescents (defined as *"pro-rich"* inequality), a negative value is computed (<0). The CI is bounded between -1 (perfect pro-rich inequality) and +1 (perfect pro-poor inequality).

Following previous studies (Wagstaff, Paci, and Van Doorslaer, 1991), the CI can be calculated as:

$$CI = \frac{2}{N\bar{y}} \sum_{i=1}^{N} y_i R_i - 1 \tag{4.1}$$

where y_i denotes the dependent variable of interest (e.g., psychological distress); $\bar{y}$ represents its means and R_i denotes the fractional rank of each individual along with the income-level and area level of deprivation index distribution. Here, $i = 1$ for the individual at the bottom

[16] The Gini index measures the extent to which the distribution of income (or, in some cases, consumption /expenditure) among individuals or households within an economy deviates from a perfectly equal distribution (OECD, 2008).

[17] A concentration index of 0 can arise either because health does not vary with income rank or because the concentration curve crosses the 45 degrees line, and pro-poor inequality in one part of the income distribution is exactly offset by pro-rich inequality in another part of the distribution. For instance, in Figure 4, the continuous red line shows the perfect equality line (45 degrees line), and the dotted red line shows the concentration curve.

of the distribution (the richest in the sample) and $i = N$ for the individual at the top of the distribution (the poorest in the sample).

However, the boundedness of the health variables has crucial implications for the properties and value judgements of the CIs (Erreygers and Van Ourti (2011); Wagstaff (2005); Erreygers (2009)). Wagstaff (2005) proposes two different normalizations that are both appropriate for bounded health variables. As most of the dependent variables of this paper are binary responses (e.g., whether adolescents have any disability or suffer psychological distress), a normalisation is required so that the CI is quantified in the range -1 to 1. These normalizations should be applied to enable inequality comparisons across health variables measured on different scales (Erreygers and Van Ourti, 2011). We use the Erreygers' normalisation as a Wagstaff's index might result in higher socioeconomic inequality when there is a lower relative differences in health status among individuals.[18] The Erreygers' corrected concentration index (CCI) is calculated as:

$$CCI_n = \frac{CI}{1-\bar{y}} \tag{4.2}$$

Note that some of the health care utilisation variables (and the GHQ-12 Likert) are continuous, and thus Generalized Concentration (GC) index (Wagstaff, Paci, and Van Doorslaer, 1991) are implemented, and can be expressed as:

$$GC(h|y) = \frac{1}{n}\sum_{i=n}^{n}[h_i(2R_i - 1)] \tag{4.3}$$

where $(2R_i - 1)$ represents the fractional rank and ranges between $\bar{h}_i[(1-n)/n]$ (maximal pro-poor) and $\hbar h_i[(1-n)/n]$ (maximal pro-rich). We provide results stratified by gender, following previous studies finding gender disparities in health inequalities (Zhang and Wang (2004); Costa-Font, Hernández-Quevedo, and Jiménez-Rubio (2014)).[19]

4.4.2 Decomposition analyses

We use the Shapley decomposition to estimate which circumstances correlate the most with the total inequality of opportunity in the health outcomes. The calculation of the Shapley value first requires the estimation of the inequality of opportunity (De Barros, Ferreira, et al., 2009).

Following the inequality of opportunity literature (Ferreira and Gignoux (2011); Jusot, Tubeuf, and Trannoy (2013)), a generalised health production function for the health outcomes (y_i) for each individual (i) can be defined as a function of a vector of circumstances (C_i) and of efforts (E_i),[20] and can be expressed as:

$$h_i = f(C_i, E(C_i, v_i), u_i) \tag{4.4}$$

[18] Wagstaff's normalisation produced similar inequality results, available upon request.

[19] We use the following command from Stata *conindex* by O'Donnell, O'Neill, et al. (2016).

[20] Assuming that circumstances are not affected by efforts, while efforts may be influenced by circumstances (Roemer (1998); Roemer (2002); Bourguignon, Ferreira, and Menéndez (2007)).

where v_i and u_i are unobserved error term which capture the random variation in the realised health outcomes. Specifically, v_i captures random variation in effort that is, independent of C, while u_i captures random variation in outcomes, including any measurement error that is independent of C and E.[21] Following the previous literature on inequality of opportunity (Davillas and Jones, 2020), an ex ante approach (Fleurbaey and Peragine, 2013) is adopted to measure the overall inequality of opportunity as a share of total inequality by focusing on inequality in the distribution of mean outcomes conditional on observed circumstances. Then, assuming additive separability and linearity of $f(.)$ and $E(.)$, a linear reduced form can be derived (Carrieri, Davillas, and Jones, 2020):

$$h_i = C_i\psi + \varepsilon_i \tag{4.5}$$

where the coefficients ψ reflect the total contribution of circumstance and include both the direct effect of circumstances on health and their indirect contribution through their efforts. Indeed, the mean-based direct parametric approach to measure *ex ante IOp* is based on $E(h_i|C_i)$ from the reduced form regression (4) as the counterfactual outcome:

$$\tilde{h_i} = C_i\hat{\psi} \tag{4.6}$$

where $\hat{\psi}$ represents the ordinary least-squares (OLS) estimates of the coefficient in Equation (3) (Ferreira and Gignoux (2011); Juárez and Soloaga (2014)). Given that some of the health outcomes are binary variables, a probit model is used to estimate the conditional probability function, given the set of circumstances, and the relevant counterfactual predictions are obtained. Hence, *IOp* can be estimated using an inequality measure, $I(.)$, applied to :

$$\theta_I = I(\tilde{h_l}) \tag{4.7}$$

We measure inequality of opportunity using the dissimilarity index, which has been used in inequality analysis employing binary variables (De Barros, Carvalho, et al. (2007); Juárez and Soloaga (2014)):

$$I(.) = \frac{2}{n\bar{h}}\sum_{i=n}^{n}[\tilde{h_l} - \bar{h}] \tag{4.8}$$

Where the predicted sample proportions $(\tilde{h_l})$ are estimated using probit models. Finally, the Shapley value decomposition is implemented. The Shapley value is a central solution concept in cooperative game theory and has been extended to inequality analysis by Shorrocks (2013). In particular, the Shapley-Shorrocks decomposition is implemented by using the previously mentioned inequality dissimilarity index and then averaging the marginal contribution of each circumstance. Formally, the change in the dissimilarity index when circumstance C is added to a subset M of circumstances is given by:

$$\Delta D_c = \sum_{M \complement C \setminus [C]} \frac{|m|!(k-|m|-1)!}{!}[D(M \cup [c]) - D(M)] \tag{4.9}$$

[21] We make no assumptions about whether the unexplained component of these outcomes reflects unobserved circumstances, unobserved effort, measurement error or pure chance.

where C denotes the entire set of k of circumstances, and M is a subset of C that includes m circumstance covariates except c. $D(M)$ is the dissimilarity index for the subset M and $D(M \cup [c])$ is the index obtained after adding circumstance c to subset M.

Let $D(k)$ be the dissimilarity index for the set of k circumstances. Therefore, the contribution of circumstances k to $D(k)$ is defined by

$$S_c = \frac{\Delta D_c}{D(K)} \tag{4.10}$$

where $\sum_{i \epsilon C} S_i = 1$.

As a result, we have an additive decomposition of the dissimilarity index that measures the contribution, in terms of correlation, of each circumstance to observed health inequality (Fajardo-Gonzalez, 2016).[22] The analysis is weighted using Next Steps sample weights to account for survey non-response and attrition, making the sample representative of English population.

4.4.3 Interrupted time-series analysis

We exploit the longitudinal nature of the data to analyse the evolution of unmet needs and investigate whether the Great Recession (2008-2009) and the subsequent austerity policies (2010-2015) affected inequalities in access to health care in England.

In particular, we implement an interrupted time series (ITS) (Cauley and Im (1988); Bloom (2003)) estimator with two structural breaks in the time dimension: the 2008 Great Recession and the sudden large-scale cuts to central and local government budgets, including the NHS, in June 2010. If multiple observations on an outcome variable of interest in the preintervention and postintervention periods can be obtained, an interrupted time-series analysis offers a quasi-experimental research design with a potentially high degree of internal validity (e.g., Stanley and Gage (1966); Cook, Campbell, and Shadish (2002)).

Specific features of an ITS make this design particularly appealing. It is an appropriate quasi-experimental design even in the absence of a comparison group (Fretheim, Soumerai, et al., 2013). Indeed, it has frequently been used to evaluate policy changes even when no comparison group is available (e.g., Hacker, Penfold, et al. (2015); Rau, Sarzosa, and Urzúa (2021)). In addition, an ITS study design also accounts for dynamic elements. In particular, health care utilisation has a secular trend and a marked seasonality. Moreover, it can accommodate design variation in which the effect of multiple treatment periods is of interest. Here, we implement an interrupted time-series analysis using a two-ordinary least-squares regression-based approach allowing for the variability within the treatment group to be accounted for during estimation.[23] We consider the following single-group ITS model with two treatment periods:

[22] The *Iop* command in Stata has been used to estimate Inequalities of Opportunities (Juárez and Soloaga, 2014), jointly with the options *shapley(ws)* and *bootstrap(500)*.

[23] More specifically, we use the Stata command *xtitsa*, which generalises the ITS design and allows for flexibility in modelling outcomes with various distributions and autocorrelation structures (Linden, 2015). In particular, this command offers great flexibility in estimating *ITSA* models with individual-level data, including the choice of distribution and link function, and the ability to specify the appropriate time related within-group correlation structure (e.g., autoregressive, stationary or non-stationary processes).

$$Y_{it} = \alpha + \beta T_{it} + \delta W_{it} + \eta W_{it} T_{it} + \gamma Z_{it} + \zeta Z_{it} T_{it} + \phi Year_t + \varepsilon_{it} \tag{4.11}$$

where Y_{it} is the outcome variable measured for each individual-level i at time point t. T_{it} is the time since the start of the study until the introduction of the first intervention, W_{it} is a dummy indicator representing the first intervention (0, pre-intervention periods, vs 1, the Great Recession - that is between 2008-2009), and $W_{it}T_{it}$ is an interaction term representing the first treatment effect. Z_{it} is the is the second intervention period which is now compared with the prior (first) intervention period (prior (first) intervention: Great Recession, 0, and 2011 onwards, 1), and $Z_{it}T_{it}$ is an interaction term with the second treatment period and represents the second treatment effect. All the regressions include year fixed-effects $(Year_t)$.

By design, a single-group ITS has no comparable control group; rather, the preintervention trend is used as the counterfactual. Yet, in the ITS approach, we must assess at least two threats to identification. First, the existence of other structural changes contemporaneous to the one we analyse (Baicker and Svoronos, 2019). Since the ITS estimate captures the discontinuities emerging at a particular moment in time, it cannot disentangle the effect coming from the structural change of interest from other contemporaneous interventions. The second threat to identification is the possible anticipation to the structural change. This would imply that the pre-break information used to fit the model in the absence of the break might not be appropriate.

This setting helps to alleviate these threats. First, we do not find confounding factors, such as other economic changes or other health shocks, that could alter health care decisions. To test for this assumption, we look at previous literature and policies report about socioeconomic inequalities in health care in England to support this assumption (Cookson, Propper, et al., 2016). Moreover, we assume that any time-varying unmeasured confounder is relatively slowly changing so that it would be distinguishable from the sharp jump of the intervention indicator. Caution is still needed when interpreting the results as we cannot categorically exclude the influence of other policies around the timing of the intervention of interest (Linden, 2015). It might also be reasonable to assume in this case that both the 2008 Great Recession and the subsequent austerity policies were not anticipated by patients.

4.5 Results

4.5.1 Descriptive analysis

Table 4.1 presents descriptive statistics for background variables, distinguishing between adolescents aged 15 (2005) and 17 (2007) years old. While we find limited differences between the two groups of individuals, 17 years old adolescents appear to report the worst mental ill-health (as measured by the GHQ-12, see Appendix C.2).

TABLE 4.1: Summary statistics for background variables

	Age 15 (2005)		**Age 17 (2007)**	
	Mean	*Std. dev.*	*Mean*	*Std. dev.*
Adolescent-level and pre-circumstances characteristics				
Non-white‡	0.133	0.340	0.128	0.334
Female‡	0.491	0.499	0.491	0.499

Table 4.1 continued from previous page

	Age 15 (2005)		Age 17 (2007)	
Young carer‡	0.051	0.221	0.044	0.205
Born outside the UK‡	0.487	0.215	0.045	0.209
No attend a nursery or pre-school‡	0.165	0.371	0.161	0.367
Mother age at birth‡				
Under 20	0.066	0.248	0.064	0.246
20-24	0.243	0.429	0.244	0.429
25-29	0.353	0.429	0.352	0.477
30-34	0.238	0.426	0.237	0.425
35+	0.098	0.297	0.099	0.299
Birth weight in kilos [0.33-6.12]	3.323	0.595	3.326	0.592
Number of weeks birth was early [0-17]	0.755	1.695	0.756	1.696
Any disability or long-standing illness‡	0.148	0.356	0.145	0.279
Mental (ill-) health index (GHQ12) [0-12]	1.717	2.555	2.018	2.708
Mother return to work after birth‡				
No	0.172	0.378	0.172	0.377
Mother returned to work full-time	0.348	0.476	0.343	0.474
Mother returned to work part-time	0.479	0.499	0.483	0.499
Total time main parent has been unemployed and seeking work since birth (in months)	1.311	10.266	1.300	10.306
Lifestyle and (health) behaviours				
Social life (amusement arcade; pub/bar; dance/party; cinema) ‡	0.758	0.428	0.865	0.341
Risk factors [0-12]	1.318	1.724	1.491	1.763
Positive attitude toward school‡	0.641	0.479	0.652	0.476
Experience bullying‡	0.388	0.487	0.493	0.499
Play an instrument‡	0.203	0.402	0.189	0.391
Reading for pleasure at least once per week	0.714	0.451	0.713	0.452
TV‡				
None or less than an hour	0.205	0.404	0.202	0.402
1-3 hours	0.633	0.481	0.636	0.481
4-6 hours	0.144	0.351	0.145	0.352
7 hours or more	0.014	0.121	0.015	0.123
Number of hours playing computer games‡	1.767	1.309	1.772	1.307
Sports at least once per week‡	0.772	0.419	0.555	0.496
Whether ever tried cannabis‡	0.207	0.405	0.380	0.485
Whether ever had proper alcohol drink‡	0.674	0.468	0.849	0.357
Whether ever smoke cigarettes‡	0.217	0.412	0.274	0.446
Parental-level characteristics				
Parental Education‡				
Degree or Higher Education	0.343	0.474	0.343	0.474
A-level	0.248	0.431	0.244	0.429
GCSE	0.410	0.491	0.404	0.490
Low or no education	0.411	0.499	0.394	0.488
Parental occupational status‡				
Managerial	0.481	0.499	0.455	0.498

Table 4.1 continued from previous page

	Age 15 (2005)		Age 17 (2007)	
Intermediate or technical	0.438	0.496	0.407	0.491
Routine occupation or not currently working	0.491	0.499	0.565	0.495
Age main parent	43.194	5.984	45.26	6.075
Non-cohabiting main parent‡	0.275	0.446	0.318	0.465
Not good general health main parent‡	0.128	0.335	0.126	0.332
Any disability limiting work main parent‡	0.135	0.342	0.135	0.342
Household-level characteristics				
Single family for at least one month‡	0.416	0.493	0.408	0.491
Household income per capita	7,276.205	35,960.34	7,767.779	39,127.77
Number of siblings‡	1.455	1.109	1.423	1.150
Owned outright or mortgage‡	0.717	0.449	0.721	0.448
Motor vehicle‡	0.858	0.348	0.858	0.348
Mobile telephone‡	0.776	0.416	0.851	0.356
Computer‡	0.913	0.280	0.895	0.305
Access internet from home‡	0.811	0.390	0.765	0.423
English not spoken at home‡	0.049	0.216	0.049	0.217
Number of dependent children in household	2.169	1.100	1.782	1.155
Regional differences				
Index of area-deprivation (IMD) ‡				
IMD area 1st quintile (most deprived)	0.198	0.399	0.196	0.397
IMD area 2nd quintile	0.191	0.393	0.188	0.394
IMD area 3rd quintile	0.191	0.393	0.192	0.394
IMD area 4th quintile	0.209	0.407	0.212	0.409
IMD area 5th quintile (least deprived)	0.208	0.406	0.209	0.407
Index of income-deprivation (IDACI) ‡				
IDACI income 1st quintile (most deprived)	0.198	0.399	0.195	0.396
IDACI income 2nd quintile	0.198	0.399	0.192	0.394
IDACI income 3rd quintile	0.205	0.404	0.205	0.404
IDACI income 4th quintile	0.191	0.393	0.195	0.396
IDACI income 5th quintile (least deprived)	0.209	0.407	0.210	0.407
London‡	0.131	0.338	0.121	0.326
Non-urban area (>= 10k – less sparse) ‡	0.196	0.397	0.199	0.399
Number of observations	13,539		11,449	

Notes: All descriptive statistics are weighted using Wave 2 or 4 final weights. ‡ Dummy indicators. *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2022). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure Access DOI: http://doi.org/10.5255/UKDA-SN-8681-1.

In Table 4.2, we show summary statistics for health care utilisation by quintiles of deprivation (from least to most deprived) using the Income Affecting Children Index. Here, we observe differences in health care utilisation by quintiles of income deprivation: the most deprived adolescents aged 17 tend to use more A&E hospital services, while the less deprived adolescents appear to use more outpatient hospital services. More deprived adolescents wait more for treatment and stay longer in the hospital when accessing A&E. These trends can also be seen in Figures C.6 and C.7 in Appendix C.6.

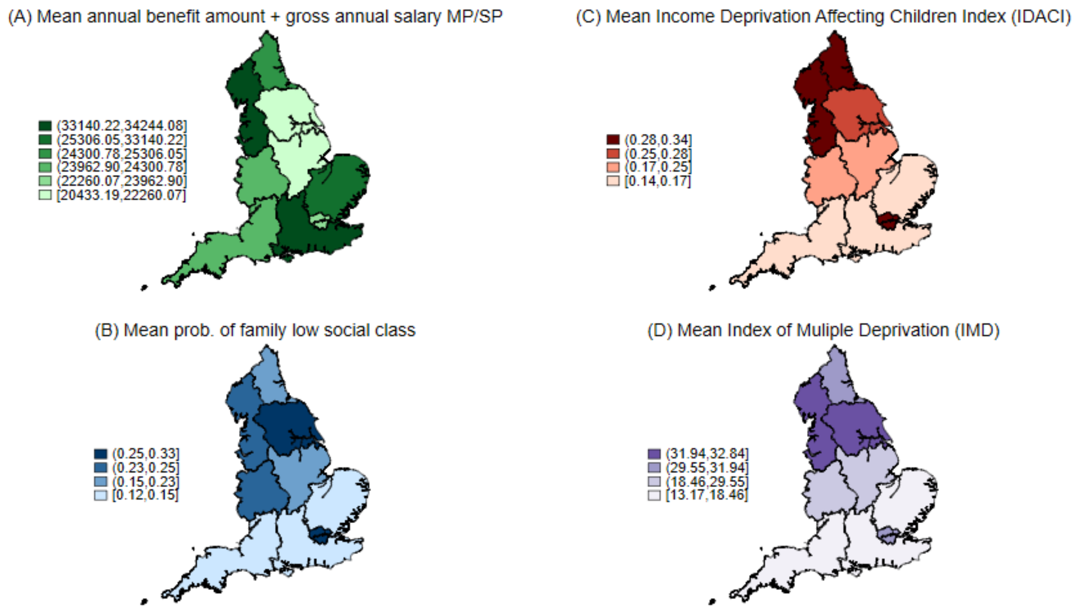
TABLE 4.2: Summary statistics for health care use by index of income-deprivation at age 17 (2007-2008)

	Income Affecting Children Index				
	Least deprived	*2nd least deprived*	*Middle*	*2nd most deprived*	*Most deprived*
Accident & Emergency (A&E)					
Number of visits	1.959	2.384	2.330	2.584	2.626
	(1.569)	(2.377)	(2.138)	(2.468)	(2.395)
Duration to treatment	83	85	85	82	89
(in minutes)	(1.569)	(2.377)	(2.138)	(2.468)	(2.240)
Duration to conclusion	129	131	134	135	134
(in minutes)	(1.569)	(2.377)	(2.138)	(2.468)	(2.240)
Duration to departure	120	130	128	131	133
(in minutes)	(7.569)	(2.377)	(2.138)	(2.468)	(2.240)
Number of observations	214	212	218	174	251
Outpatient care (OP)					
Number of appointments	8.732	5.950	9.029	7.212	7.066
	(8.577)	(3.862)	(9.051)	(5.930)	(5.640)
Not attended nor seen	0.188	0.193	0.188	0.201	0.224
	(0.391)	(0.394)	(0.391)	(0.400)	(0.417)
Treatment speciality:	0.033	0.054	0.060	0.043	0.033
Mental Health Care	(0.179)	(0.226)	(0.237)	(0.204)	(0.179)
Treatment speciality:	0.156	0.125	0.093	0.092	0.088
Orthodontic Service	(0.362)	(0.330)	(0.290)	(0.290)	(0.284)
Treatment speciality: Obstetrics, Sexual and Reproductive Health Services	0.155	0.198	0.242	0.311	0.321
	(0.362)	(0.398)	(0.428)	(0.462)	(0.466)
Number of observations	900	872	614	691	716

Notes: Standard deviation in brackets. *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2022). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure Access DOI: http://doi.org/10.5255/UKDA-SN-8681-1.

Figure 4.1 shows the distribution of key socioeconomic variables by regions (Government Office Regions - GOR). Panel A shows that, on average, those in the South East of England have a higher total household income in the sample. Panel B also shows that, on average, the North of England and London have a higher concentration of families in lower social classes. Higher indices of income- and small area-related deprivation are concentrated in the North-West, Yorkshire and London, see in Panel C and D of Figure 4.1. Figure 4.2 shows the mean probability of suffering from long-standing illness or disability by area-level deprivation, showing that adolescents living in the most deprived areas have a higher mean probability of suffering from a health condition. Figure 4.3 provides kernel density plots for mental ill-health (using the GHQ-12) by age, gender, and region. We can see that kernel density plots suggest a higher prevalence of mental ill-health for those aged 17 and for females. There are no apparent differences in the distribution of mental ill-health between the North and South of England.

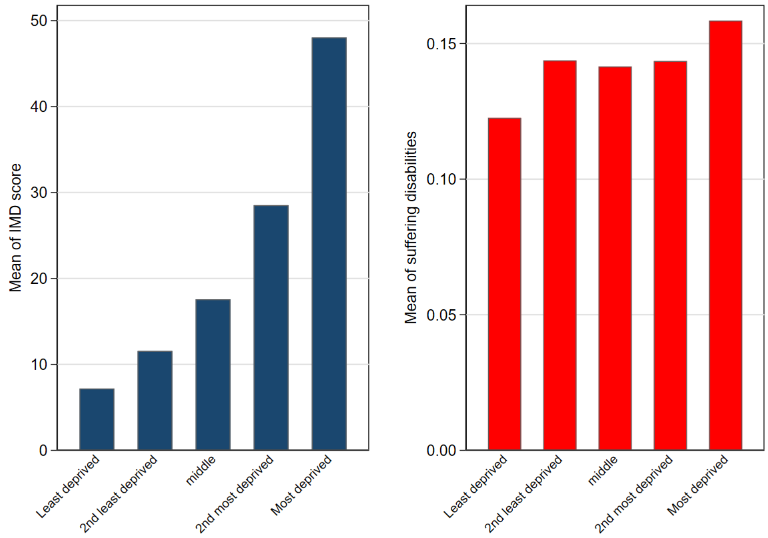
FIGURE 4.1: Socioeconomic key variables by Government Office Regions (GOR)



Notes: Figure (A) shows the mean of annual benefit plus gross annual salary of both main parent (MP) and second parent (SP); Figure (B) shows the mean probability of participant living in a low social class family defined as whether the highest parental social class of the family mentioned was *"Routine occupations or not currently working"* (social class is measured using the National Statistics Socio-Economic Classification (NS-SEC)); Figure (C) shows the mean of Income Deprivation Affecting Child Index (IDACI); Figure (D) shows the mean of Income Deprivation Index (IMD). *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2021). Next Steps: Sweeps 1-8, 2004-2016. [data collection]. 16th Edition. UK Data Service. SN: 5545, DOI: 10.5255/UKDA-SN-5545-8.

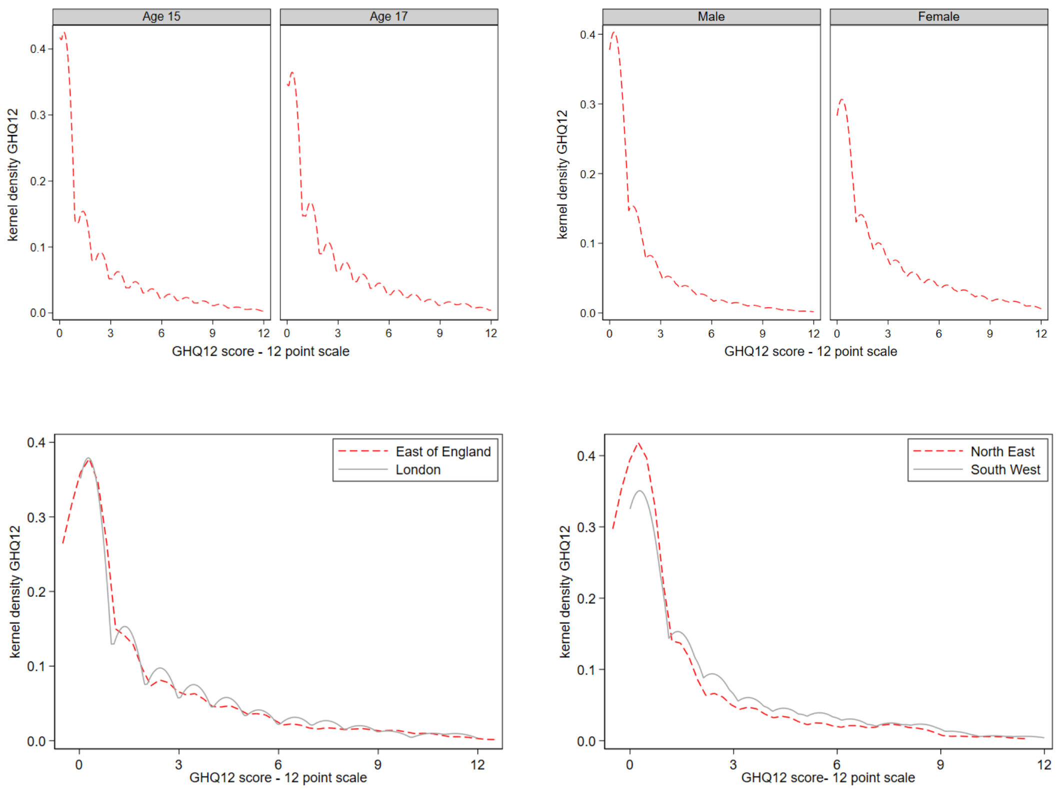
Finally, we present descriptive data from hospital records in Figures C.3- C.5 in Appendix C.6 for three outpatient treatment services: orthodontic, obstetrics/sexual/ reproductive care, and mental health care. Here, we can see a clear socioeconomic gradient for access to services such as orthodontic (in which less deprived individuals use more) and obstetrics/sexual/reproductive care (in which more deprived individuals use more). In contrast, access to mental health care services seems to be more concentrated among those in the middle of the income distribution.

FIGURE 4.2: Mean probability of suffering from long-standing illness or disability by area-level deprivation quintiles (IMD)



Notes: IMD: Income Deprivation Index. *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2021). Next Steps: Sweeps 1-8, 2004-2016. [data collection]. 16th Edition. UK Data Service. SN: 5545, DOI: 10.5255/UKDA-SN-5545-8.

FIGURE 4.3: Kernel densities for mental health index (GHQ-12) by age, gender and region



Notes: The GHQ-12 score is a single continuous index that combines all twelve dimensions, named Likert-scaled GHQ-12. *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2021). Next Steps: Sweeps 1-8, 2004-2016. [data collection]. 16th Edition. UK Data Service. SN: 5545, DOI: 10.5255/UKDA-SN-5545-8.

4.5.2 Income-related and small area deprivation-related health inequalities

Tables 4.3 and 4.4 present income and area-related inequality indices for the discrete and continuous health measures of adolescents aged 15 by gender. Results confirm the existence of statistically significant inequalities for adolescents' long-term illness, particularly concentrated among more deprived male individuals, and for both socioeconomic (income and area) indicators.

Koolman and Van Doorslaer (2004) suggest an intuitive way to interpret the value of the concentration index, e.g., a health concentration index value of 0.10 would imply that transferring 10% of the health problems from the poorest half to the richest half of the income distribution, would lead to perfect equality. Since we use a slightly different measure of inequality by normalising the index (due to the boundedness of the health outcomes), results from Table 4.3 Panel B would suggest that a redistribution of approximately 3.7% of the disability rate from the poorest half to the richest half of the income distribution would result in perfect equality in the prevalence of adolescents' disability.

TABLE 4.3: Income-related corrected concentration indices (CCI) for health measures at aged 15

	Males		Females	
	CCI	*Standard error*	*CCI*	*Standard error*
Panel A: Psychological distress				
GHQ-12 elements[1]				
Concentration	-0.007	0.010	-0.014	0.013
Sleep	-0.021**	0.011	-0.007	0.014
Role	0.026***	0.008	0.013	0.011
Decisions	0.028***	0.007	-0.008	0.009
Strain	-0.070***	0.014	-0.103***	0.016
Overcoming difficulties	0.008	0.013	-0.024*	0.014
Enjoy activities	0.003	0.009	0.005	0.011
Face up problems	0.014**	0.008	-0.003	0.011
Depressed	-0.012	0.023	-0.006	0.017
Confidence	-0.016	0.010	-0.001	0.014
Worthlessness	-0.013	0.008	0.021	0.013
Happiness	0.008	0.009	-0.007	0.012
GHQ-12 Likert[2]	-0.019	0.018	-0.048*	0.025
GHQ-12 Caseness ≥ 4[3]	-0.002	0.011	-0.017	0.014
Panel B: Disability/long-term illness				
Disability/long-term illness	0.037***	0.012	0.006	0.011
Sample size	6,789		6,609	

Notes: ***p≺0.01;**p≺0.05;*p≺0.10. Robust standard errors clustered by sampling schools. Weighted using final Wave 2 weights. [1] For each of the GHQ dimensions, the two categories indicating the most depressed states are coded as one and the remaining two categories, that reflect better mental health, are coded as zero (dichotomous variables). [2] Continuous GHQ-12 measure based on the overall score across all 12 dimensions using the Likert scoring (ranging between zero and 36). For continuous variables, a Generalized Concentration Index has been used. [3] Discrete variables taking the value of one if the overall GHQ-12 Caseness score≥4 and zero otherwise. Erreygers' Concentration Index are used for discrete outcome variables and Generalized concentration index (GCI) for continuous one.

Comparing results from Tables 4.3 and 4.4 for the long-term illness outcome, results indicate that health inequalities with respect to income are quantitatively larger than those with respect to small area deprivation. Unlike males, income- and area-related inequalities in long-term illness are not statistically significant for females. These gender differences may reflect the gender disparities in income- and area-level inequalities in health conditions/disabilities observed in previous studies (Zhang and Wang (2004); Costa-Font, Hernández-Quevedo, and Jiménez-Rubio (2014)).

TABLE 4.4: Area-related corrected concentration indices (CCI) for health measures at aged 15

	Males		Females	
	CCI	*Standard error*	*CCI*	*Standard error*
Panel A: Psychological distress				
GHQ-12 elements[1]				
Concentration	-0.006	0.010	-0.014	0.013
Sleep	-0.021**	0.010	-0.009	0.014
Role	0.020**	0.009	0.004	0.010
Decisions	0.024***	0.008	-0.006	0.009
Strain	-0.072***	0.014	-0.094***	0.016
Overcoming difficulties	0.005	0.012	-0.027**	0.014
Enjoy activities	-0.002	0.009	0.005	0.011
Face up problems	0.011	0.008	-0.002	0.010
Depressed	-0.008	0.011	-0.013	0.015
Confidence	-0.020*	0.010	-0.009	0.013
Worthlessness	-0.016	0.009	0.021	0.013
Happiness	0.00	0.009	-0.012	0.012
GHQ-12 Likert[2]	-0.031	0.018	-0.053*	0.024
GHQ-12 Caseness ≥ 4[3]	-0.009	0.011	-0.022	0.013
Panel B: Disability/long-term illness				
Disability/long-term illness	0.026**	0.013	0.002	0.011
Sample size	6,789		6,609	

Notes: ***p≺0.01;**p≺0.05;*p≺0.10. Robust standard errors clustered by sampling schools. Weighted using final Wave 2 weights. [1] For each of the GHQ dimensions, the two categories indicating the most depressed states are coded as one and the remaining two categories, that reflect better mental health, are coded as zero (dichotomous variables). [2] Continuous GHQ-12 measure based on the overall score across all 12 dimensions using the Likert scoring (ranging between zero and 36). For continuous variables, a Generalized Concentration Index has been used. [3] Discrete variables taking the value of one if the overall GHQ-12 Caseness score≥4 and zero otherwise. Erreygers' Concentration Index are used for discrete outcome variables and Generalized concentration index (GCI) for continuous one.

Different patterns are observed for the mental ill-health measures. Results suggest no income- and area-related gradient in the distribution of mental ill-health among adolescents aged 15 years old. We do observe a significant concentration of several components of the mental ill-health index among the better-off for both genders (i.e., sleep; strain; and overcoming difficulties). In contrast, we also find a statistically significant concentration of further items among the worse-off, although just for males (i.e., role; decisions; and face up problems).

TABLE 4.5: Income-related corrected concentration indices (CCI) for health measures at aged 17

	Males		Females	
	CCI	*Standard error*	*CCI*	*Standard error*
Panel A: Psychological distress				
GHQ-12 elements[1]				
Concentration	-0.024**	0.011	-0.059***	0.014
Sleep	-0.006	0.014	-0.040***	0.015
Role	0.029**	0.011	0.007	0.012
Decisions	0.017**	0.007	-0.030***	0.010
Strain	-0.088***	0.015	-0.115***	0.017
Overcoming difficulties	0.010	0.013	-0.055***	0.014
Enjoy activities	0.015	0.012	-0.001	0.013
Face up problems	0.011	0.009	-0.016	0.012
Depressed	0.008	0.023	-0.002	0.018
Confidence	-0.001	0.011	-0.011	0.015
Worthlessness	0.012*	0.010	0.016	0.012
Happiness	0.003	0.010	-0.006	0.013
GHQ-12 Likert[2]	-0.001	0.021	-0.083***	0.026
GHQ-12 Caseness ≥ 4[3]	-0.001	0.013	-0.041***	0.015
Panel B: Disability/long-term illness				
Disability/long-term illness	0.029***	0.011	-0.004	0.009
Sample size	5,772		5,627	

Notes: ***p≺0.01;**p≺0.05;*p≺0.10. Robust standard errors clustered by sampling schools. Weighted using final Wave 2 weights. [1] For each of the GHQ dimensions, the two categories indicating the most depressed states are coded as one and the remaining two categories, that reflect better mental health, are coded as zero (dichotomous variables). [2] Continuous GHQ-12 measure based on the overall score across all 12 dimensions using the Likert scoring (ranging between zero and 36). For continuous variables, a Generalized Concentration Index has been used. [3] Discrete variables taking the value of one if the overall GHQ-12 Caseness score≥4 and zero otherwise. Erreygers' Concentration Index are used for discrete outcome variables and Generalized concentration index (GCI) for continuous one.

Tables 4.5 and 4.6 present the income and area-related inequality indices for the discrete and continuous health measures by gender when adolescents are aged 17. Here, we find similar patterns as those above for the health inequalities in long-term illness among adolescents aged 17, i.e., these inequalities are concentrated among more deprived adolescents. We now observe the presence of statistically significant inequalities for mental-ill health, especially among less deprived females, and for both socioeconomic (income and area) indicators. Unlike females, income- and area-related inequalities in long-term illness were not statistically significant for males. Comparing results from Tables 4.5 and 4.6 for the GHQ-12 Likert vs GHQ-12 caseness outcomes, results show that health inequalities with respect to small-area deprivation are considerably larger than those with respect to income level deprivation.

TABLE 4.6: Area-related corrected concentration indices (CCI) for health measures at aged 17

	Males		Females	
	CCI	*Standard error*	*CCI*	*Standard error*
Panel A: Psychological distress				
GHQ-12 elements[1]				
Concentration	-0.029***	0.011	-0.066***	0.014
Sleep	-0.015	0.014	-0.050***	0.015
Role	0.024**	0.011	0.001	0.012
Decisions	0.016**	0.008	-0.034***	0.010
Strain	-0.094***	0.015	-0.122***	0.017
Overcoming difficulties	0.002	0.013	-0.059***	0.014
Enjoy activities	0.006	0.012	-0.012	0.012
Face up problems	0.006	0.008	-0.016	0.012
Depressed	-0.002	0.013	-0.006	0.015
Confidence	-0.001	0.011	-0.018	0.015
Worthlessness	0.011	0.010	0.001	0.012
Happiness	-0.004	0.010	-0.016	0.012
GHQ-12 Likert[2]	-0.020	0.022	-0.107***	0.026
GHQ-12 Caseness ≥ 4[3]	-0.008	0.013	-0.052***	0.015
Panel B: Disability/long-term illness				
Disability/long-term illness	0.022**	0.011	-0.015	0.009
Sample size	5,772		5,627	

Notes: ***p≺0.01;**p≺0.05;*p≺0.10. Robust standard errors clustered by sampling schools. Weighted using final Wave 2 weights. [1] For each of the GHQ dimensions, the two categories indicating the most depressed states are coded as one and the remaining two categories, that reflect better mental health, are coded as zero (dichotomous variables). [2] Continuous GHQ-12 measure based on the overall score across all 12 dimensions using the Likert scoring (ranging between zero and 36). For continuous variables, a Generalized Concentration Index has been used. [3] Discrete variables taking the value of one if the overall GHQ-12 Caseness score≥4 and zero otherwise. Erreygers' Concentration Index are used for discrete outcome variables and Generalized concentration index (GCI) for continuous one.

4.5.3 Income-related inequality in health care utilisation

Table 4.7 presents CCI of income-related inequality for the continuous and discrete measures of health care utilisation by gender. Table 4.7 reveals pro-poor inequalities in the number of visits to emergency hospital departments among female adolescents. A higher waiting time between a patient's arrival and the start of their treatment is concentrated among male adolescents at the bottom of the income distribution. For outpatient care, Table 4.7 shows systematic pro-rich inequalities in the number of appointments to outpatient hospital services among female adolescents aged 17 years old.

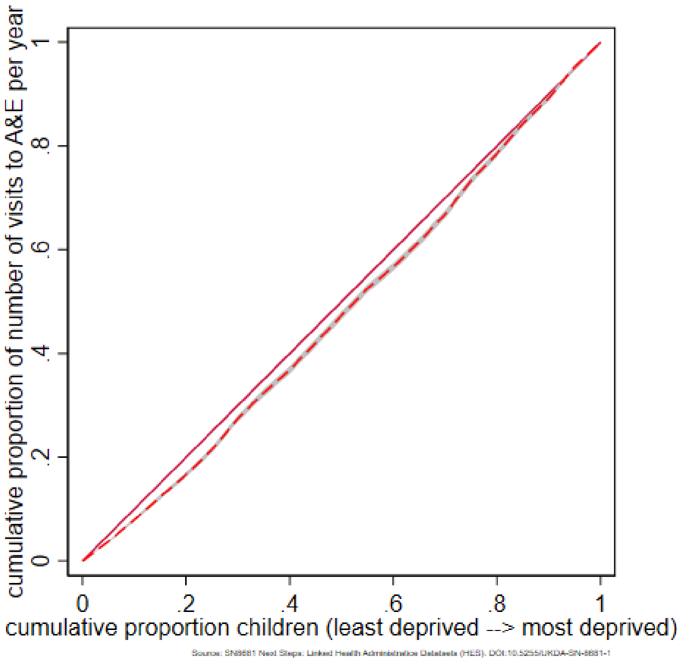
TABLE 4.7: Income-related concentration indices for health care measures at aged 17 (2007-2008)

	Males		Females	
	CCI	*Standard error*	*CCI*	*Standard error*
Panel A: Accident & Emergency (A&E)				
Number of visits per year	0.007	0.024	0.134***	0.035
Duration to treatment (in minutes)	9.395**	3.965	3.962	4.793
Duration to conclusion (in minutes)	2.132	2.622	0.658	1.930
Duration to departure (in minutes)	2.153	2.529	0.969	1.875
Number of observations	528		541	
Panel B: Outpatient care (OP)				
Number of appointments per patient and year	0.369	0.064	-0.665***	0.109
Not attended nor seen	0.073***	0.024	0.032	0.020
Treatment speciality: Mental Health Care	0.001	0.010	-0.013***	0.013
Treatment speciality: Orthodontic Service	-0.076***	0.023	-0.061***	0.019
Treatment speciality: Obstetrics, Sexual and Reproductive Health Services	0.002	0.002	0.275***	0.019
Number of observations	1,560		2,128	

Notes: ***p≺0.01;**p≺0.05;*p≺0.10. Standard errors in parentheses. Erreygers' Concentration Index is used for discrete outcome variables. Generalised concentration index (GCI) is used for continuous health care utilisation measures. *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2022). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure Access DOI: `http://doi.org/10.5255/UKDA-SN-8681-1`.

Similar results are found for the number of appointments to mental health care and orthodontic services, where utilisation is concentrated among female adolescents at the top of the income distribution. In the case of orthodontic services, pro-rich inequalities are found among both genders. In contrast, Panel B from Table 4.7 shows pro-poor inequalities in the utilisation of sexual and reproductive health services in hospitals. We also find pro-poor inequalities in the probability of not attending an outpatient hospital appointment, suggesting that adolescents at the bottom of the income distribution are more prone to cancel or not attend their medical appointments.

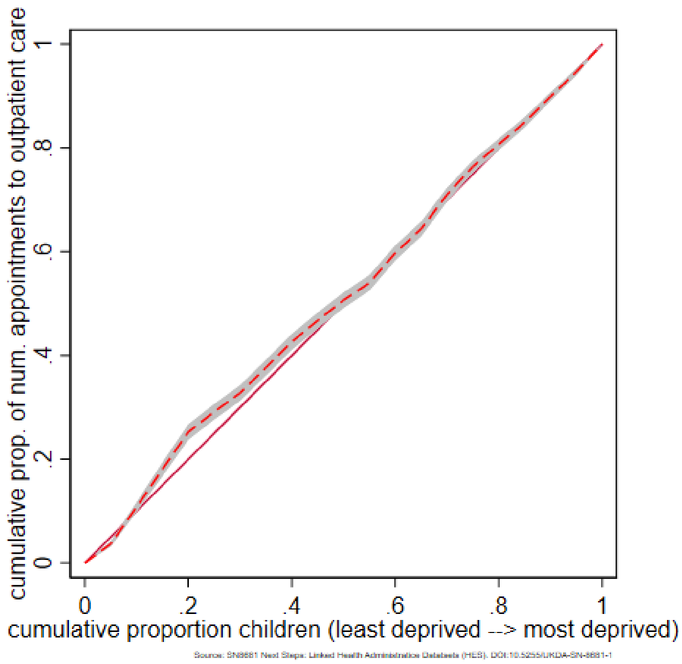
FIGURE 4.4: Concentration curve of the number of visits to A&E at aged 17



Notes: The continuous red line shows the perfect equality line, and the dotted line shows the concentration curve. The number of visits to the A&E per person has been created summarising observation per patient in a year (2007/08) at aged 17. The cumulative proportion of children is created using the Income Affecting Children Index and divided by 5 quantiles from least to most deprive. *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2020). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure access. [data collection]. UK Data Service. SN:8681, `http://doi.org/10.5255/UKDA-SN-8681-1`.

As mentioned above, concentration indices can also be represented graphically using concentration curves as we can see in Figures 4-5. Figure 4.4 shows the relationship between the cumulative proportion of children (ordered from least deprived to most deprived using the IDACI index) on the horizontal axis and the cumulative proportion of number of visits to emergency department on the vertical axis. The 45 degree line represents the line of perfect equality (equivalent to a concentration index equal to zero), such that concentration curves lying below this line indicates "pro-poor" inequality, e.g., higher numbers of visits to emergency department is more prevalent amongst poorer adolescents. In contrast, Figure 4.5 reveals that higher numbers of appointments to outpatient services are more prevalent amongst richer adolescents.

FIGURE 4.5: Concentration curve of the number of appointments to outpatient care at aged 17



Notes: The continuous red line shows the perfect equality line, and the dotted line shows the concentration curve. The number of appointments to outpatient care per person has been created summarising observation per patient in a year (2007/08) at aged 17. The cumulative proportion of children is created using the Income Affecting Children Index and divided by 5 quantiles from least to most deprive. *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2020). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure access. [data collection]. UK Data Service. SN:8681, http://doi.org/10.5255/UKDA-SN-8681-1.

We further analyse horizontal inequity in health care utilisation conditional on need. In order to do that, we restrict the sample to those diagnosed with long-standing health conditions.[24] The corresponding results for measures of unmet need are presented in Table C.6, Appendix C.5. Results reveal that, after adjusting for health care needs, the corrected concentration indices for emergency and outpatient hospital visits are not statistically different from zero and are consistent with the principle of horizontal equity with respect to income. For outpatient care, Table C.6 shows systematic pro-rich inequity in orthodontic services for adolescents aged 17. In contrast, pro-poor inequities are found for mental health care as well as sexual and reproductive health care services. Pro-poor inequity is also observed for time waiting between arrival to the A&E and receiving treatment, with results statistically significant at the 5% level.

4.5.4 Decomposition analyses of Inequalities of Opportunity (IOp)

The results from the Shapley-Shorrocks decomposition of IOp dissimilarity indices for the health and health care utilisation measures are presented in Tables 4.8 and 4.9, respectively. The Shapley decomposition of the IOp shows the contribution of each of the explanatory

[24] Note that in most of the existing literature, horizontal inequity is measured as the degree to which individuals' socioeconomic status is associated with their health services use adjusted for differences in health care need (Cookson, Propper, et al., 2016). Here, following Davillas and Jones (2021), we use a more direct approach by restricting the sample to those with a health condition to condition utilisation on having a current health care need directly.

variables (the so-called ex ante circumstances) to the variance in health and health care explained by the model specifications (expressed in relative terms as a ratio of the overall variance). We have included ex-ante circumstances measures before Wave 4 (aged 17) for individual-, parental-, household-, and regional-level characteristics. In Tables C.7 and C.8 in Appendix C.5, we further included these circumstances in different sets of specifications, where Specification 1 solely includes individual and regional inequalities; Specification 2 further augments the model with lifestyle and health behaviours indicators. Finally, we further include a set of household, parental and regional indicators in Specification 3.

TABLE 4.8: Dissimilarity indices and decomposition of IOp in health outcomes for participants aged 17

	Long-standing illness or disability for males		Mental ill-health (GHQ-12) for females	
Panel (A). Inequality of Opportunity				
	Absolute inequality		*Absolute inequality*	
Dissimilarity Index[1]	0.275		0.201	
	(0.009)		(0.012)	
Modified dissimilarity index[2]	0.090		0.230	
	(0.022)		(0.010)	
Panel (B). Shapley-Sharrock decomposition of circumstances to IOp				
	Shapley value	%	*Shapley value*	%
Demographics (non-white ethnicity; young carer)	0.002	1.74	0.007	3.35
Regional dummies (GOR) and rural indicator	0.009	9.86	0.029	12.46
Pre-circumstances between birth and nursery age	0.007	8.53	0.005	2.38
Individual-level characteristics				
Lifestyle and school experiences	0.020	22.44	0.085	37.14
Health behaviour-related	0.022	24.48	0.059	25.81
Parental-level characteristics				
SES – educational and occupational status	0.005	5.91	0.023	10.34
Demographics characteristics	0.006	6.64	0.012	5.24
Ownerships	0.011	11.90	0.002	0.80
Household-level characteristics				
Household income	0.001	0.73	0.001	0.36
Type of family and number of siblings	0.007	7.76	0.004	2.09
Number of observations	4,704		4,286	

Notes: Bootstrapped standard errors in parenthesis (500 replications). Weights used. [1] De Barros, Ferreira, et al. (2009): propose to first estimate a probit on the dummy variable (for ordered variables, a threshold must be chosen, and a dummy must be constructed). The predicted probability (conditional probability) is then used to compute the dissimilarity index, which is an absolute measure of inequality of opportunity. The measure is scale invariant but not translation invariant. [2] Juárez and Soloaga (2014): This method is basically the same as the one proposed by De Barros, Ferreira, et al. (2009), except it uses a modified dissimilarity index that is translation invariant but not scale invariant. Circumstance covariates: Demographics (non-white ethnicity, young carer); nine regional dummies (GOR) and rural indicator; pre-circumstances between birth and nursery age (nursery school, birth weight, early birth); lifestyle and school experiences (social life indicator, attitude toward school, bullying indicator, play an instrument, reading, hours watching TV dummies); health behaviour-related (practice sport, cannabis, alcohol, cigarettes); Parental SES (Occupational status and education attainment); Parental demographics (age of the main parent, cohabitation status, disabilities); parental ownership (tenure, internet); household income (as a total annual benefit amount plus gross annual salary of the main parental and the second parent per capita); type of family (single family, number of siblings, non-English spoken).

The dissimilarity indices presented in Table 4.8 Panel A is 9% for long-standing illness among male adolescents and 23% for mental ill-health among female adolescents. The dissimilarity index is interpreted as the share of total opportunities for gaining better health status that would need to be redistributed from individuals who feel healthier to individuals who fell less healthy for equality of opportunity to prevail. In Panel B, we show the Shapley-Shorrocks decomposition of the modified dissimilarity index. The decomposition results for long-standing illness among males' adolescents reveal that lifestyle, school experiences, health behaviours and parental ownership (of house) present the largest contributions to the dissimilarity index (22.44%, 24.48% and 11.90%, respectively). Similarly, the decomposition results for mental ill-health among female adolescents show that lifestyle, school experiences, health behaviours and parental socioeconomic status present the largest contributions to the dissimilarity index (37.14%, 25.81%, and 10.34%).

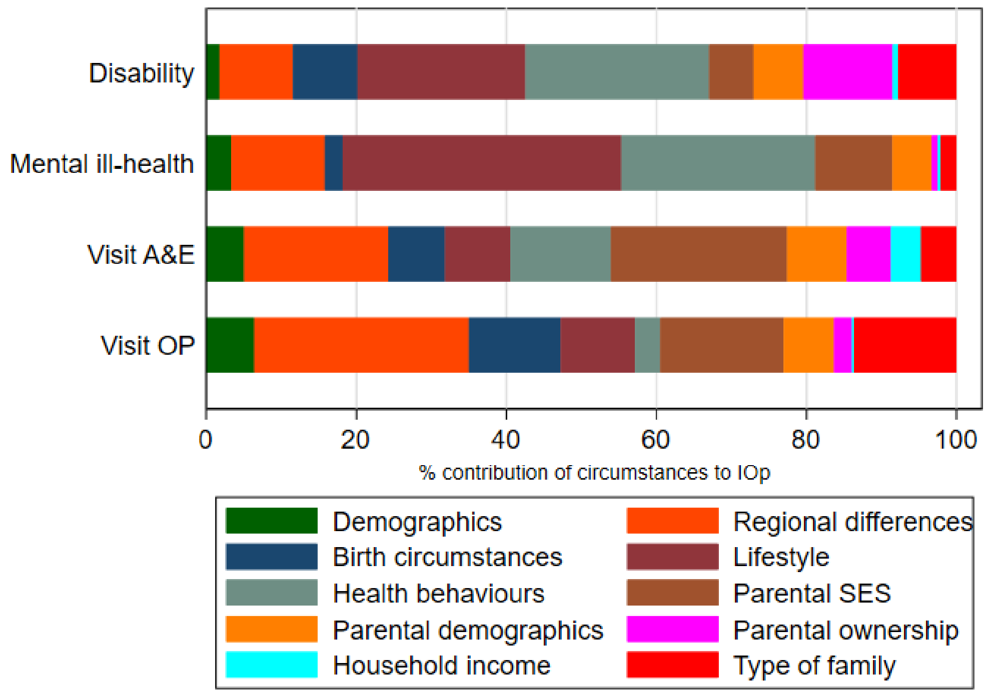
TABLE 4.9: Dissimilarity indices and decomposition of IOp in health care outcomes for participants aged 17 (2007-2008)

	A&E: More than one visit per year		OP: More than three appointments per year	
Panel (A). Inequality of Opportunity				
	Absolute inequality		*Absolute inequality*	
Dissimilarity Index[1]	0.160		0.088	
	(0.030)		(0.015)	
Modified dissimilarity index[2]	0.321		0.235	
	(0.016)		(0.006)	
Panel (B). Shapley-Sharrock decomposition of circumstances to IOp				
	Shapley value	%	*Shapley value*	%
Demographics (non-white ethnicity; young carer)	0.016	5.02	0.015	6.41
Regional dummies (GOR) and rural indicator	0.061	19.26	0.067	28.58
Pre-circumstances between birth and nursery age	0.024	7.54	0.028	12.24
Individual-level characteristics				
Lifestyle and school experiences	0.028	8.71	0.023	9.95
Health behaviour-related	0.043	13.41	0.008	3.36
Parental-level characteristics				
SES – educational and occupational status	0.075	23.48	0.039	16.43
Demographics characteristics	0.025	7.96	0.015	6.69
Ownerships	0.019	5.92	0.005	2.39
Household-level characteristics				
Household income	0.012	3.97	0.001	0.27
Type of family and number of siblings	0.015	4.73	0.03	13.66
Number of observations	697		2,515	

Notes: Bootstrapped standard errors in parenthesis (500 replications). Weights used. [1] De Barros, Ferreira, et al. (2009): propose to first estimate a probit on the dummy variable (for ordered variables, a threshold must be chosen, and a dummy must be constructed). The predicted probability (conditional probability) is then used to compute the dissimilarity index, which is an absolute measure of inequality of opportunity. The measure is scale invariant but not translation invariant. [2] Juárez and Soloaga (2014): This method is basically the same as the one proposed by De Barros, Ferreira, et al. (2009), except it uses a modified dissimilarity index that is translation invariant but not scale invariant. Circumstance covariates: Demographics (non-white ethnicity, young carer); nine regional dummies (GOR) and rural indicator; pre-circumstances between birth and nursery age (nursery school, birth weight, early birth); lifestyle and school experiences (social life indicator, attitude toward school, bullying indicator, play an instrument, reading, hours watching TV dummies); health behaviour-related (practice sport, cannabis, alcohol, cigarettes); Parental SES (occupational status and education attainment); Parental demographics (age of the main parent, cohabitation status, disabilities); parental ownership (tenure, internet); household income (as a total annual benefit amount plus gross annual salary of the main parental and the second parent per capita); type of family (single family, number of siblings, non-English spoken).

Turning to the results for the health care utilisation measures, Table 4.9 reports dissimilarity indices of 32.1% for visiting A&E hospital services more than one time per year and 23.5% for more than three appointments with outpatient hospital services, when all of the circumstances are included. That is, 32.1% (23.5%) of total opportunities would need to be redistributed from individuals who are using more A&E (outpatient) services to individuals who are using less for equality of opportunity to prevail. The decomposition of the indices show that regional differences (19.26% and 28.58%) and parental SES (23.48% and 16.43%) are the two circumstances that are most influential in inequality of opportunity in health care utilisation (A&E and outpatient hospital services, respectively) among adolescents in England. Figure 4.6 visually presents the same Shapley-Shorrocks decomposition of the variance share results for the health and health care utilisation measures.

FIGURE 4.6: Shapley-Shorrocks decomposition of circumstances to Inequality of Opportunity



Notes: Decomposition analysis of health and health care outcomes. First row, *"Disability"* outcome, includes the contribution of covariates for the *"Long-standing illness or disability for males"* outcome. Second row, *"Mental-ill health"* includes same analysis for *"Mental ill-health (GHQ-12) for females"*. The same occurs for health care outcomes, where Visit A&E and Visit OP include the results for *"A&E: More than one visit per year"* and *"OP: More than three appointments per year"*, respectively. Factor contributions are ordered according to their contributions. Circumstance covariates: Demographics (non-white ethnicity, young carer); nine regional dummies (GOR) and rural indicator; pre-circumstances between birth and nursery age (nursery school, birth weight, early birth); lifestyle and school experiences (social life indicator, attitude toward school, bullying indicator, play an instrument, reading, hours watching TV dummies); health behaviour-related (practice sport, cannabis, alcohol, cigarettes); Parental SES (Occupational status and education attainment); Parental demographics (age of the main parent, cohabitation status, disabilities); parental ownership (tenure, internet); household income (as a total annual benefit amount plus gross annual salary of the main parental and the second parent per capita); type of family (single family, number of siblings, non-English spoken). *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2020). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure access. [data collection]. UK Data Service. SN:8681, http://doi.org/10.5255/UKDA-SN-8681-1.

We present additional sets of results in Tables C.9 and C.10 in Appendix C.5 reporting the statistically significance of the set of circumstances by outcomes and specifications. Here, we can see that both sets of most relevant contributed variables – lifestyle, school experiences, health behaviours and parental SES for health outcomes and regional differences and parental SES for health care utilisation measures – are statistically significant. This indicates that addressing these adolescent circumstances will help to reduce inequality of opportunity on health outcomes and access to health care.

4.5.5 Interrupted time-series analysis

Table 4.10 presents results from the ITS analysis on the effect of the Great Recession and the subsequent austerity policies on the number of visits and appointments to the accident and emergency department and outpatient department, respectively.[25] Results suggest that, on average, the number of appointments for outpatient hospital services increases by 0.249 appointments per year during the period of the Great Recession compared to the previous years. Figure 4.7 shows evidence of an effect of the 2008 economic crisis in the number of appointments for outpatient services.

TABLE 4.10: Interrupted time-series analysis: the effect of economic shocks on health care utilisation

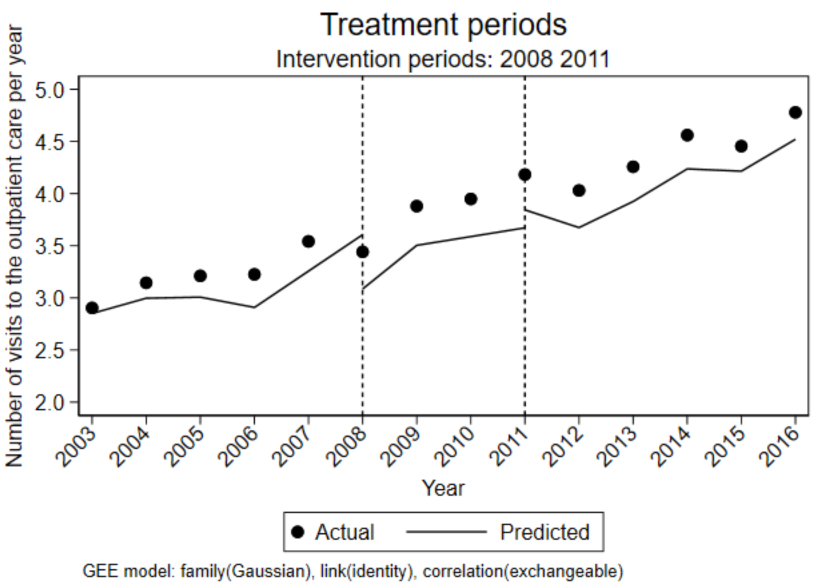
	A&E: Number of visits per year	OP: Number of appointments per year
Panel (A): Generalized estimation equation population-averaged model		
Time	0.040***	0.093***
	(0.005)	(0.020)
First intervention period: 2008	-0.068	-0.045
	(0.077)	(0.127)
Interaction term (Time*2008)	0.065	0.249***
	(0.049)	(0.091)
Second intervention period: 2011	0.098	-0.320
	(0.218)	(0.218)
Interaction term (Time*2011)	-0.152**	-0.125
	(0.064)	(0.1001)
Year FE	*Yes*	*Yes*
Panel (B): Postintervention trends analysis		
Post-intervention linear trend: 2008	0.106**	0.342***
	(0.049)	(0.091)
Post-intervention linear trend: 2011	-0.046*	0.217***
	(0.043)	(0.038)
Number of observations	3,596	16,615

Notes: ***p≺0.01;**p≺0.05;*p≺0.10. Standard errors in parentheses. All regressions include year fixed-effects. Time variable covers from the start of the study until the introduction of the first intervention. *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2022). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure Access DOI: `http://doi.org/10.5255/UKDA-SN-8681-1`.

[25] We graphically present the evolution of the average number of visits to the A&E and appointments to outpatient per financial year in Figures C.6 and C.7 in Appendix C.6.

As for the use of A&E department, we find an association suggesting a decrease of 0.152 visits per year for emergency hospital services after the implementation of austerity policies, compared to previous years. Results from Panel B of Table 4.10 reveal an additional utility of defining multiple treatment periods (the Great Recession and the austerity policies) in the ITS analysis when analysing single-group data. As shown in Panel B, the increase in the number of appointments to outpatient care after the Great Recession was slightly larger, at 0.342 appointments per year and patient compared to the period of austerity cuts. Although these results need to be interpreted with caution, such small magnitudes appear to suggest only a moderate effect of the Great Recession and austerity on health care utilisation among adolescents.

FIGURE 4.7: Single-group interrupted-times series analysis and two intervention periods for the number of appointments to outpatient care



Notes: First intervention period: 2008 Great Recession. Second intervention period is the implementation of expenditures cuts in 2011. *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2020). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure access. [data collection]. UK Data Service. SN:8681, http://doi.org/10.5255/UKDA-SN-8681-1.

4.6 Discussion and conclusions

This paper explores associations between adolescent health and socioeconomic deprivation at income and small-area levels in England using administrative records from the Health Episode Statistics (HES) linked to socioeconomic information included in the cohort study Next Steps. We employ Erreygers' corrected concentration index and Shapley-Shorrocks decomposition techniques to explore the relative contribution of childhood circumstances in inequality of opportunity of adolescent's health and health care utilisation. An interrupted time-series analysis is then implemented to examine whether health care utilisation in emergency and outpatient care was influenced by the Great Recession and subsequent austerity policies. Results suggest that small area deprivation and income both yield inequalities in health among adolescents, favouring the better-off. Results from the interrupted time series suggest that the Great Recession and related austerity policies may have an influence on the number of appointments (and visits) for outpatient (and emergency) hospital services.

More specifically, we find that income and small area-related inequalities in long-term illness are concentrated among males aged between 15-17 at the bottom of the income distribution. Significant inequalities for adolescents' mental-ill health are only evident among less deprived females aged at least 17. These gender-based differences may reflect broader gender disparities in health inequalities observed in previous literature (Zhang and Wang (2004); Costa-Font, Hernández-Quevedo, and Jiménez-Rubio (2014)). In particular, these studies suggest that patterns of inequality in unhealthy lifestyles vary significantly depending on gender. The corrected concentration indices measuring income-related inequalities in health care utilisation reveal that a higher number of visits to the accident and emergency department are concentrated among adolescents with low SES. Conversely, outpatient medical services are mostly used by adolescents with high SES. After adjusting for health care needs, the corrected concentration indices for both the emergency and outpatient hospital visits are not statistically different from zero, implying equity between adolescents with the same health care needs. This result is consistent with the principle of horizontal equity with respect to income (Cookson, Propper, et al., 2016).

Our decomposition analysis highlights the role of several socioeconomic factors and their contributions to socioeconomic inequalities in health and health care utilisation. For instance, adolescents' lifestyle; school experiences (e.g., attitude toward school, play an instrument); health behaviours (e.g., practice sport, consume alcohol); and parental ownership (e.g., home ownership) appear to be among the most relevant contributors to inequality of opportunity in adolescents' health. In contrast, regional differences and parental socioeconomic status are the two most influential circumstances in inequality of opportunity in health care utilisation. Finally, the analysis of the role played the Great Recession and related austerity policies suggest that while the number of appointments for outpatient hospital services slightly increased after the Great Recession, visits to accident and emergency departments appear to decrease, following the austerity policies.

This study contributes to the current literature on health inequalities among adolescents. It helps in the identification of the key factors driving current trends of SES inequalities in psychological distress and disability/long-term illness among adolescents. This study also investigates trends in such inequalities before and after the Great Recession and related austerity policies.

As usual, this study has some potential limitations. First, as in similar studies measuring health inequalities, the analyses presented here do not aim to establish a causal link between the explanatory variables and the health and health care utilisation measures. While we do not provide causal evidence, the findings identify the relative roles of adolescent circumstances versus lifestyle in shaping inequality of opportunity in health and health care use among adolescents. Second, measuring health inequities involves quantifying "unfair" health inequalities due to disparities in the underlying social determinants of health. While some may have different opinions about what constitutes "fairness", this analysis has used variables identified in the previous literature as important drivers of health inequities (Rosa Dias (2009); Davillas and Jones (2020)). Finally, an interrupted time series analysis is used to examine changes in health care use in both emergency and outpatient care during the years of Great Recession and subsequent austerity policies. Results need to be interpreted with caution given the absence of a well-defined control group as well as the small magnitudes of the effects identified by this approach.

Children and young people are among the most vulnerable groups in the society, and the most deprived of this group particularly so. Reducing health inequalities is usually an explicit objective of any National Health System. Also, reducing the rates of unplanned admissions to the level experienced by the least disadvantaged groups would substantially reduce financial and human costs. Therefore, designing and implementing policies that might help reducing deprivation and improve the socioeconomic status of individuals, including adolescents and their families, is often an overall long-term objective for policymakers. This study may aid policymakers by providing a first analysis of the main socioeconomic determinants of health inequalities in health and health case use among adolescents and on the effects of economic shocks on such health inequalities.

5 Conclusions

5.1 Main findings and contributions

This thesis sought to provide new insights into the relationship between economic shocks and health. To this end, analyses on whether and how economic shocks affect the health of different age groups of the population (children, young adults and elderly) have been performed.

Accordingly, this thesis provides new evidence on the following main themes.

First, Chapter 2 focuses on elderly individuals (i.e., those around retirement age) to study how macroeconomic shocks influence the health effects of retirement. Findings suggest that, overall, retirement appears to negatively impact both mental and physical health. Specifically, this analysis shows that retirement increases the risk of depression, stroke, pulmonary related conditions and psychiatric disorders. When economic shocks are accounted for, the picture appears to change. This study finds that retiring after the Great Recession improves mental health and decreases the probability of suffering from angina and heart attacks, with some differences by gender. Since these conditions are strongly associated with chronic stress, this could also support the hypothesis that leaving the labour market shortly after an economic shock could improve health via reduced work-related strain, anxiety and/or pressure. This finding would also be in line with recent UK evidence suggesting a negative impact on mental health among women caused by the prolonged exposure to high strain jobs due to the increase in the state pension age.

Second, Chapter 3 focuses on the long-term effects of experiencing parental unemployment during childhood on child health and the potential mechanisms underlying such effects. This analysis finds that experiencing parental unemployment during early childhood (0-5) and early adolescence (11-15) increases the likelihood of reporting long-standing illnesses later on in life (at ages 18-33). Results also reveal that experiencing parental unemployment during "middle" childhood (6-10) also increases the probability of suffering from mental ill-health later on in life. Findings from the heterogeneity analysis indicate that the effects of parental unemployment on children's health greatly depend on the socioeconomic status of the family of origin (measured by families' income and parental educational attainment). That is, experiencing parental unemployment among less-educated families is associated with larger negative long-term effects on child mental and physical health. This may imply that the negative effect of income losses after unemployment can be more severe in already income-deprived families, as previous literature has also pointed out. Further analyses on whether others potential mechanisms, such as parents' health behaviour and personality traits, may drive the long-term health effects of parental unemployment are performed. In particular, control variables for parental smoking behaviour and the "Big-5" personality traits are included in the baseline regressions, obtaining similar results.

The effect of parental unemployment appears to differ by parent's gender: while *paternal* unemployment is associated with detrimental long-term health outcomes for children, the effect of *maternal* unemployment appears to be negligible. Results also appear to differ by child biological characteristics (specifically, children's gender). Findings suggest that parental unemployment at ages 0-5 and 11-15 increases the likelihood of suffering disabilities and worse general health levels among adult men. Further exploration of potential mechanisms shows that experiencing multiple parental unemployment spells is associated with worse long-term health outcomes, and such effects may last longer. It also appears that the negative effects of experiencing parental unemployment during childhood might become apparent only when individuals are between around 25-33 years old(rather than in earlier years, i.e., 18-24).

Third, Chapter 4 explores associations between adolescent health and socioeconomic deprivation at income and small-area levels in England. This analysis focuses on income-related inequalities in health care utilisation by employing an inequality of opportunity approach and decomposition techniques to explore the relative contributions of childhood circumstances. Moreover, this study examines the evolution of health care utilisation in emergency and outpatient care during the years of Great Recession and subsequent austerity policies. Findings confirm the existence of significant disparities in adolescent health and health care utilisation, with different effects by gender and age group. Key findings confirm the presence of income and small area-related inequalities in long-term illness, favouring better-off males aged 15 and 17. In contrast, statistically significant inequalities for adolescents' mental ill-health only appear among least deprived females aged 17.

Results using healthcare utilisation measures reveal that a higher number of visits to emergency hospital departments are concentrated among the worst-off, while a higher number of appointments for outpatient hospital services are found among better-off adolescents. Importantly, this gradient disappears after adjusting for health care needs (defined as having an underlying health condition). The decomposition analysis highlights the role of different socioeconomic factors and their contributions to socioeconomic inequalities in health and health care utilisation. Adolescent lifestyle (e.g., social life), health behaviours (e.g., practice sport) and parental socioeconomic status (e.g., occupational status) are among the main contributors to adolescents' health inequalities. In contrast, regional difference and parental socioeconomic status are the two circumstances that are most influential in health care inequalities among adolescents in England. As for the effect of economic shock and the subsequent austerity policies on health care utilisation among adolescents, slightly statistically significant effects on adolescents' health care utilisation are observed.

This thesis provides several potentially relevant contributions. Chapter 2 contains one of the first analyses providing a systematic exploration of the key mediating factors and mechanisms influencing the health effects of retirement on both mental and physical health. In addition, new evidence is provided on the impact of retirement on health shortly after the 2008 Great Recession, a recent and severe economic shock. This is especially relevant in policy terms as most OECD countries are currently experiencing rapid trends of population ageing with increasing larger proportions of individuals near retirement age coupled with a succession of economic shocks, such as the Great Recession and the one induced by the ongoing COVID-19 pandemic. Although some governments have decided to raise the state pension age as a response to macroeconomic shock, these findings suggest that the adverse health consequences of prolonging (manual workers') working life during an economic crisis have been overlooked and should be considered in cost-effective policy evaluations, as they might outweigh some of the potential benefits from later retirement.

Chapter 3 contributes to the understanding of the long-term consequences of parental unemployment on children's physical and mental health. Evidence produced throughout this analysis build on and complement earlier studies on the consequences of parental unemployment which typically focus on short-term health outcomes. It focuses on a broad set of childhood circumstances that might be relevant for children's human capital and health formation but have not yet been explored extensively. Therefore, this research contributes to the growing literature on the relationship between family environment and long-term health by exploring the heterogeneous effects of parental unemployment during childhood along several dimensions (including by socioeconomic groups). This study also analyses the potential mechanisms underlying the effects of parental unemployment on child future health by, for instance, frequencies of parental unemployment spells and different timings during young adulthood when parental unemployment effects arise. Overall, findings from this empirical exploration may provide potentially relevant insights to policymakers interested in alleviating the long-term health costs of parental unemployment.

Chapter 4 contributes to the literature in several ways. To the best of our knowledge, it is the first study systematically exploring income-related inequalities by focusing on access to health care among millennials in England. More specifically, this analysis contributes to the identification of the key factors driving current trends of SES inequalities in psychological distress and disability/long-term illness among adolescents, using different SES measures, such as the Income Deprivation Affecting Children Index (IDACI) and the Index of Multiple Deprivation (IMD). Second, this is the first attempt to quantify the relative contributions of "unavoidable" factors versus adolescents' lifestyle to SES-related health inequalities in health care use among adolescents. Third, this study also investigates trends in such inequalities before and after the Great Recession and related austerity policies. The evidence produced by this analysis on the relationship between health-inequalities and economic shocks may help policymakers to design new and more targeted policies aimed at reducing health disparities at a critical stage of an individual's life cycle.

5.2 Policy implications

This thesis employs several rich and complex datasets coupled with modern econometric methods to provide new evidence on the effects of economic shocks on health and health inequalities. Importantly, the body of evidence presented in this thesis might not just be of interest to the specialised academic literature but could ultimately help governments and decision-makers to design evidence-based policies aimed at improving the health and wellbeing of the people they serve. This section provides an in-depth discussion of the potential policy implications of the main empirical contributions of this thesis.

Chapter 2 suggests that macroeconomic shocks may play an important role in shaping the relationship between retirement and health. Understanding the different pathways linking economic shocks, retirement and health among older individuals is crucial for devising targeted policies to ensure the wellbeing of an increasingly larger proportion of the population. Government policies increasing state retirement age may need to consider strategies to prevent potentially adverse health consequences, especially among individuals in manual and routine occupations. For instance, national policies may need to commit to more inclusive labour market policies facilitating smoother transitions to retirement for blue-collar workers. Moreover, the fact that workers with physically demanding occupations are the most affected by the ever-increasing state retirement age, raises questions about fairness and whether eligibility rules should more explicitly consider the type of occupation (blue vs white collar). This study provides potentially useful information to policy makers, especially through the identification of the main drivers of retirement during economic shocks, which will inevitably reoccur. These findings might also be relevant to policy makers as they highlight the importance of considering resilience into policies impacting vulnerable and at-risk populations, as well as into the labour market itself, well in advance of increasing numbers of potentially severe shocks may pay health and economic dividends.

Chapter 3 might provide some useful insight to the design of public policies aimed to tackle widening inequalities derived from parental unemployment, especially among already income-deprived households. Findings suggest that the intergenerational effects of parental unemployment are significant and under-emphasise societal cost. Understanding its spillover effects can help shape appropriate policy responses to tackle widening inequalities stemming from parental unemployment, especially among children living in disadvantaged households. Therefore, programmes targeting unemployed parents might help in alleviating the persistent health burden of children in the longer term. In particular, job protection schemes targeting the most disadvantaged parents may help diminishing the children's probability of suffering from worse health later on in life.[1] On the whole, the strategic objectives of policymakers should be to develop childhood policy interventions that can potentially provide life-long health benefits and thus result in potentially significant savings in public finances and societal outcomes.

Further contribution of this thesis is to decompose health inequalities among adolescents and, in turn, provide evidence for government policy in reducing inequalities in health. Reducing health inequalities has been an explicit objective of the English National Health System (NHS) for the past two decades (Health, 2003). Yet, children and adolescents suffer particularly from increasing poverty (UNICEF, 2021), and the consequences of socioeconomic disparities in health outcomes (Viner, Arkell, et al., 2017). Chapter 4 reveals that income deprivation is linked to a higher incidence of poor health among adolescents. Children and young people are among the most vulnerable groups in the society, especially those living in deprived households. Therefore, policymakers need to focus on designing and implementing policies that help reducing deprivation.

Moreover, findings provide notable implications for policy roles in reducing inequalities in access to health care through the analysis of health care utilisation in emergency and outpatient care across the years of Great Recession and subsequent austerity policies. It seems clear that there is an urgent need for coordinated transition services for young people as they move from child to adult health services, particularly those living in the most deprived areas. A more integrated approach between the NHS and social care might be needed to tackle this issue and design health care models for young people. Reducing the rates of unplanned admissions to the level experienced by the least disadvantaged groups would allow saving potentially significant financial resources while also improving health outcomes. Overall,

[1] For instance, Hope, Osam, et al. (2021) suggest that children of mentally ill mothers are a health vulnerable group for whom targeted intervention may create benefit for individuals, families, as well as limited NHS resources.

evidence from this chapter appears to suggest that unless government and policymakers focus on improving adolescents and young individuals SES conditions, it may not be possible to break the persistence of health inequalities across the life-cycle.

The COVID-19 pandemic has led to a renewed interest in the effect of economic shocks on health and health inequalities, with a particular focus on the most income-deprived individuals (Munford, Khavandi, et al., 2021). Policymakers have expressed concerns that socioeconomic health disparities may have been exacerbated among adolescents and young adults, given that the adverse effects of economic shocks and Covid lockdowns seem to have affected these members of society disproportionately. This thesis aims at contributing to this policy debate by providing rigorous scientific evidence exploiting the latest data available on these issues.

5.3 Limitations and future research avenues

Whilst this thesis has generated new insights around the relationship between economic shocks and health, it is important to clearly discuss its limitations while suggesting future research avenues. Firstly, possible methodological issues of Chapter 2 might impact the conclusions drawn from this study. The identification strategy adopted in the first part of the analysis of the health effects of retirement (inverse probability weighting regression adjustment) relies on selection on observables by exploiting state-of-art (re)weighting and matching methods. Yet, this approach is based on the conditional independence assumption and does not explicitly account for the roles of unobservables. While this might be a concern in the identification of the effect of interest, this chapter also provides evidence suggesting that results should be robust to varying degrees of selection on unobservable. One may suggest to employ a source of exogenous variation in the retirement decision to deal more directly with the potential endogeneity issues in the relationship between retirement and health. Future research might explore the opportunity of exploiting the geographical variation provided by the varying eligibility rules across different pension systems/countries. This type of analysis might be based on multi-country datasets which typically provide more limited individual-level information, therefore limiting the investigation of potentially relevant mechanisms and heterogeneity in the effects of retirement.

The difference-in-difference approach used to identify the impact of the Great Recession on the health effects of retirement allows the retirement effect to vary between the years before and those after the Great Recession. To do so, it exploits the variation on the unemployment rate across regions and time due to the Great Recession. This approach is open to criticism around the use of changes in unemployment rates due to the Great Recession as an economic indicator. There are several trade-offs associated with performing analysis with more or less aggregated economic indicators. Future studies may want to consider using other economic (conditions) indicators at different levels of aggregation as this could help understanding the mechanisms behind the estimated relationships. Finally, further research on the longer-term impact on the labour market of losing those who retire earlier than planned, especially highly skilled workers and those who can afford an early exit, might be useful.

Secondly, the analysis from Chapter 3 relies on econometric specifications accounting for unobserved heterogeneity, selection bias and the possible dependency structure of the data while controlling for a wide range of confounding factors. The assumption of these methods relies on having sufficient variation over the sample period of the time-varying explanatory variables. Several studies have tried to overcome the endogeneity of parental unemployment by comparing children whose parents suffered involuntary unemployment coming from factory closures with children whose parents continued to be employed. One caveat to that approach though is that the timing of layoff can potentially be non-random. Unfortunately, neither the BHPS nor UKHLS include reliable information on unemployment status due to such closures or dismissals. Hence, this study opts to rely on a different methodology by controlling for time-invariant unobserved heterogeneity using a Mundlak approach (Mundlak, 1978). Another more minor challenge is the use of subjective health outcomes and the potential for reporting bias. However, if reporting bias is systematic but time-invariant, the inclusion in the models of parameters accounting for time-invariant unobservables should help account for that.

Future efforts in data collection including aspects such as the evolution of parent-child interactions after job loss and more detailed time-use data might help to shed light on mechanisms driving this relationship which has not been comprehensively explored in the economics literature to date. Moreover, data collection on cumulative household income and parental unemployment duration could help in exploring potential mechanisms underlying the long-term health effects of parental unemployment. Another area where more research might be needed concerns the impact of parental unemployment on non-cognitive skills, overall life satisfaction and happiness. Finally, future research focusing on changes in parents' (mental) health and health-behaviours following a job displacement in disadvantaged families might also lead to potentially policy relevant research insights.

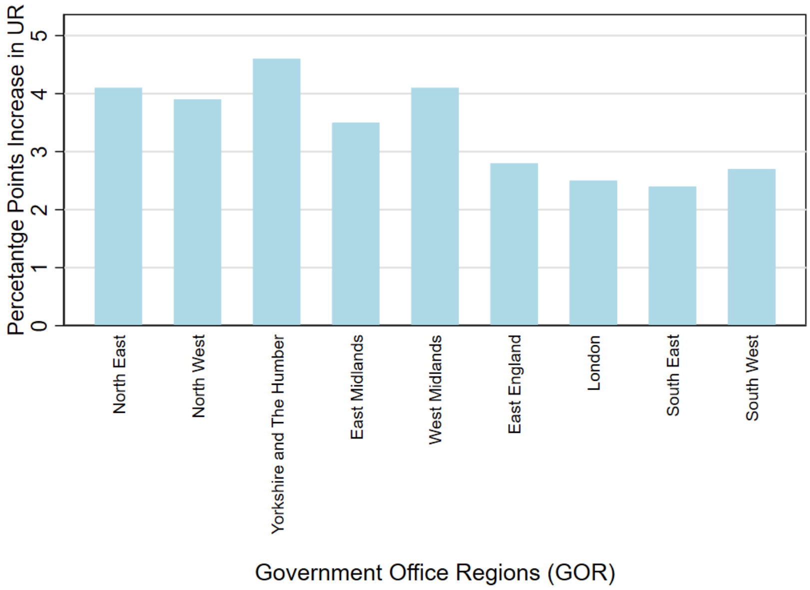
There are also some limitations to the findings from Chapter 4. It is worth reminding that the analyses performed in this chapter do not aim to address the potential endogeneity biases or establish any causal links between the explanatory variables and the health and health care utilisation measures. Moreover, measuring health inequities involves quantifying unfair health inequalities due to disparities in the underlying social determinants of health. While there may be different opinions about what constitutes "fairness", this analysis has used variables identified in the previous literature as important drivers of health inequities. This study also uses the concept of *equality of opportunity*, which allows to distinguish between “circumstances”, i.e., factors that cannot be changed, and “effort” variables, i.e., factors that can be changed. Finally, an interrupted time series analysis is used to examine changes in health care use in both emergency and outpatient care during the years of Great Recession and subsequent austerity policies. Results need to be interpreted with caution given the absence of a well-defined control group as well as the small magnitudes of the effects identified.

Aside from addressing many of the limitations discussed above, this work could be expanded along several paths. While describing health inequalities is crucial to highlight where the health gaps lie, there is a need to move forward by assessing the impact of current and new policies in sectors outside health. This includes the effects that housing, education, and employment policy have on the health inequalities faced by young people. Also, future research may seek to understand whether young people have access to the core building blocks of health – housing, secure work, and supportive relationships with friends, family. This study hopes to provide a solid base upon which future research on the effects of economic shocks on health inequalities can be built.

A Appendix to Chapter 2

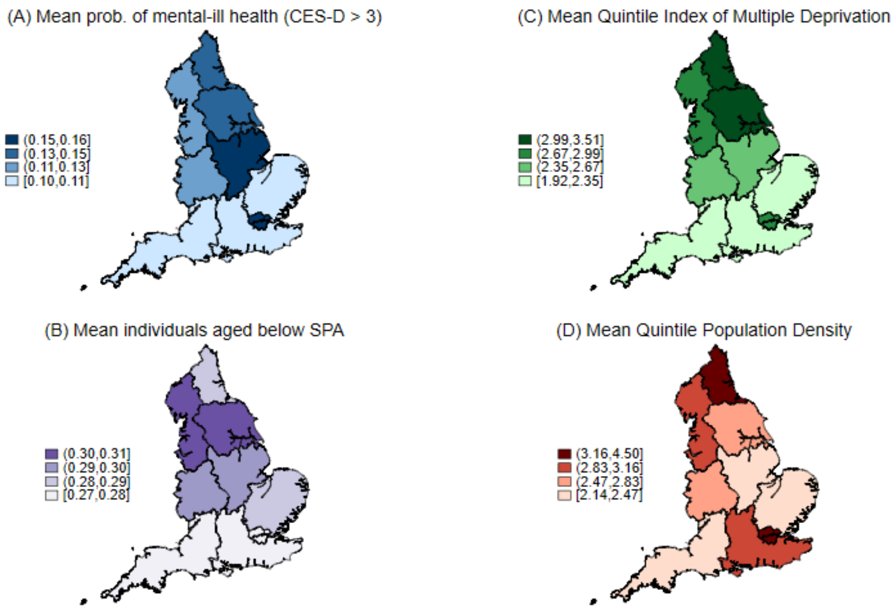
A.1 Additional figures and tables references in text

FIGURE A.1: Percentage point increases in unemployment rates during the period of study



Notes: These were calculated as the difference between the maximum and the minimum value (before the economic crisis) of the unemployment rate in our sample for each regional unit. *Source:* Office for National Statistics (ONS).

FIGURE A.2: Mean of key health outcome and other socioeconomic variables by region (GOR)



Notes: Panel (A) shows the mean probability of mental-ill- health; Panel (B) shows the mean individuals aged below the state pension age (SPA); Panel (C) shows the mean index of multiple deprivation; Panel (D) mean of population density. GOR= Government Office Regions; own maps based on drawn and combined data from an ELSA special license restricted dataset.

A.2 Exploring the main identifying assumptions

First, we check whether there is sufficient overlap in the observed characteristics by comparing the distributions of the propensity scores across individuals in treated and control groups. The corresponding plot (Figure A.1) suggests the presence of suitable matches.[1] This appears to satisfy the common support assumption. Figure A.3 presents the Kernel density plot which shows the estimated densities of the probability of getting the treatment for both retirees and employees. Visually, we can see a significant overlap in the distribution of the retirees and employees.

[Insert Figures A.3-A.5 around here]

Second, we assess whether the balance of covariates is achieved after matching. Table A.1 reports a summary of the covariate balancing tests pre- and post-matching. The standardized mean difference for all covariates used in the IPWRA is reduced from 10.7% pre-matching to 1.9% post-matching. Matching leads to a bias reduction of about 90%. The p-values of the likelihood ratio tests indicate that the joint significance of covariates was always rejected post-matching. Yet, pre-matching the joint significance of the differences between the covariates is never rejected. The pseudo-R2 also dropped from 8.8% pre-matching to 0.3% post-matching. Overall, the low mean standardized bias, joint insignificance of the covariates and low pseudo-R2 are indicative of successfully balancing the distribution of covariates between retirees and employees through matching.

[Insert Table A.1 around here]

Finally, based on data for the years preceding the economic crisis, we explore the validity of the common trend assumption between treated and the control groups. This is investigated by comparing trends in health outcomes before the crisis across treatment and control groups (2004-2007). For the KPSM-DD estimator to be valid, there should be no significant differences in health outcomes trends prior to the Great Recession. Indeed, this assumption can be made more reasonable through careful selection of the comparison group, and appropriate adjustment for covariates (Stuart, Huskamp, et al., 2014). In our case, the kernel propensity score matching is considered when choosing a subset of the treatment and comparison groups with similar pre-intervention levels or trends. Figure A.4 shows that before the onset of the crisis in 2008/9, trends in the post-matching sample are overall very similar during the two waves prior to the Great Recession (2004/5 and 2006/7).

[Insert Figure A.6 around here]

[1] We have also conducted post-estimation balancing tests which indicate that our model significantly improved the level of balance, i.e., the weighted standardised differences are all close to 0 and the variance ratios are all close to 1. However, the full tables are too large to be included in the paper (but are all available upon request).

FIGURE A.3: Propensity score distribution and common support for propensity score estimation

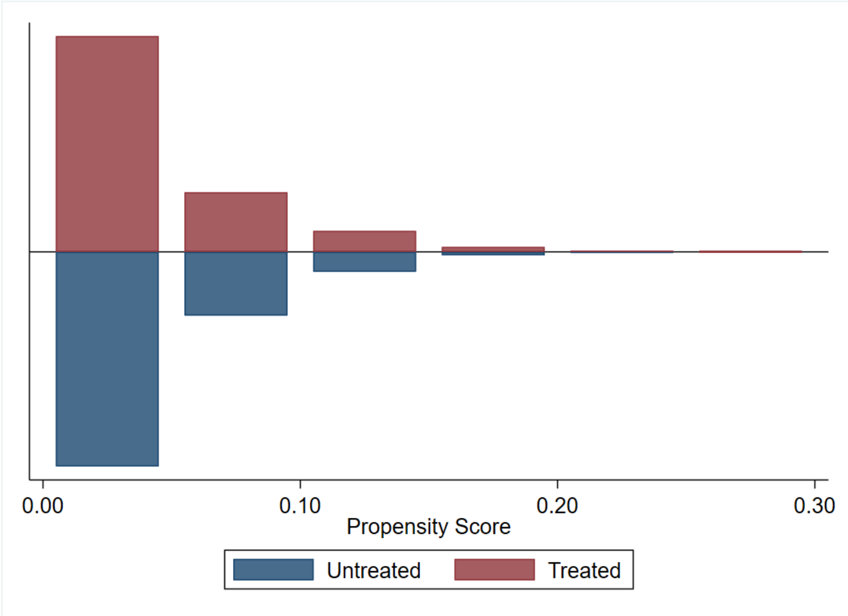


FIGURE A.4: Kernel densities of the probability of getting the treatment-IPWRA

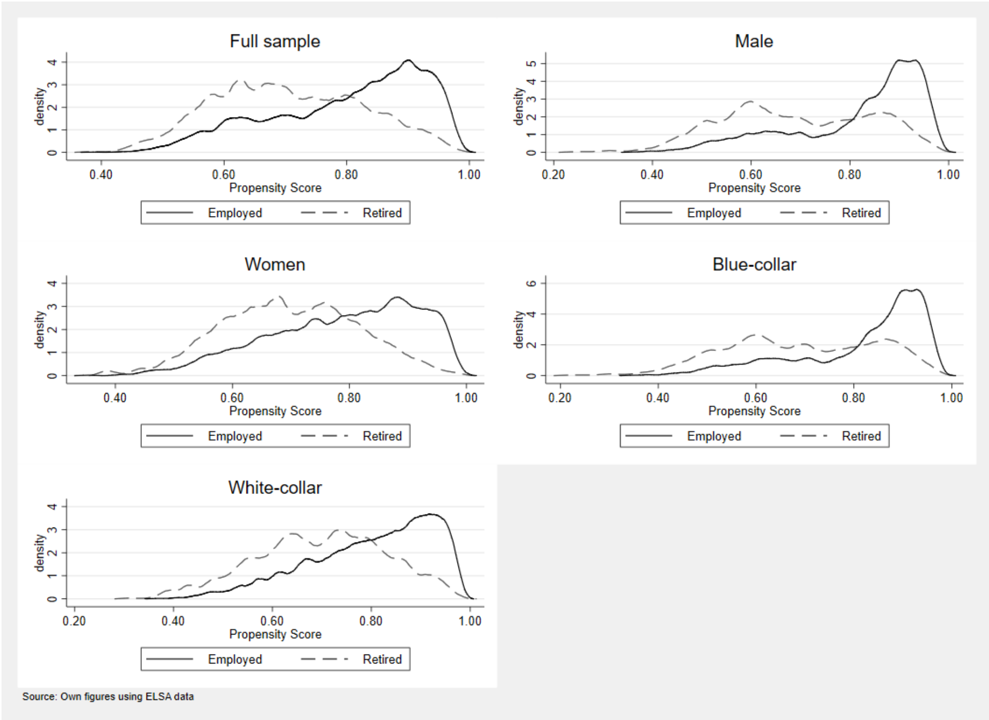


FIGURE A.5: Standardised percentage bias across covariates before and after matching

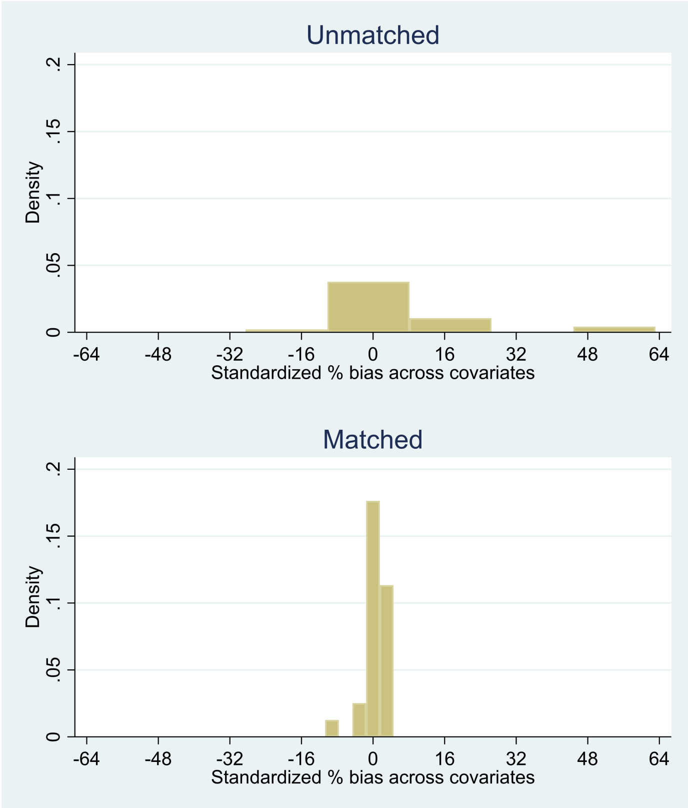
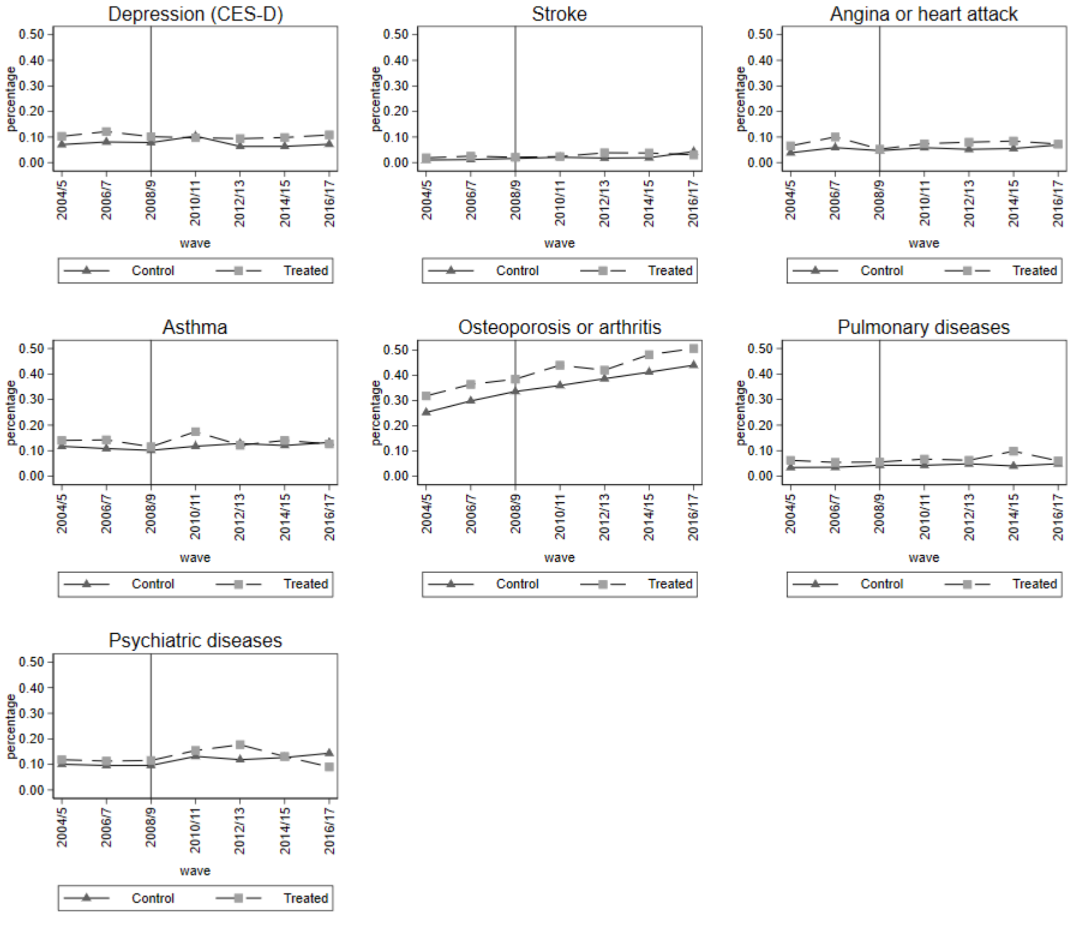


FIGURE A.6: Trends of health outcomes in treated and control groups (post-matching)



Source: Own figures based on the ELSA data from 2004 to 2017.

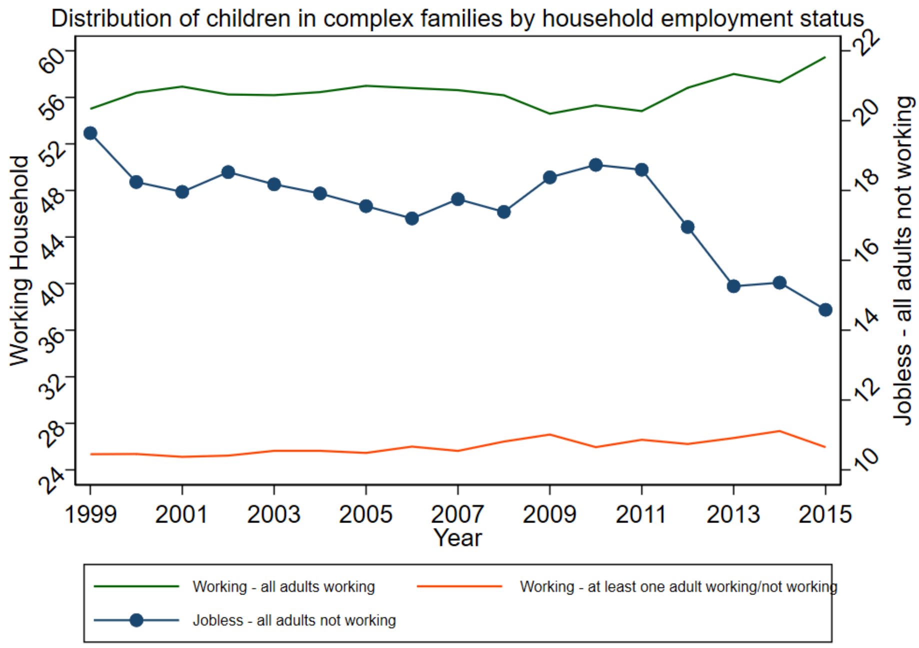
TABLE A.1: Matching quality test

	(1) Pseudo R^2	(2) LR X^2	(3) p-value	(4) Mean bias
Pre-matching	0.088	544.10	0.000	10.7
Post-matching	0.003	11.50	0.994	1.9

B Appendix to Chapter 3

B.1 Additional figures and tables references in text

FIGURE B.1: Distribution (%) of children (aged 0-14) by the employment status of adults in the household, 1999-2015 in UK



Notes: Distribution of children by household employment status. *Source:* Eurostat. https://ec.europa.eu/eurostat/web/lfs/overview

TABLE B.1: Summary statistics, selected variables, parental unemployment at ages 0-5 sample

	Overall, N= 8,480		No parental unemployment, N= 6,598		Parental unemployment, N= 1,882	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	20.37	1.704	20.39	1.781	20.34	1.75
Female	0.519	0.499	0.513	0.499	0.504	0.504
Year of birth						
1988	0.143	0.351	0.141	0.348	0.154	0.360
1989	0.141	0.348	0.142	0.349	0.128	0.346
1990	0.154	0.361	0.161	0.367	0.142	0.337
1991	0.195	0.396	0.193	0.395	0.203	0.402
1992	0.187	0.389	0.183	0.387	0.198	0.399
1993	0.177	0.381	0.178	0.382	0.173	0.378
Education						
Degree	0.072	0.259	0.081	0.273	0.044	0.205
Other higher	0.066	0.248	0.071	0.258	0.047	0.211
A level etc	0.534	0.498	0.543	0.498	0.506	0.500
GCSE etc	0.248	0.432	0.236	0.425	0.290	0.454
Other qualification	0.038	0.193	0.036	0.186	0.047	0.213
No qualification	0.031	0.173	0.023	0.150	0.058	0.234
Migration background						
White British	0.841	0.365	0.857	0.349	0.785	0.410
No white British	0.068	0.252	0.058	0.233	0.105	0.306
Government Office Region						
North East	0.028	0.165	0.027	0.164	0.029	0.169
North West	0.078	0.269	0.081	0.273	0.069	0.254
Yorkshire and the Humber	0.063	0.242	0.064	0.245	0.058	0.234
East Midlands	0.077	0.266	0.075	0.264	0.082	0.275
West Midlands	0.061	0.240	0.067	0.250	0.041	0.199
East of England	0.046	0.211	0.044	0.205	0.055	0.229
London	0.037	0.188	0.035	0.186	0.040	0.198
South East	0.121	0.326	0.130	0.337	0.089	0.285
South West	0.068	0.252	0.069	0.255	0.063	0.243
Wales	0.156	0.363	0.152	0.359	0.169	0.374
Scotland	0.142	0.350	0.143	0.351	0.139	0.346
Northern Ireland	0.114	0.319	0.101	0.302	0.160	0.367
Father: age when child born						
20 and younger	0.054	0.227	0.055	0.228	0.051	0.221
21-25	0.121	0.326	0.110	0.313	0.158	0.365
26-30	0.288	0.452	0.302	0.459	0.239	0.426
31-35	0.290	0.454	0.307	0.461	0.234	0.423
36-40	0.142	0.349	0.141	0.348	0.147	0.354
41 and older	0.076	0.265	0.061	0.239	0.129	0.335
Father: Education						
Degree	0.162	0.368	0.178	0.383	0.105	0.307
Other higher	0.071	0.257	0.083	0.275	0.031	0.174
A level etc	0.249	0.432	0.266	0.442	0.187	0.390
GCSE etc	0.247	0.431	0.248	0.432	0.242	0.428
Other qualification	0.106	0.308	0.100	0.300	0.129	0.335

TABLE B.1: Summary statistics, selected variables, parental unemployment at ages 0-5 sample

	Overall, N= 8,480		No parental unemployment, N= 6,598		Parental unemployment, N= 1,882	
No qualification	0.137	0.344	0.099	0.299	0.269	0.443
Father: Smoking						
No	0.639	0.480	0.671	0.469	0.530	0.499
Yes	0.262	0.439	0.234	0.423	0.357	0.479
Mother: age when child born						
20 and younger	0.074	0.262	0.067	0.250	0.098	0.298
21-25	0.210	0.407	0.207	0.405	0.222	0.415
26-30	0.370	0.483	0.378	0.485	0.343	0.475
31-35	0.222	0.416	0.233	0.423	0.184	0.387
36-40	0.076	0.266	0.073	0.261	0.087	0.282
41 and older	0.018	0.134	0.016	0.128	0.024	0.153
Mother: Education						
Degree	0.139	0.346	0.159	0.365	0.071	0.257
Other higher	0.089	0.285	0.093	0.291	0.076	0.266
A level etc	0.159	0.365	0.163	0.369	0.145	0.352
GCSE etc	0.326	0.468	0.332	0.471	0.304	0.460
Other qualification	0.145	0.353	0.144	0.351	0.151	0.358
No qualification	0.130	0.337	0.105	0.307	0.217	0.412
Mother: Smoking						
No	0.711	0.453	0.740	0.438	0.609	0.488
Yes	0.221	0.415	0.195	0.396	0.309	0.462
Household grow-up characteristics						
Equivalised monthly household income	1,401.97	1,051.18	1,498.08	1,037.06	1,071.06	1,032.36
Number of Persons in Household [3-14]	4.499	1.160	4.427	1.023	4.74	1.51
Number of nat/step/adopt siblings in household [0-8]	1.006	1.17	0.961	1.062	1.16	1.48
Unemployment rate	6.18	1.98	6.01	1.83	6.45	2.14

TABLE B.2: Summary statistics, selected variables, parental unemployment at ages 6-10 sample

	Overall, N= 4,234		No parental unemployment, N= 3,268		Parental unemployment, N= 966	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	25.39	1.56	25.38	1.55	25.42	1.609
Female	0.519	0.500	0.530	0.500	0.527	0.499
Year of birth						
1983	0.201	0.401	0.221	0.415	0.195	0.396
1984	0.177	0.382	0.172	0.377	0.194	0.396
1985	0.174	0.379	0.179	0.384	0.156	0.363
1986	0.183	0.386	0.183	0.387	0.183	0.386
1987	0.263	0.440	0.268	0.443	0.244	0.429
Education						
Degree	0.315	0.464	0.340	0.474	0.228	0.419
Other higher	0.051	0.221	0.050	0.219	0.055	0.228
A level etc	0.339	0.473	0.338	0.473	0.341	0.474
GCSE etc	0.186	0.389	0.177	0.382	0.216	0.412
Other qualification	0.072	0.258	0.065	0.248	0.093	0.291
No qualification	0.022	0.146	0.017	0.132	0.036	0.187
Migration background						
White British	0.904	0.293	0.914	0.279	0.871	0.335
No white British	0.086	0.281	0.075	0.264	0.122	0.327
Government Office Region						
North East	0.032	0.177	0.039	0.193	0.009	0.098
North West	0.105	0.306	0.103	0.304	0.112	0.315
Yorkshire and the Humber	0.083	0.276	0.087	0.282	0.068	0.253
East Midlands	0.086	0.281	0.094	0.292	0.062	0.241
West Midlands	0.055	0.228	0.055	0.228	0.055	0.228
East of England	0.078	0.268	0.073	0.261	0.092	0.289
London	0.041	0.199	0.037	0.189	0.055	0.228
South East	0.131	0.338	0.146	0.354	0.081	0.274
South West	0.067	0.250	0.065	0.248	0.071	0.258
Wales	0.131	0.337	0.120	0.325	0.166	0.372
Scotland	0.086	0.280	0.078	0.268	0.112	0.315
Northern Ireland	0.101	0.301	0.097	0.297	0.112	0.315
Father: age when child born						
20 and younger	0.063	0.243	0.063	0.244	0.062	0.243
21-25	0.151	0.358	0.154	0.361	0.138	0.345
26-30	0.316	0.465	0.327	0.469	0.282	0.450
31-35	0.262	0.440	0.264	0.440	0.256	0.437
36-40	0.116	0.320	0.115	0.319	0.120	0.325
41 and older	0.040	0.197	0.027	0.162	0.085	0.279
Father: Education						
Degree	0.143	0.351	0.155	0.362	0.105	0.307
Other higher	0.110	0.313	0.123	0.328	0.065	0.248
A level etc	0.224	0.417	0.230	0.421	0.206	0.405
GCSE etc	0.230	0.421	0.236	0.424	0.211	0.408
Other qualification	0.101	0.302	0.087	0.282	0.149	0.356
No qualification	0.170	0.376	0.150	0.358	0.237	0.425

TABLE B.2: Summary statistics, selected variables, parental unemployment at ages 6-10 sample

	Overall, N= 4,234		No parental unemployment, N= 3,268		Parental unemployment, N= 966	
Father: Smoking						
No	0.643	0.478	0.677	0.467	0.532	0.499
Yes	0.253	0.435	0.226	0.418	0.345	0.475
Mother: age when child born						
20 and younger	0.066	0.249	0.063	0.244	0.074	0.263
21-25	0.294	0.455	0.295	0.456	0.293	0.455
26-30	0.325	0.468	0.338	0.473	0.279	0.448
31-35	0.187	0.390	0.183	0.387	0.201	0.401
36-40	0.066	0.249	0.062	0.241	0.082	0.275
41 and older	0.009	0.099	0.008	0.091	0.014	0.120
Mother: Education						
Degree	0.127	0.333	0.141	0.348	0.082	0.275
Other higher	0.115	0.319	0.127	0.333	0.074	0.263
A level etc	0.150	0.357	0.147	0.354	0.163	0.369
GCSE etc	0.306	0.460	0.315	0.464	0.275	0.447
Other qualification	0.132	0.338	0.128	0.334	0.144	0.351
No qualification	0.152	0.359	0.132	0.339	0.217	0.412
Mother: Smoking						
No	0.720	0.448	0.738	0.439	0.658	0.474
Yes	0.204	0.403	0.192	0.394	0.247	0.431
Household grow-up characteristics						
Equivalised monthly household income	1380.04	809.97	1,465.11	807.16	1,094.18	752.19
Number of Persons in Household [3-14]	4.55	1.17	4.44	0.959	4.94	1.64
Number of nat/step/adopt siblings in household [0-8]	0.428	0.908	0.365	0.739	0.641	1.305
Unemployment rate	6.31	2.08	6.19	1.97	6.51	2.25

TABLE B.3: Summary statistics, selected variables, parental unemployment at ages 11-15 sample

	Overall, N= 2,942		No parental unemployment, N= 2,084		Parental unemployment, N= 858	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	29.31	1.53	29.31	1.53	29.31	1.54
Female	0.457	0.498	0.442	0.496	0.496	0.500
Year of birth						
1978	0.169	0.375	0.162	0.369	0.186	0.389
1979	0.153	0.360	0.164	0.370	0.125	0.331
1980	0.244	0.429	0.241	0.427	0.253	0.434
1981	0.167	0.373	0.160	0.366	0.186	0.389
1982	0.265	0.441	0.272	0.445	0.247	0.431
Education						
Degree	0.294	0.455	0.305	0.460	0.267	0.442
Other higher	0.084	0.278	0.079	0.270	0.099	0.299
A level etc	0.294	0.455	0.317	0.465	0.238	0.426
GCSE etc	0.220	0.414	0.219	0.414	0.222	0.415
Other qualification	0.065	0.247	0.056	0.230	0.089	0.285
No qualification	0.032	0.177	0.015	0.125	0.074	0.261
Migration background						
White British	0.916	0.276	0.927	0.259	0.889	0.313
No white British	0.073	0.261	0.064	0.245	0.097	0.296
Government Office Region						
North East	0.048	0.214	0.045	0.207	0.056	0.230
North West	0.127	0.333	0.109	0.312	0.173	0.378
Yorkshire and the Humber	0.082	0.274	0.084	0.277	0.077	0.267
East Midlands	0.077	0.267	0.081	0.273	0.068	0.252
West Midlands	0.053	0.225	0.062	0.242	0.030	0.173
East of England	0.103	0.304	0.103	0.304	0.102	0.303
London	0.074	0.262	0.070	0.256	0.083	0.277
South East	0.126	0.331	0.141	0.348	0.087	0.282
South West	0.050	0.219	0.061	0.239	0.025	0.157
Wales	0.083	0.276	0.082	0.275	0.086	0.280
Scotland	0.100	0.301	0.093	0.290	0.119	0.324
Northern Ireland	0.071	0.257	0.064	0.245	0.088	0.284
Father: age when child born						
20 and younger	0.070	0.256	.060	0.237	0.097	0.296
21-25	0.183	0.387	0.182	0.386	0.185	0.389
26-30	0.313	0.463	0.346	0.475	0.229	0.420
31-35	0.234	0.423	0.230	0.421	0.243	0.429
36-40	0.114	0.317	0.093	0.291	0.164	0.371
41 and older	0.011	0.104	0.006	0.081	0.022	0.147
Father: Education						
Degree	0.121	0.326	0.130	0.336	0.100	0.300
Other higher	0.077	0.266	0.085	0.280	0.055	0.228
A level etc	0.299	0.458	0.291	0.454	0.318	0.466
GCSE etc	0.180	0.384	0.193	0.394	0.149	0.356
Other qualification	0.112	0.316	0.103	0.305	0.134	0.341
No qualification	0.174	0.379	0.160	0.367	0.206	0.405

TABLE B.3: Summary statistics, selected variables, parental unemployment at ages 11-15 sample

	Overall, N= 2,942		No parental unemployment, N= 2,084		Parental unemployment, N= 858	
Father: Smoking						
No	0.689	0.462	0.719	0.449	0.614	0.487
Yes	0.198	0.399	0.170	0.375	0.270	0.444
Mother: age when child born						
20 and younger	0.098	0.298	0.094	0.292	0.109	0.312
21-25	0.253	0.434	0.247	0.431	0.268	0.443
26-30	0.326	0.469	0.356	0.478	0.253	0.434
31-35	0.206	0.405	0.190	0.392	0.247	0.431
36-40	0.040	0.196	0.031	0.174	0.062	0.243
41 and older	0.001	0.017			0.001	0.033
Mother: Education						
Degree	0.066	0.248	0.076	0.265	0.041	0.200
Other higher	0.124	0.329	0.130	0.337	0.107	0.309
A level etc	0.162	0.369	0.172	0.378	0.138	0.345
GCSE etc	0.293	0.455	0.307	0.461	0.258	0.438
Other qualification	0.137	0.344	0.124	0.329	0.170	0.375
No qualification	0.204	0.403	0.179	0.383	0.267	0.442
Mother: Smoking						
No	0.710	0.453	0.748	0.434	0.614	0.487
Yes	0.207	0.405	0.169	0.375	0.301	0.459
Household grow-up characteristics						
Equivalised monthly household income	1489.61	906.25	1597.91	876.77	1,219.3	922.51
Number of Persons in Household [3-14]	4.26	1.04	4.15	0.837	4.53	1.41
Number of nat/step/adopt siblings in household [0-8]	0.158	0.530	0.125	0.388	0.239	0.775
Unemployment rate	7.03	2.34	6.95	1.90	7.05	2.25

C Appendix to Chapter 4

C.1 Health data linkage

TABLE C.1: Health data linkage

Database	**Content**	**Number in Next Steps at Age 25**	**Total number of matched HES data**	**Number of research participants**
A&E	Attendance to accident and emergency care facility years 2007-2017	7,707	4,579	3,746
APC	Attendance to Admitted Patient Care years 1997-2017	7,707	4,579	3,036
OP	Attendance to Outpatient Years 2009-2017	7,707	4,579	4,099
CC	Attendance to Critical Care years 2009-2017	7,707	4,579	35

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2022). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure Access DOI: http://doi.org/10.5255/UKDA-SN-8681-1.

C.2 GHQ module variables in Next Steps

concenYP [GHQ: concentration]

Universe: Young Participant (YP)

The next questions are about how you have been feeling over the last few weeks. Have you recently been able to concentrate on whatever you're doing?

1. Better than usual
2. Same as usual
3. Less than usual
4. Much less than usual

nosleepYP [GHQ: loss of sleep]

Universe: Young Participant (YP)

Have you recently lost much sleep over worry?

1. Not at all
2. No more than usual
3. Rather more than usual
4. Much more than usual

usefulYP [GHQ: playing a useful role]

Universe: Young Participant (YP)

Have you recently felt that you were playing a useful part in things?

1. More so than usual
2. About the same as usual
3. Less so than usual
4. Much less than usual

decideYP [GHQ: capable of making decisions]

Universe: Young Participant (YP)

Have you recently felt capable of making decisions about things?

1. More so than usual
2. Same as usual
3. Less so than usual
4. Much less capable

strainYP [GHQ: constantly under strain]

Universe: Young Participant (YP)

Have you recently felt constantly under strain?

1. Not at all
2. No more than usual
3. Rather more than usual
4. Much more than usual

difficYP [GHQ: problem overcoming difficulties]

Universe: Young Participant (YP)

Have you recently felt you couldn't overcome your difficulties?

1. Not at all
2. No more than usual
3. Rather more than usual
4. Much more than usual

activYP [GHQ: enjoy day-to-day activities]

Universe: Young Participant (YP)

Have you recently been able to enjoy your normal day-to-day activities?

1. More so than usual
2. About the same as usual
3. Less so than usual
4. Much less than usual

probsYP [GHQ: ability to face problems]

Universe: Young Participant (YP)

Have you recently been able to face up to problems?

1. More so than usual
2. Same as usual
3. Less able than usual
4. Much less able

depressYP [GHQ: unhappy or depressed]

Universe: Young Participant (YP)

Have you recently been feeling unhappy or depressed?

1. Not at all
2. No more than usual
3. Rather more than usual
4. Much more than usual

noconfYP [GHQ: losing confidence]

Universe: Young Participant (YP)

Have you recently been losing confidence in yourself?

1. Not at all
2. No more than usual
3. Rather more than usual
4. Much more than usual

wthlessYP [GHQ: believe worthless]

Universe: Young Participant (YP)

Have you recently been thinking of yourself as a worthless person?

1. Not at all
2. No more than usual
3. Rather more than usual
4. Much more than usual

happyYP [GHQ: general happiness]

Universe: Young Participant (YP)

Have you recently been feeling reasonably happy, all things considered?

1. More so than usual
2. About the same as usual
3. Less so than usual
4. Much less than usual

C.3 Description of the variables

TABLE C.2: Description of the variables

Variable	Description	Min	Max
Ethnicity	Indicator variable for whether the participant is non-white ethnicity group (including mixed, Indian, Pakistani, Bangladeshi, black and other)	0	1
Gender	Indicator variable for whether the participant is a female	0	1
Month of birth	Months of the calendar year (January to December)	12	
Young Carer	Indicator variable for whether the participant has any caring responsibilities within the household	0	1
Disabled	Indicator variable for whether the participant has a disability or a long-term illness or health problems	0	1
Child mental health	Mental Health index using the Generalised Health Indicator (GHQ-12) score – 12-point scale		
Non-born in the UK	Indicator variable for whether the participant has born elsewhere from the United Kingdom	0	1
Nursery School	Indicator variable for whether the participant attended a nursery school or pre-school class	0	1
Mother's age at birth	Categorical variable based on the age of the mother when the child was born: Under 20; 20-24; 25-29; 30-34; and 35+	1	5
Birth Weigh	Birth weight in kilos	0.33	6.12
Early Birth	Number of weeks that participant's birth was early at birth	0	17
Mother return to work	Categorical variable based on whether the mother has returned to work after birth: no; Yes, mother returned to work full-time; Yes, mother returned to work part-time	1	3
Time main person is unemployed	Total time main person (MP) has been unemployed and seeking work since the participant's birth (in months)	0	185
Social life	Indicator variable for whether the participant has been to or done in any of the following events during the last 4-weeks: gone to see a football match; gone to a party, dance, or nightclub; gone to a pub or bar; go to the cinema, theatre, or concert	0	1
Risk	Number of risks factors the participant has experienced in the last 12 months	0	8
Attitude at school	Indicator variable for whether the participant has an excellent attitude toward school is defined as the following feeling about school: work as hard as I can; work is worth doing; school is not a waste of time; the work I do in lessons is interesting	0	1
Bullying	Indicator variable for whether the participant experienced bullying at school. Bullying is defined as experiencing one of the following in the last 12 months: being excluded from a group of friends; upset by name-calling, including text or email; threatened with violence by students; experiencing violence from students	0	1
Play an instrument	Indicator variable for whether the participant has mentioned that plays an instrument	0	1
Reading	Indicator variable for whether the participant has mentioned that reads for pleasure at least once per week	0	1
TV Hours	Categorical variable based on the hours that participants spend watching the TV: none or less than an hour; 1-3 hours; 4-6 hours; 7 or more hours	1	4

Table C.2 continued from previous page

Variable	Description	Min	Max
Computer games	Number of hours per day spent playing computer games	0	24
Sport	Indicator variable for whether the participant does sport at least once a week	0	1
Cannabis	Indicator variable for whether the participant ever tried cannabis	0	1
Alcohol	Indicator variable for whether the participant has ever a had proper alcoholic drink	0	1
Cigarettes	Indicator variable for whether the participant has ever smoked cigarettes	0	1
Parental Education	Categorical variable based on the highest educational attainment of the main parent in the household: degree or above; GCE A level; GCSE level; or have low education or no education	1	4
Occupation group	Categorical variables based on the reported occupation of the main parent in the household: managerial occupation; intermediate or technical occupation; routine or not currently working	1	3
Age main parent	The current age of the main parent	17	78
Parental cohabitation status	Indicator variable for whether the main parent cohabitation status is single, separated, divorced, or widowed	0	1
Parental health	Indicator variable for whether the participants' main parent general health in the last 12 months is not very good and not good at all	0	1
Parental disabilities	Indicator variable for whether the participants' main parent has any disability limiting work	0	1
Single Family	Indicator variable for whether the participant's household has ever been a single-parent family for at least a month up to Wave 1	0	1
Household Income	Total annual benefit amount plus the gross annual salary of the main parental and the second parent per capita	2.4	2,602,777
Siblings	Number of siblings that participants have in the household	0	13
Tenure	Indicator variable for whether the participants' house tenure is owned outright or mortgage /bank loan	0	1
Vehicle	Indicator variable for whether anyone in the participants' household has used of motor vehicle	0	1
Telephone	Indicator variable for whether the participants' households have a mobile telephone	0	1
Computer	Indicator variable for whether the participants' households have computer	0	1
Internet	Indicator variable for whether the participants' household have access to the internet	0	1
Non-English spoken	Indicator variable for whether the participants' households do not speak English	0	1
Dependent children	Number of dependent children in the household	1	12
Index of Multiple Deprivation (IMD)	The Index of Multiple Deprivation (IMD) is the official measure of relative deprivation for small areas in England constructed by the Department for Communities and Local Government. The IMD ranks Lower-Layer Super Output Areas (LSOA) based on seven domains of deprivation (income, employment, education, health, crime, barriers to housing, living environment) from least to most deprived. These scores were computed into five quintiles.	1	5

Table C.2 continued from previous page

Variable	Description	Min	Max
Income Deprivation Affecting Children Index (IDACI)	The Income Deprivation Affecting Children Index (IDACI) score is an index which represents the proportion of children under the age of 16 living in a low-income household by Lower-Layer Super Output Area (LSOA). These scores were computed into five quintiles.	1	5
Regions	Government Office Regions (GOR): North East, North West, Yorkshire and The Humber, East Midlands, West Midlands, East of England, London, South East, and South West	1	9
Rural	Indicator variable for whether the participant lives in a non-urban area ($\geq$ 10,000 population and less sparse)	0	1
A&E: Number of visits per patient and year	Number of times a patient visits A&E per financial year	1	19
A&E: Duration to treatment	The time (expressed as a whole number of minutes) between the patient's arrival (arrivaltime) and the start of their treatment (trettime)	0	1438
A&E: Duration to assessment	The time (expressed as a whole number of minutes) between the patient's arrival and their initial assessment.	0	1439
A&E: Duration to conclusion	The time (expressed as a whole number of minutes) between the patient's arrival and conclusion of their attendance or treatment (whichever is later)	0	1438
A&E: Duration to departure	The time (expressed as a whole number of minutes) between the patient's arrival and the time the A&E attendance has concluded, and the department is no longer responsible for the care of the patient	0	1433
A&E: Arrival date (year)	Year of arrival to A&E	2007	2017
A&E: Arrival date (month)	Month of arrival to A&E	1	12
A&E: Arrival date (day)	Day of arrival to A&E	1	31
A&E/OP: Financial Year	A&E: 2007-2008 to 2016-17 OP: 2003-2004 to 2016-17	0 0	12 31
OP: Number of appointments per patient and year	Number of appointments to the outpatient care per patient and year	1	35
OP: Not attended and seen	This variable indicates whether or not a patient attended an appointment. If the patient did not attend it also indicates whether or not advanced warning was given. It takes values 1 if the appointment was cancelled by, or on behalf of, the patient; did not attend – no advance warning given; appointment cancelled or postponed by the Health Care Provider; and did not attend – patient arrived late and could not be seen. It takes 0 whether the patient has been seen, having attended on time or, if late, before the relevant care professional was ready to see the patient; or arrived late, after the relevant care professional was ready to see the patient, but was seen.	0	1
OP: Waiting	This variable gives the period in days between the date of the appointment date and either the referral request received date or the DNA (did not attend) date, if given. If the calculation returns a negative the waiting time is set as a fault.	0	2031

Table C.2 continued from previous page

Variable	Description	Min	Max
OP: Treatment speciality	This field contains a code that defines the speciality in which the consultant was working during the period of care. It can be compared with the speciality under which the consultant is contracted. Using the April 2004 list of treatment specialists.	100	920

C.4 Treatment function code

A unique identifier for a *treatment function*. A *treatment function* code is recorded to report the specialised service within which the *patient* is treated. It is based on main *speciality* but also includes approved sub-specialties and treatment specialties used by lead *care professionals* including *consultants*.

TABLE C.3: Treatment function Code for the patient treated by a Mental Health Service

Code	Description	Code	Description
319	Respite Care Service	720	Eating Disorders Service
656	Clinical Psychology Service	721	Addiction Service
700	Learning Disability Service	722	Liaison Psychiatry Service
710	Adult Mental Health Service	723	Psychiatric Intensive Care Service
711	Child and Adolescent Psychiatry Service	724	Perinatal Mental Health Service
712	Forensic Psychiatry Service	725	Mental Health Recovery and Rehabilitation Service
713	Medical Psychotherapy Service	726	Mental Health Dual Diagnosis Service
715	Old Age Psychiatry Service		

Source: NHS Data Model and Dictionary. Main Specialty and Treatment Function Codes Table. Access available in the following link: https://www.datadictionary.nhs.uk/attributes/treatment_function_code.html

TABLE C.4: Treatment function Code for the patient treated for Obstetrics, Sexual and Reproductive Health Services

Code	**Description**	**Code**	**Description**
501	Obstetrics Service	504	Community Sexual and Reproductive Health Service
502	Gynaecology Service	505	Fetal Medicine Service
503	Gynaecological Oncology Service	560	Midwifery service

Source: NHS Data Model and Dictionary. Main Specialty and Treatment Function Codes Table. Access available in the following link: `https://www.datadictionary.nhs.uk/attributes/treatment_function_code.html`

TABLE C.5: Treatment function Code for the patient treated for Orthodontic Service

Code	Description	Code	Description
140	Oral surgery	144	Maxillofacial Surgery Service
141	Restorative Dentistry Service	145	Oral and Maxillofacial Surgery Service
143	Orthodontic Service		

Source: NHS Data Model and Dictionary. Main Specialty and Treatment Function Codes Table. Access available in the following link: https://www.datadictionary.nhs.uk/attributes/treatment_function_code.html

C.5 Further results

TABLE C.6: CCI measure of income-related inequity in unmet health care utilisation at aged 17-18

	Males		Females	
	CCI	*Standard error*	*CCI*	*Standard error*
Panel A: Accident & Emergency (A&E)				
Number of visits per year	-0.054	0.051	0.013	0.055
Duration to treatment (in minutes)	15.491**	6.580	11.258**	4.648
Duration to conclusion (in minutes)	3.404	2.251	0.378	2.663
Duration to departure (in minutes)	2.002	2.138	2.054	2.470
Number of observations	271		279	
Panel B: Outpatient care (OP)				
Number of appointments per patient and year	0.001	0.090	0.129	0.097
Not attended nor seen	0.005	0.024	0.031	0.023
Treatment speciality: Mental Health Care	0.026***	0.006	0.051***	0.011
Treatment speciality: Orthodontic Service	-0.046**	0.023	-0.085***	0.019
Treatment speciality: Obstetrics, Sexual and Reproductive Health Services	0.043***	0.010	0.099***	0.016
Number of observations	1,440		1,580	

Notes: ***p≺0.01;**p≺0.05;*p≺0.10. . Erreygers' CI is used for binary outcomes variables, i.e., for not attended nor seen binary, and treatment speciality set of variables. Generalised CI is used for count outcome variables. *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2022). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure Access DOI: http://doi.org/10.5255/UKDA-SN-8681-1.

TABLE C.7: Shapley decomposition for the contribution of the covariates in health outcomes at age 17

	Specification 1		**Specification 2**		**Specification 3**	
	Shapley value	%	*Shapley value*	%	*Shapley value*	%
Panel (A): Long-standing illness or disability for males						
Demographics (non-white ethnicity; young carer)	0.004	10.74	0.003	3.63	0.002	1.74
Regional dummies (GOR) and rural indicator	0.019	43.95	0.011	14.75	0.009	9.86
Pre-circumstances between birth and nursery age	0.020	45.31	0.011	14.27	0.007	8.53
Individual-level characteristics						
Lifestyle and school experiences			0.026	33.55	0.020	22.44
Health behaviour-related			0.026	33.81	0.022	24.48
Parental-level characteristics						
SES – educational and occupational status					0.005	5.91
Demographics characteristics					0.006	6.64
Ownerships					0.011	11.90
Household-level characteristics						
Household income					0.001	0.73
Type of family and number of siblings					0.007	7.76
Share of the total variance explained	*0.043*	*100*	*0.077*	*100*	*0.090*	*100*
Panel (B): Mental ill-health (GHQ-12) for females						
Demographics (non-white ethnicity; young carer)	0.008	10.56	0.007	3.78	0.007	3.35
Regional dummies (GOR) and rural indicator	0.065	78.70	0.028	13.90	0.029	12.46
Pre-circumstances between birth and nursery age	0.009	10.74	0.005	2.39	0.005	2.38
Individual-level characteristics						
Lifestyle and school experiences			0.098	48.30	0.085	37.14
Health behaviour-related			0.064	31.63	0.059	25.81
Parental-level characteristics						
SES – educational and occupational status					0.023	10.34
Demographics characteristics					0.012	5.24
Ownerships					0.002	0.80
Household-level characteristics						
Household income					0.001	0.36
Type of family and number of siblings					0.004	2.09
Share of the total variance explained	*0.082*	*100*	*0.204*	*100*	*0.230*	*100*

Notes: Circumstance covariates: Demographics (non-white ethnicity, young carer); nine regional dummies (GOR) and rural indicator; pre-circumstances between birth and nursery age (nursery school, birth weight, early birth); lifestyle and school experiences (social life indicator, attitude toward school, bullying play an instrument, reading, hours watching TV dummies); health behaviour-related (practice sport, cannabis, alcohol, cigarettes); Parental SES (Occupational status and education attainment); Parental demographics (age of the main parent, cohabitation status, disabilities); parental ownership (tenure, internet); household income (as a total annual benefit amount plus gross annual salary of the main parental and the second parent per capita); type of family (single family, number of siblings, non-English spoken).

TABLE C.8: Shapley decomposition for the contribution of the covariates in health care outcomes

	Specification 1		**Specification 2**		**Specification 3**	
	Shapley value	%	*Shapley value*	%	*Shapley value*	%
Panel (A): More than one visit to the A&E per year						
Demographics (non-white ethnicity; young carer)	0.032	21.71	0.023	11.05	0.016	5.02
Regional dummies (GOR) and rural indicator	0.085	57.23	0.059	28.59	0.061	19.26
Pre-circumstances between birth and nursery age	0.031	21.06	0.030	14.40	0.024	7.54
Individual-level characteristics						
Lifestyle and school experiences			0.047	22.55	0.028	8.71
Health behaviour-related			0.049	23.40	0.043	13.41
Parental-level characteristics						
SES – educational and occupational status					0.075	23.48
Demographics characteristics					0.025	7.96
Ownerships					0.019	5.92
Household-level characteristics						
Household income					0.012	3.97
Type of family and number of siblings					0.015	4.73
Share of the total variance explained	*0.149*	*100*	*0.209*	*100*	*0.321*	*100*
Panel (B): More than three appointments to OP care per year						
Demographics (non-white ethnicity; young carer)	0.024	16.07	0.019	11.35	0.015	6.41
Regional dummies (GOR) and rural indicator	0.080	52.95	0.067	38.60	0.067	28.58
Pre-circumstances between birth and nursery age	0.047	30.98	0.035	19.91	0.028	12.24
Individual-level characteristics						
Lifestyle and school experiences			0.037	21.50	0.023	9.95
Health behaviour-related			0.015	8.64	0.008	3.36
Parental-level characteristics						
SES – educational and occupational status					0.039	16.43
Demographics characteristics					0.015	6.69
Ownerships					0.005	2.39
Household-level characteristics						
Household income					0.001	0.27
Type of family and number of siblings					0.03	13.66
Share of the total variance explained	*0.152*	*100*	*0.174*	*100*	*0.235*	*100*

Notes: Health care outcomes are dichotomous variables taking 1 if the young participant has attended more than one time per year to A&E or more than three times to outpatient hospital care per year and 0 if has attended just one time. Bootstrapped standard errors in parenthesis (500 replications). Weights used. Circumstance covariates: Demographics (female; non-white ethnicity, young carer); nine regional dummies (GOR) and rural indicator; pre-circumstances between birth and nursery age (nursery school, birth weight, early birth); lifestyle and school experiences (social life indicator, attitude toward school, bullying play an instrument, reading, hours watching TV dummies); health behaviour-related (practice sport, cannabis, alcohol, cigarettes); Parental SES (Occupational status and education attainment); Parental demographics (age of the main parent, cohabitation status, disabilities); parental ownership (tenure, internet); household income (as a total annual benefit amount plus gross annual salary of the main parental and the second parent per capita); type of family (single family, number of siblings, non-English spoken). *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2022). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure Access DOI: `http://doi.org/10.5255/UKDA-SN-8681-1`.

TABLE C.9: Health outcomes regression models: Probit estimates

	Long-standing illness or disability for males			**Mental ill-health (GHQ-12) for females**		
	Spec. 1	*Spec. 2*	*Spec. 3*	*Spec. 1*	*Spec. 2*	*Spec. 3*
Ethnicity	-0.190**	-0.311***	-0.247**	0.148**	0.344***	0.309***
	(0.089)	(0.103)	(0.121)	(0.063)	(0.072)	(0.086)
Young Carer	-0.030	-0.020	-0.024	-0.112	-0.165*	-0.169
	(0.130)	(0.136)	(0.143)	(0.096)	(0.090)	(0.114)
North East	-0.237*	-0.241*	-0.252*	-0.059	-0.007	-0.041
	(0.130)	(0.141)	(0.143)	(0.093)	(0.096)	(0.104)
North West	-0.065	-0.042	-0.040	-0.228***	-0.174**	-0.202**
	(0.087)	(0.093)	(0.096)	(0.071)	(0.073)	(0.079)
Yorkshire	-0.362***	-0.401***	-0.399***	-0.189**	-0.185**	-0.194**
	(0.110)	(0.118)	(0.122)	(0.077)	(0.080)	(0.086)
East Midlands	-0.110	-0.150	-0.158	-0.125	-0.082	-0.054
	(0.103)	(0.111)	(0.111)	(0.080)	(0.083)	(0.087)
West Midlands	-0.114	-0.142	-0.165	-0.275***	-0.247***	-0.265***
	(0.096)	(0.103)	(0.107)	(0.077)	(0.079)	(0.083)
East of England	-0.070	-0.022	-0.053	-0.005	-0.021	0.007
	(0.096)	(0.100)	(0.104)	(0.073)	(0.075)	(0.079)
London	-0.043	-0.059	-0.130	0.009	0.033	0.048
	(0.101)	(0.111)	(0.120)	(0.075)	(0.077)	(0.084)
South West	0.042	0.049	0.007	0.094	0.043	0.052
	(0.096)	(0.102)	(0.106)	(0.076)	(0.078)	(0.082)
Rural area	-0.174***	-0.102	-0.096	0.075	0.088*	0.102**
	(0.068)	(0.071)	(0.073)	(0.049)	(0.051)	(0.053)
No attended to nursery school	0.168***	0.108	0.085	-0.084	-0.085	-0.114*
	(0.064)	(0.071)	(0.075)	(0.055)	(0.057)	(0.063)
Birth Weigh	-0.058	-0.062	-0.085	0.021	0.023	-0.001
	(0.050)	(0.053)	(0.056)	(0.041)	(0.042)	(0.046)
Early Birth	0.046***	0.041***	0.028**	-0.005	-0.002	-0.012
	(0.015)	(0.016)	(0.018)	(0.013)	(0.014)	(0.015)
Social life		-0.221***	-0.168***		-0.097	-0.080
		(0.069)	(0.074)		(0.066)	(0.074)
Attitude at school		-0.077	-0.092		0.101**	0.104**
		(0.056)	(0.058)		(0.044)	(0.046)
Bullying		0.237***	0.236***		0.482***	0.478***
		(0.055)	(0.057)		(0.040)	(0.046)
Play an instrument		0.104	0.105		0.163***	0.118**
		(0.055)	(0.068)		(0.054)	(0.058)
Reading		-0.009	-0.027		0.116**	0.080
		(0.057)	(0.059)		(0.048)	(0.051)
TV hours: non or less than an hour		-0.102	-0.097		0.050	0.095
		(0.091)	(0.094)		(0.067)	(0.072)
TV hours: 1-3 hours		-0.126*	-0.110		0.014	0.039
		(0.076)	(0.078)		(0.057)	(0.062)
TV hours: 7 or more		0.702***	0.674***		-0.119	-0.061
		(0.161)	(0.168)		(0.177)	(0.191)
Sport		-0.219***	-0.201***		-0.042	-0.121***
		(0.056)	(0.059)		(0.041)	(0.044)
Cannabis		-0.262***	-0.303***		0.329***	0.331***
		(0.064)	(0.067)		(0.048)	(0.050)
Alcohol		-0.306***	-0.285***		0.131**	0.172**
		(0.081)	(0.086)		(0.070)	(0.079)
Cigarettes		0.116	0.114		0.088**	0.074
		(0.072)	(0.075)		(0.049)	(0.053)
Parent education: GCE A level			-0.039			0.031
			(0.070)			(0.053)
Parent education: GCSE level			-0.052			-0.028
			(0.070)			(0.049)

Table C.9 continued from previous page

	Long-standing illness or disability for males			Mental ill-health (GHQ-12) for females		
	Spec. 1	*Spec. 2*	*Spec. 3*	*Spec. 1*	*Spec. 2*	*Spec. 3*
Parent education: low education or no education			-0.092 (0.072)			-0.204*** (0.054)
Parent occupation: intermediate or technical occupation			-0.050 (0.063)			-0.055 (0.047)
Parent occupation: routine or not currently working			-0.025 (0.068)			0.046 (0.050)
Age main parent			0.006 (0.005)			0.010** (0.004)
Non-cohabitation status			-0.124 (0.077)			0.005 (0.059)
Parental disabilities			0.145** (0.079)			0.107** (0.063)
Tenure			-0.226*** (0.073)			0.040 (0.060)
Internet			-0.030 (0.074)			0.005 (0.059)
Household Income per capita			-0.007 (0.001)			-0.002 (0.002)
Single Family			0.132** (0.070)			-0.018 (0.054)
Siblings			0.016 (0.026)			0.015 (0.021)
Non-English spoken			-0.176 (0.230)			0.295** (0.143)
Sample size	5,260	5,080	4,704	4,806	4,769	4,286

Notes: ***p≺0.01;**p≺0.05;*p≺0.10. Boostrapped standard errors. Base categories: South East; TV hours: 4-6 hours; Parental education: degree or above; Parental occupation: managerial.

TABLE C.10: Health care utilisation outcomes regression models: Probit estimates

	More than one visit to the A&E per year			**More than three appointments to OP care per year**		
	Spec. 1	*Spec. 2*	*Spec. 3*	*Spec. 1*	*Spec. 2*	*Spec. 3*
Female	-0.055	-0.044	-0.068	0.120**	0.085	0.005
	(0.093)	(0.107)	(0.116)	(0.052)	(0.057)	(0.062)
Ethnicity	-0.231	-0.178	-0.203	0.198**	0.245**	0.451***
	(0.180)	(0.209)	(0.253)	(0.098)	(0.108)	(0.135)
Young Carer	0.633***	0.595**	0.558*	-0.374***	-0.386***	-0.504***
	(0.236)	(0.242)	(0.297)	(0.117)	(0.122)	(0.135)
North East	0.643***	0.570**	0.661*	0.096	0.123	0.230*
	(0.231)	(0.242)	(0.297)	(0.119)	(0.122)	(0.132)
North West	0.604***	0.599***	0.629**	-0.044	-0.384	-0.074
	(0.231)	(0.203)	(0.264)	(0.115)	(0.094)	(0.107)
Yorkshire	0.485**	0.535**	0.696***	-0.218*	-0.233**	-0.085
	(0.224)	(0.233)	(0.256)	(0.115)	(0.116)	(0.127)
East Midlands	0.332	0.293	0.425*	-0.128	-0.117	-0.039
	(0.224)	(0.233)	(0.254)	(0.102)	(0.105)	(0.113)
West Midlands	0.518**	0.492**	0.580**	-0.362***	-0.396***	-0.446***
	(0.205)	(0.216)	(0.236)	(0.109)	(0.114)	(0.123)
East of England	0.296	0.244	0.126	0.377***	0.365***	0.447***
	(0.207)	(0.215)	(0.237)	(0.098)	(0.100)	(0.109)
London	0.451**	0.457**	0.605**	0.076	0.084	0.148
	(0.217)	(0.222)	(0.237)	(0.103)	(0.109)	(0.118)
South West	0.664***	0.658***	0.950***	0.278***	0.314***	0.400***
	(0.233)	(0.239)	(0.249)	(0.102)	(0.105)	(0.114)
Rural area	-0.103	-0.116	-0.210	0.023	0.012	0.076
	(0.125)	(0.131)	(0.144)	(0.070)	(0.066)	(0.070)
No attended to	-0.190	-0.307**	-0.404**	0.029	0.077	0.091
nursery school	(0.135)	(0.142)	(0.158)	(0.070)	(0.073)	(0.080)
Birth Weigh	-0.089	-0.088	-0.057	-0.175***	-0.165***	-0.128**
	(0.100)	(0.104)	(0.112)	(0.053)	(0.054)	(0.058)
Early Birth	0.022	0.038	0.043	0.035**	0.034*	0.051***
	(0.0350	(0.036)	(0.039)	(0.017)	(0.018)	(0.016)
Social life		-0.429	-0.326*		0.030	-0.029
		(0.155)	(0.177)		(0.081)	(0.092)
Attitude at school		0.184	0.213		0.143**	0.180**
		(0.120)	(0.131)		(0.064)	(0.069)
Bullying		0.035	-0.034		0.005	0.039
		(0.100)	(0.109)		(0.053)	(0.057)
Play an instrument		-0.153	-0.202		0.014	-0.033
		(0.133)	(0.146)		(0.053)	(0.073)
Reading		0.041	0.022		0.017	-0.031
		(0.109)	(0.116)		(0.059)	(0.073)
TV hours: non or		0.036	0.026		0.016	0.018
less than an hour		(0.170)	(0.191)		(0.092)	(0.101)
TV hours: 1-3 hours		0.012	0.003		-0.233***	-0.143
		(0.144)	(0.162)		(0.076)	(0.084)
TV hours: 7 or more		-0.518	-0.569		-0.053	0.028
		(0.512)	(0.571)		(0.227)	(0.255)
Sport		0.273	0.357**		-0.162***	-0.141**
		(0.106)	(0.115)		(0.055)	(0.084)
Cannabis		0.090	0.077		-0.013	-0.079
		(0.115)	(0.122)		(0.062)	(0.067)
Alcohol		0.086	0.150		0.037	0.146
		(0.202)	(0.233)		(0.095)	(0.109)
Cigarettes		0.266**	0.351**		-0.129	-0.076
		(0.117)	(0.128)		(0.068)	(0.075)
Parent education:			0.126			-0.296***
GCE A level			(0.129)			(0.069)

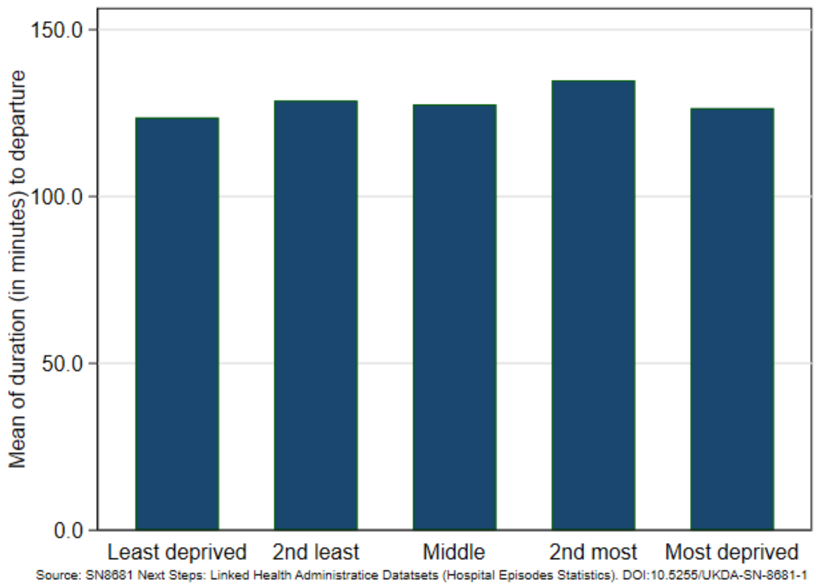
Table C.10 continued from previous page

	More than one visit to the A&E per year			More than three appointments to OP care per year		
	Spec. 1	*Spec. 2*	*Spec. 3*	*Spec. 1*	*Spec. 2*	*Spec. 3*
Parent education: GCSE level			-0.146 (0.1220			-0.191*** (0.067)
Parent education: low education or no education			0.098 (0.131)			-0.153** (0.071)
Parent occupation: intermediate or technical occupation			0.173 (0.116)			0.151** (0.064)
Parent occupation: routine or not currently working			0.186 (0.123)			0.307*** (0.065)
Age main parent			-0.018* (0.011)			0.006 (0.005)
Non-cohabitation status			0.621 (0.146)			-0.031 (0.078)
Parental disabilities			0.285* (0.160)			0.244*** (0.081)
Tenure			0.146 (0.140)			-0.104 (0.081)
Internet			-0.244* (0.136)			0.070 (0.085)
Household Income per capita			-0.001 (0.001)			-0.002 (0.002)
Single Family			-0.328** (0.133)			-0.016 (0.074)
Siblings			0.002 (0.055)			-0.167*** (0.032)
Non-English spoken			0.606 (0.506)			-1.377*** (0.317)
Sample size	766	750	697	2,791	2,759	2,515

Notes: ***p≺0.01;**p≺0.05;*p≺0.10. Boostrapped standard errors. Base categories: South East; TV hours: 4-6 hours; Parental education: degree or above; Parental occupation: managerial.

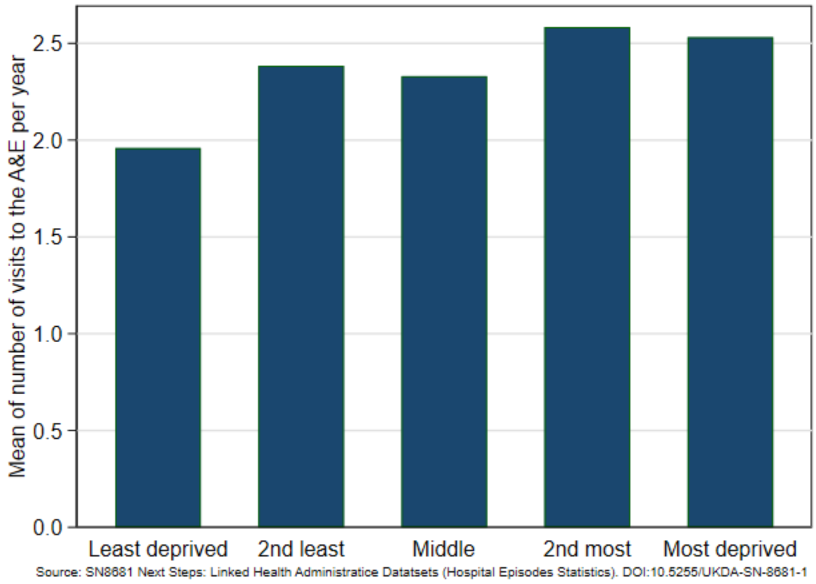
C.6 Descriptive figures using the secure access dataset – Hospital Episode Statistics

FIGURE C.1: Mean of the duration (in minutes) to departure in A&E by socioeconomic group



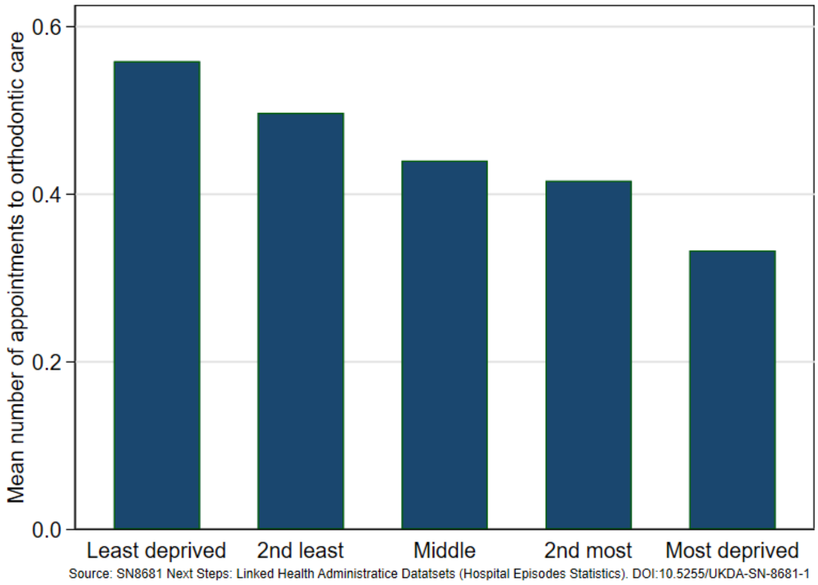
Notes: Duration to departure variable from the A&E field is defined as the time (expressed as a whole number of minutes) between the patient's arrival, and the time the A&E attendance has concluded, and the department is no longer responsible for the care of the patient. Quantiles of SES are created using the Income Affecting Children Index and divided by 5 quantiles from least to most deprived. *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2020). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure access. [data collection]. UK Data Service. SN:8681, http://doi.org/10.5255/UKDA-SN-8681-1.

FIGURE C.2: Mean number of visits to the A&E per year and patient by socioeconomic group



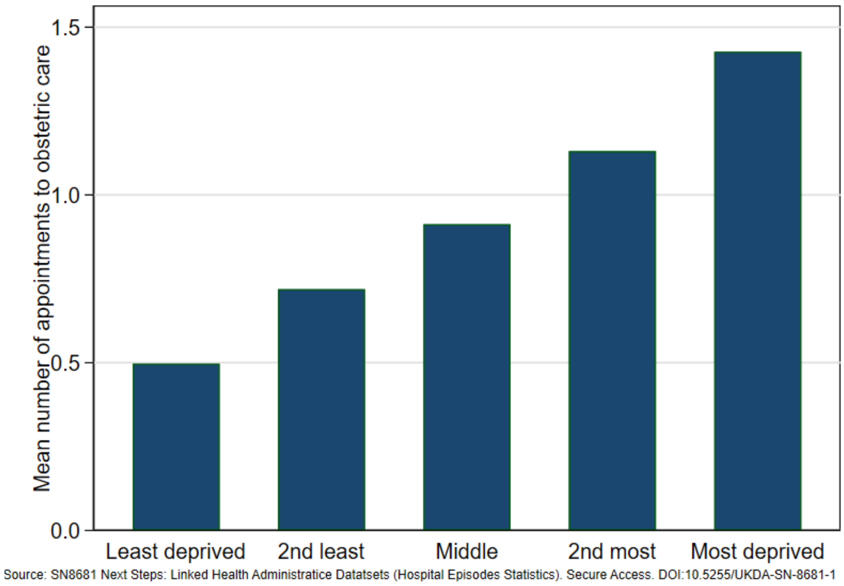
Notes: The mean number of visits to the A&E per person and year has been created summarising observation per patient in a year. Quantiles of SES are created using the Income Affecting Children Index and divided by 5 quantiles from least to most deprived. *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2020). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure access. [data collection]. UK Data Service. SN:8681, http://doi.org/10.5255/UKDA-SN-8681-1.

FIGURE C.3: Mean probability to receive orthodontic treatment by socioeconomic group



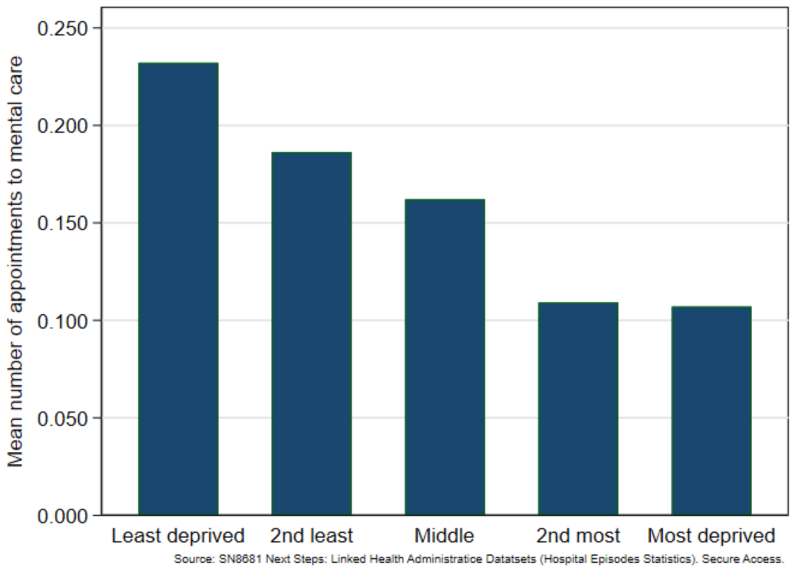
Notes: Mean probability of receiving orthodontic treatment was created using information from the *"Treatment Function code"*. In particular, the following codes have been considered for a orthodontic treatment: 140, 141, 143, 144, and 145. Quantiles of SES are created using the Income Affecting Children Index and divided by 5 quantiles from least to most deprive. *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2020). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure access. [data collection]. UK Data Service. SN:8681, http://doi.org/10.5255/UKDA-SN-8681-1.

FIGURE C.4: Mean probability to receive obstetrics/sexual/reproductive care treatment by socioeconomic group



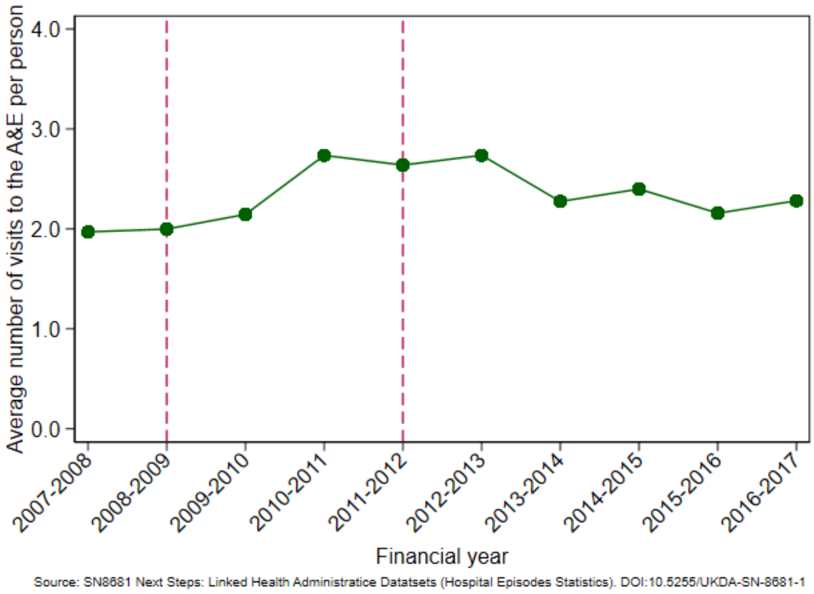
Notes: Mean probability to receive obstetrics/sexual/reproductive care treatment has created using information from the *"Treatment Funtion code"*. In particular, the following codes have been considererd as an obstetrics/sexual/reproductive care treatment: 501-505, and 560. Quantiles of SES are created using the Income Affecting Children Index and divided by 5 quantiles from least to most deprive. *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2020). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure access. [data collection]. UK Data Service. SN:8681, http://doi.org/10.5255/UKDA-SN-8681-1.

FIGURE C.5: Mean probability to receive mental health care treatment by socioeconomic group



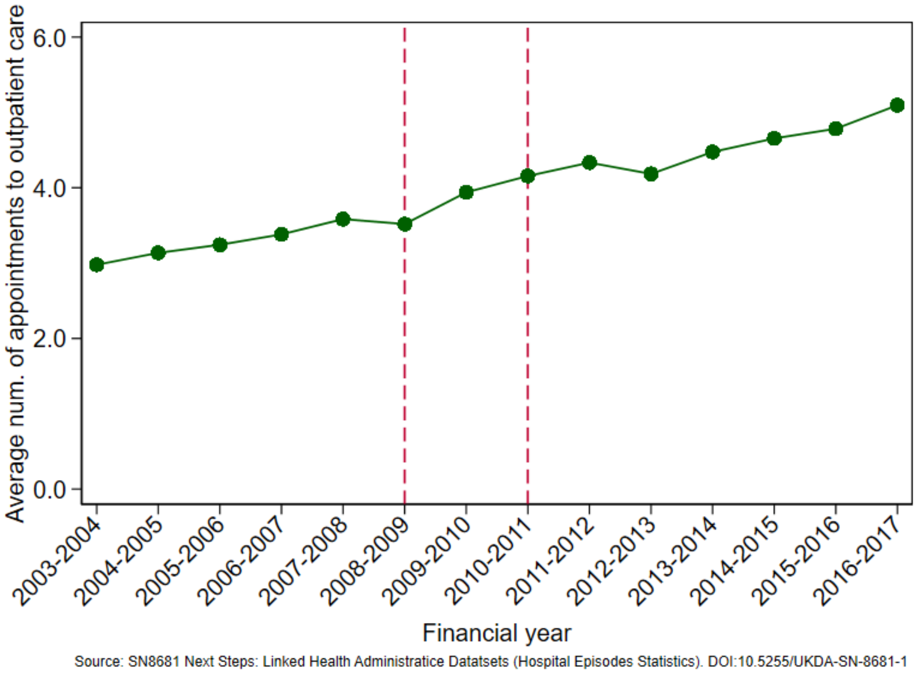
Notes: Mean probability to receive mental health care treatment has created using information from the *"Treatment Funtion code"*. In particular, the following codes have been considererd as a mental health care treatment: 501-505, and 560. Quantiles of SES are created using the Income Affecting Children Index and divided by 5 quantiles from least to most deprive. *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2020). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure access. [data collection]. UK Data Service. SN:8681, http://doi.org/10.5255/UKDA-SN-8681-1.

FIGURE C.6: Evolution of the average number of visits to the A&E per financial year



Notes: The continuous green line shows the evolution of the mean number of visits to A&E per patient and financial year, and the dotted red vertical line shows two periods of time (Great Recession and austerity policies). The number of visits to the A&E per person and year has been created summarising observation per patient in a year. The financial year variable is named as *fyear*. *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2020). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure access. [data collection]. UK Data Service. SN:8681, http://doi.org/10.5255/UKDA-SN-8681-1.

FIGURE C.7: Evolution of the average number of appointments to outpatient care per financial year



Notes: The continuous green line shows the evolution of the mean number of appointments to outpatient care per patient and financial year, and the dotted red vertical line shows two periods of time (Great Recession and austerity policies). The number of appointments to outpatient care per person and year has been created summarising observation per patient in a year. The financial year variable is named as *fyear*. *Source:* University College London, UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital. (2020). SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure access. [data collection]. UK Data Service. SN:8681, http://doi.org/10.5255/UKDA-SN-8681-1.

D Ethics Approval

[RESTRICTED DUE TO LANCASTER UNIVERSITY REGULATIONS]

References

Adda, J., J. Banks, and H.-M. Von Gaudecker (2009). “The impact of income shocks on health: evidence from cohort data”. In: *Journal of the European Economic Association* 7.6, pp. 1361–1399.

Almond, D., J. Currie, and V. Duque (2018). “Childhood circumstances and adult outcomes: Act II”. In: *Journal of Economic Literature* 56.4, pp. 1360–1446.

Altonji, J. G., T. E. Elder, and C. R. Taber (2005). “Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools”. In: *Journal of Political Economy* 113.1, pp. 151–184.

Andrew, A., S. Cattan, M. Costa-Dias, C. Farquharson, L. Kraftman, S. Krutikova, A. Phimister, and A. Sevilla (2020). “Learning during the lockdown: real-time data on children’s experiences during home learning”. In: *Institute for Fiscal Studies*.

Arbeit, C. A. (2013). “Is timing everything? Parental unemployment and children’s educational attainment”. In: *Minnesota Population Center Working Paper*.

Ariizumi, H. and T. Schirle (2012). “Are recessions really good for your health? Evidence from Canada”. In: *Social Science & Medicine* 74.8, pp. 1224–1231.

Arnett, J (2011). “Bridging cultural and developmental approaches to psychology: new synthesis in theory, research, and policy. Jensen, LA”. In: *Development Phases and Culture*, pp. 255–275.

Avdic, D., S. C. De New, and D. A. Kamhöfer (2021). “Economic downturns and mental health in Germany”. In: *European Economic Review* 140, p. 103915.

Baicker, K. and T. Svoronos (2019). “Testing the validity of the single interrupted time series design”. In: *National Bureau of Economic Research*.

Bambra, C, A Copeland, C Nylen, S Curtis, A Kasim, and B Burstrom (2013). “All in it together? Recessions, health and health inequalities in England and Sweden, 1991 to 2010”. In: *The European Journal of Public Health* 23.suppl_1, ckt126–017.

Bambra, C., K. Garthwaite, A. Copeland, and B. Barr (2015). “All in it together? Health inequalities, austerity, and the ‘Great Recession’”. In: *Health Inequalities. Oxford University Press, Oxford*, pp. 164–176.

Bamia, C., A. Trichopoulou, and D. Trichopoulos (2007). “Age at retirement and mortality in a general population sample: the Greek EPIC study”. In: *American Journal of Epidemiology* 167.5, pp. 561–569.

Bartley, M. (2016). “Health inequality: an introduction to concepts, theories and methods”. In: *John Wiley & Sons*.

Baum II, C. L. and C. J. Ruhm (2009). “Age, socioeconomic status and obesity growth”. In: *Journal of Health Economics* 28.3, pp. 635–648.

Beatty, C. and S. Fothergill (2014). “The local and regional impact of the UK’s welfare reforms”. In: *Cambridge Journal of Regions, Economy and Society* 7.1, pp. 63–79.

Behncke, S. (2012). “Does retirement trigger ill health?” In: *Health Economics* 21.3, pp. 282–300.

Bell, D. N. and D. G. Blanchflower (2010). “UK unemployment in the great recession”. In: *National Institute Economic Review* 214.1, R3–R25.

Bell, D. N. and D. G. Blanchflower (2011). "Young people and the Great Recession". In: *Oxford Review of Economic Policy* 27.2, pp. 241–267.

Bellés-Obrero, C. and J. V. Castelló (2018). "The business cycle and health". In: *Oxford Research Encyclopedia of Economics and Finance*.

Belloni, M., E. Meschi, and G. Pasini (2016). "The effect on mental health of retiring during the economic crisis". In: *Health Economics* 25, pp. 126–140.

Black, N., A. Jackson, and D. W. Johnston (2022). "Whose mental health declines during economic downturns?" In: *Health Economics* 31.1, pp. 250–257.

Bloemen, H., S. Hochguertel, and J. Zweerink (2017). "The causal effect of retirement on mortality: Evidence from targeted incentives to retire early". In: *Health Economics* 26.12, e204–e218.

Bloemen, H., S. Hochguertel, and J. Zweerink (2018). "Job loss, firm-level heterogeneity and mortality: Evidence from administrative data". In: *Journal of Health Economics* 59, pp. 78–90.

Bloom, H. S. (2003). "Using "short" interrupted time-series analysis to measure the impacts of whole-school reforms: With applications to a study of accelerated schools". In: *Evaluation Review* 27.1, pp. 3–49.

Blundell, R. and M. Costa Dias (2000). "Evaluation methods for non-experimental data". In: *Fiscal Studies* 21.4, pp. 427–468.

Bonsang, E. and T. J. Klein (2012). "Retirement and subjective well-being". In: *Journal of Economic Behavior & Organization* 83.3, pp. 311–329.

Bound, J. and T. Waidmann (2007). "Estimating the health effects of retirement". In: *Michigan Retirement Research Center Research* 168.

Bourguignon, F., F. H. Ferreira, and M. Menéndez (2007). "Inequality of opportunity in Brazil". In: *Review of Income and Wealth* 53.4, pp. 585–618.

Bowling, A. (1991). "Measuring health: a review of quality of life measurement scales". In: *Open University Press Milton Keynes*.

Brand, J. E. and J. Simon Thomas (2014). "Job displacement among single mothers: Effects on children's outcomes in young adulthood". In: *American Journal of Sociology* 119.4, pp. 955–1001.

Brannon, L., J. Feist, and J. A. Updegraff (2013). "Health psychology: An introduction to behavior and health". In: *Cengage Learning*.

Browning, M. and E. Heinesen (2012). "Effect of job loss due to plant closure on mortality and hospitalization". In: *Journal of Health Economics* 31.4, pp. 599–616.

Bubonya, M., D. A. Cobb-Clark, and M. Wooden (2017). "Job loss and the mental health of spouses and adolescent children". In: *IZA Journal of Labor Economics* 6.1, pp. 1–27.

Buchmueller, T. C., F. Jusot, M. Grignon, et al. (2007). "Unemployment and mortality in France, 1982-2002". In: *Centre for Health Economics and Policy Analysis*.

Buheji, M., K. da Costa Cunha, G. Beka, B. Mavric, Y. De Souza, S. S. da Costa Silva, M. Hanafi, and T. C. Yein (2020). "The extent of covid-19 pandemic socio-economic impact on global poverty. a global integrative multidisciplinary review". In: *American Journal of Economics* 10.4, pp. 213–224.

Burstrom, B., M. Whitehead, S. Clayton, S. Fritzell, F. Vannoni, and G. Costa (2010). "Health inequalities between lone and couple mothers and policy under different welfare regimes–the example of Italy, Sweden and Britain". In: *Social Science & Medicine* 70.6, pp. 912–920.

Cable, N, T Chandola, J Aida, M Sekine, and G. Netuveli (2017). "Can sleep disturbance influence changes in mental health status? Longitudinal research evidence from ageing studies in England and Japan". In: *Sleep Medicine* 30, pp. 216–221.

Calderwood, L. and C. Sanchez (2016). “Calderwood, L. and Sanchez, C.(2016). Next Steps (formerly known as the Longitudinal Study of Young People in England). Journal of Open Health Data, 4”. In: *Open health data*.

Carrieri, V., A. Davillas, and A. M. Jones (2020). “A latent class approach to inequity in health using biomarker data”. In: *Health Economics* 29.7, pp. 808–826.

Carrino, L., K. Glaser, and M. Avendano (2020). “Later retirement, job strain, and health: Evidence from the new State Pension age in the United Kingdom”. In: *Health Economics* 29.8, pp. 891–912.

Casey, B., S. Duhoux, and M. M. Cohen (2010). “Adolescence: what do transmission, transition, and translation have to do with it?” In: *Neuron* 67.5, pp. 749–760.

Cattaneo, M. D. (2010). “Efficient semiparametric estimation of multi-valued treatment effects under ignorability”. In: *Journal of Econometrics* 155.2, pp. 138–154.

Cauley, J. and E. I. Im (1988). “Intervention policy analysis of skyjackings and other terrorist incidents”. In: *The American Economic Review* 78.2, pp. 27–31.

Chang, H., S. L. Olson, A. J. Sameroff, and H. R. Sexton (2011). “Child effortful control as a mediator of parenting practices on externalizing behavior: Evidence for a sex-differentiated pathway across the transition from preschool to school”. In: *Journal of Abnormal Child Psychology* 39.1, pp. 71–81.

Charles, K. K. and M. Stephens Jr (2004). “Job displacement, disability, and divorce”. In: *Journal of Labor Economics* 22.2, pp. 489–522.

Chetty, R., M. Stepner, S. Abraham, S. Lin, B. Scuderi, N. Turner, A. Bergeron, and D. Cutler (2016). “The association between income and life expectancy in the United States, 2001-2014”. In: *JAMA* 315.16, pp. 1750–1766.

Chiappori, P.-A. and C. Meghir (2014). “Intra-household welfare”. In: *National Bureau of Economic Research*.

Clark, A., A. Knabe, and S. Rätzel (2010). “Boon or bane? Others’ unemployment, well-being and job insecurity”. In: *Labour Economics* 17.1, pp. 52–61.

Clark, A. E., P. Frijters, and M. A. Shields (2008). “Relative income, happiness, and utility: An explanation for the Easterlin paradox and other puzzles”. In: *Journal of Economic Literature* 46.1, pp. 95–144.

Clark, A. E. and A. Lepinteur (2019). “The causes and consequences of early-adult unemployment: evidence from cohort data”. In: *Journal of Economic Behavior & Organization* 166, pp. 107–124.

Clayborne, Z. M., M. Kingsbury, H. Sampasa-Kinyaga, L. Sikora, K. M. Lalande, and I. Colman (2021). “Parenting practices in childhood and depression, anxiety, and internalizing symptoms in adolescence: a systematic review”. In: *Social Psychiatry and Psychiatric Epidemiology* 56.4, pp. 619–638.

Coe, N. B. and G. Zamarro (2011). “Retirement effects on health in Europe”. In: *Journal of Health Economics* 30.1, pp. 77–86.

Coile, C. C., P. B. Levine, and R. McKnight (2014). “Recessions, older workers, and longevity: How long are recessions good for your health?” In: *American Economic Journal: Economic Policy* 6.3, pp. 92–119.

Communities & Local Government, D. for (2015). “Annual Report and Accounts 2014-15”. In: *House of Lords by Command of Her Majesty* https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/440498/50208_HC_21_DCLG_2014-15_print.pdf.

Conti, G., J. Heckman, and S. Urzua (2010). “The education-health gradient”. In: *The American Economic Review* 100.2, pp. 234–38.

Conti, G., J. J. Heckman, and R. Pinto (2016). “The effects of two influential early childhood interventions on health and healthy behaviour”. In: *The Economic Journal* 126.596, F28–F65.

Contoyannis, P. and A. M. Jones (2004). "Socio-economic status, health and lifestyle". In: *Journal of Health Economics* 23.5, pp. 965–995.

Cook, T. D., D. T. Campbell, and W. Shadish (2002). "Experimental and quasi-experimental designs for generalized causal inference". In: *Houghton Mifflin Boston*.

Cookson, R., C. Propper, M. Asaria, and R. Raine (2016). "Socio-economic inequalities in health care in England". In: *Fiscal Studies* 37.3-4, pp. 371–403.

Costa-Font, J., C. Hernández-Quevedo, and D. Jiménez-Rubio (2014). "Income inequalities in unhealthy life styles in England and Spain". In: *Economics & Human Biology* 13, pp. 66–75.

Couch, K. A. and D. W. Placzek (2010). "Earnings losses of displaced workers revisited". In: *The American Economic Review* 100.1, pp. 572–89.

Currie, C. and A. Y. Alemán-Díaz (2015). "Building knowledge on adolescent health: reflections on the contribution of the Health Behaviour in School-aged Children (HBSC) study". In: *The European Journal of Public Health* 25.suppl_2, pp. 4–6.

Currie, C., C. Zanotti, A. Morgan, D. Currie, M. De Looze, C. Roberts, O. Samdal, O. R. Smith, and V. Barnekow (2009). "Social determinants of health and well-being among young people". In: *Health Behaviour in School-aged Children* 2010, p. 271.

Currie, J. (2009). "Healthy, wealthy, and wise: Socioeconomic status, poor health in childhood, and human capital development". In: *Journal of Economic Literature* 47.1, pp. 87–122.

Currie, J. and H. Schwandt (2016). "Mortality inequality: The good news from a county-level approach". In: *Journal of Economic Perspectives* 30.2, pp. 29–52.

Currie, J., M. Stabile, P. Manivong, and L. L. Roos (2010). "Child health and young adult outcomes". In: *Journal of Human Resources* 45.3, pp. 517–548.

Dave, D., I. Rashad, and J. Spasojevic (2006). "The effects of retirement on physical and mental health outcomes". In: *National Bureau of Economic Research*.

Davillas, A. and A. M. Jones (2020). "Ex ante inequality of opportunity in health, decomposition and distributional analysis of biomarkers". In: *Journal of Health Economics* 69, p. 102251.

Davillas, A. and A. M. Jones (2021). "Unmet health care need and income-Related horizontal equity in use of health care during the COVID-19 pandemic". In: *Health Economics* 30.7, pp. 1711–1716.

De Barros, R. P., M. de Carvalho, S. Franco, R. Mendonça, et al. (2007). "Determinantes imediatos da queda da desigualdade de renda brasileira". In: *Desigualdade de renda no Brasil uma análise da queda recente*.

De Barros, R. P., F. Ferreira, J. Vega, and J. Chanduvi (2009). "Measuring inequality of opportunities in Latin America and the Caribbean". In: *World Bank publications*.

Di Tella, R., R. J. MacCulloch, and A. J. Oswald (2001). "Preferences over inflation and unemployment: Evidence from surveys of happiness". In: *The American Economic Review* 91.1, pp. 335–341.

Doiron, D. and S. Mendolia (2012). "The impact of job loss on family dissolution". In: *Journal of Population Economics* 25.1, pp. 367–398.

Eibich, P. (2015). "Understanding the effect of retirement on health: Mechanisms and heterogeneity". In: *Journal of Health Economics* 43, pp. 1–12.

Elgar, F. J., T.-K. Pförtner, I. Moor, B. De Clercq, G. W. Stevens, and C. Currie (2015). "Socioeconomic inequalities in adolescent health 2002–2010: a time-series analysis of 34 countries participating in the Health Behaviour in School-aged Children study". In: *The Lancet* 385.9982, pp. 2088–2095.

Eliason, M. (2012). "Lost jobs, broken marriages". In: *Journal of Population Economics* 25.4, pp. 1365–1397.

Eliason, M. and D. Storrie (2009). "Does job loss shorten life?" In: *Journal of Human Resources* 44.2, pp. 277–302.

Ermisch, J., M. Francesconi, and D. J. Pevalin (2004). "Parental partnership and joblessness in childhood and their influence on young people's outcomes". In: *Journal of the Royal Statistical Society* 167.1, pp. 69–101.

Erreygers, G. (2009). "Correcting the concentration index". In: *Journal of Health Economics* 28.2, pp. 504–515.

Erreygers, G. and T. Van Ourti (2011). "Putting the cart before the horse: a reply to Wagstaff on inequality measurement in the presence of binary variables". In: *Health Economics* 20.10, p. 1161.

European-Commission (2020). "Labour Market and Wage Developments in Europe (LMD)". In: *Employment, Social Affairs & Inclusion.*

Fajardo-Gonzalez, J. (2016). "Inequality of opportunity in adult health in Colombia". In: *The Journal of Economic Inequality* 14.4, pp. 395–416.

Ferreira, F. H. and J. Gignoux (2011). "The measurement of inequality of opportunity: Theory and an application to Latin America". In: *Review of Income and Wealth* 57.4, pp. 622–657.

Fitzpatrick, M. D. and T. J. Moore (2018). "The mortality effects of retirement: Evidence from Social Security eligibility at age 62". In: *Journal of Public Economics* 157, pp. 121–137.

Fleurbaey, M. and V. Peragine (2013). "Ex ante versus ex post equality of opportunity". In: *Economica* 80.317, pp. 118–130.

Fleurbaey, M. and E. Schokkaert (2009). "Unfair inequalities in health and health care". In: *Journal of Health Economics* 28.1, pp. 73–90.

Forret, M. L., S. E. Sullivan, and L. A. Mainiero (2010). "Gender role differences in reactions to unemployment: Exploring psychological mobility and boundaryless careers". In: *Journal of Organizational Behavior* 31.5, pp. 647–666.

Fretheim, A., S. B. Soumerai, F. Zhang, A. D. Oxman, and D. Ross-Degnan (2013). "Interrupted time-series analysis yielded an effect estimate concordant with the cluster-randomized controlled trial result". In: *Journal of Clinical Epidemiology* 66.8, pp. 883–887.

Fumagalli, L., G. Knies, and N. Buck (2017). "Understanding Society, The UK Household Longitudinal Study, Harmonised British Household Panel Survey (BHPS) User Guide". In: *ISER University of Essex*.

Gathmann, C., K. Huttunen, L. Jernström, L. Sääksvuori, and R. Stitzing (2021). "In sickness and in health: job displacement and health spillovers in couples". In: *CEPR Discussion Paper No. DP15856*.

Gauvain, M. and M. Cole (2005). "Readings on the development of children". In: *Macmillan*.

Gibson, M., M. Petticrew, C. Bambra, A. J. Sowden, K. E. Wright, and M. Whitehead (2011). "Housing and health inequalities: a synthesis of systematic reviews of interventions aimed at different pathways linking housing and health". In: *Health & Place* 17.1, pp. 175–184.

Gilman, S. E., I. Kawachi, G. M. Fitzmaurice, and S. L. Buka (2002). "Socioeconomic status in childhood and the lifetime risk of major depression". In: *International Journal of Epidemiology* 31.2, pp. 359–367.

Glymour, M. M., M. Avendano, and I. Kawachi (2014). "Socioeconomic status and health". In: *Social Epidemiology* 2, pp. 17–63.

Goldberg, D. P. (1988). "User's guide to the General Health Questionnaire". In: *Windsor*.

Goldberg, D. P., R. Gater, N. Sartorius, T. B. Ustun, M. Piccinelli, O. Gureje, and C. Rutter (1997). "The validity of two versions of the GHQ in the WHO study of mental illness in general health care". In: *Psychological Medicine* 27.1, pp. 191–197.

Gonzalez, F. and T. Quast (2011). "Macroeconomic changes and mortality in Mexico". In: *Empirical Economics* 40.2, pp. 305–319.

Gorry, A., D. Gorry, and S. N. Slavov (2018). "Does retirement improve health and life satisfaction?" In: *Health Economics* 27.12, pp. 2067–2086.

Granados, J. A. T. (2005). "Recessions and mortality in Spain, 1980–1997". In: *European Journal of Population/Revue Européenne de Démographie* 21.4, pp. 393–422.

Griffith, R., M. O'Connell, and K. Smith (2016). "Shopping around: how households adjusted food spending over the great recession". In: *Economica* 83.330, pp. 247–280.

Grossman, M. (1972). "On the concept of health capital and the demand for health". In: *Journal of Political Economy* 80.2, pp. 223–255.

Grossman, M. (2000). "The human capital model". In: *Handbook of Health Economics* 1, pp. 347–408.

Grusky, D. B., B. Western, and C. Wimer (2011). "The consequences of the great recession". In: *The Great Recession book*, pp. 3–20.

Hacker, K. A., R. B. Penfold, L. N. Arsenault, F. Zhang, S. B. Soumerai, and L. S. Wissow (2015). "Effect of pediatric behavioral health screening and colocated services on ambulatory and inpatient utilization". In: *Psychiatric Services* 66.11, pp. 1141–1148.

Hagell A., S. R. C. J. (2019). "Key data on young people 2019". In: *Association for Young People's Health*.

Hanson, M. D. and E. Chen (2007). "Socioeconomic status and health behaviors in adolescence: a review of the literature". In: *Journal of Behavioral Medicine* 30.3, pp. 263–285.

Hastings, A., N. Bailey, K. Besemer, G. Bramley, M. Gannon, and D. Watkins (2013). "Coping with the Cuts?: Local Government and Poorer Communities". In: *Joseph Rowntree Foundation York*.

Health, D. of (2003). "Care homes for older people: National minimum standards: And the care homes regulations 2001". In: *The Stationery Office* 1.

Heckman, J. J., H. Ichimura, and P. Todd (1998). "Matching as an econometric evaluation estimator". In: *The Review of Economic Studies* 65.2, pp. 261–294.

Heckman, J. J., H. Ichimura, and P. E. Todd (1997). "Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme". In: *The Review of Economic Studies* 64.4, pp. 605–654.

Heckman, J. J. and S. Mosso (2014). "The economics of human development and social mobility". In: *Annual Review of Economics* 6.1, pp. 689–733.

Henkel, D. (2011). "Unemployment and substance use: a review of the literature (1990-2010)". In: *Current Drug Abuse Reviews* 4.1, pp. 4–27.

Hernaes, E., S. Markussen, J. Piggott, and O. L. Vestad (2013). "Does retirement age impact mortality?" In: *Journal of Health Economics* 32.3, pp. 586–598.

Hilger, N. G. (2016). "Parental job loss and children's long-term outcomes: Evidence from 7 million fathers' layoffs". In: *American Economic Journal: Applied Economics* 8.3, pp. 247–83.

Holford, A. (2020). "Youth employment, academic performance and labour market outcomes: Production functions and policy effects". In: *Labour Economics* 63, p. 101806.

Holm, S. (1979). "A simple sequentially rejective multiple test procedure". In: *Scandinavian Journal of Statistics*, pp. 65–70.

Hope, H., C. S. Osam, E. Kontopantelis, S. Hughes, L. Munford, D. M. Ashcroft, M. Pierce, and K. M. Abel (2021). "The healthcare resource impact of maternal mental illness on children and adolescents: UK retrospective cohort study". In: *The British Journal of Psychiatry* 219.3, pp. 515–522.

Hsu, Y.-C., M. Huber, and T.-C. Lai (2019). "Nonparametric estimation of natural direct and indirect effects based on inverse probability weighting". In: *Journal of Econometric Methods* 8.1.

Huttunen, K., J. Møen, and K. G. Salvanes (2011). "How destructive is creative destruction? Effects of job loss on job mobility, withdrawal and income". In: *Journal of the European Economic Association* 9.5, pp. 840–870.

Imbens, G. W. and J. M. Wooldridge (2009). "Recent developments in the econometrics of program evaluation". In: *Journal of Economic Literature* 47.1, pp. 5–86.

Imo, U. O. (2017). "Burnout and psychiatric morbidity among doctors in the UK: a systematic literature review of prevalence and associated factors". In: *BJPsychology bulletin* 41.4, pp. 197–204.

Inchley, J. C., D. B. Currie, J. M. Todd, P. C. Akhtar, and C. E. Currie (2005). "Persistent socio-demographic differences in physical activity among Scottish schoolchildren 1990–2002". In: *The European Journal of Public Health* 15.4, pp. 386–388.

Insler, M. (2014). "The health consequences of retirement". In: *Journal of Human Resources* 49.1, pp. 195–233.

Irwin, W. (1999). "Intentionalist interpretation: A philosophical explanation and defense". In: *Greenwood Press Westport, CT*.

Jessiman, P. E., K. Powell, P. Williams, H. Fairbrother, M. Crowder, J. G. Williams, and R. Kipping (2021). "A systems map of the determinants of child health inequalities in England at the local level". In: *PloS one* 16.2, e0245577.

Jofre-Bonet, M., V. Serra-Sastre, and S. Vandoros (2018). "The impact of the Great Recession on health-related risk factors, behaviour and outcomes in England". In: *Social Science & Medicine* 197, pp. 213–225.

Joshi, H. and G. Verropoulou (2000). "Maternal employment and child outcomes: Analysis of two birth cohort studies". In: *Smith Institute*.

Juárez, F. W. C. and I. Soloaga (2014). "iop: Estimating ex-ante inequality of opportunity". In: *The Stata Journal* 14.4, pp. 830–846.

Jusot, F., S. Tubeuf, and A. Trannoy (2013). "Circumstances and efforts: how important is their correlation for the measurement of inequality of opportunity in health?" In: *Health Economics* 22.12, pp. 1470–1495.

Kakwani, N. C. (1977). "Applications of Lorenz curves in economic analysis". In: *Econometrica: Journal of the Econometric Society*, pp. 719–727.

Kalil, A. and K. M. Ziol-Guest (2008). "Parental employment circumstances and children's academic progress". In: *Social Science Research* 37.2, pp. 500–515.

Karanikolos, M., P. Mladovsky, J. Cylus, S. Thomson, S. Basu, D. Stuckler, J. P. Mackenbach, and M. McKee (2013). "Financial crisis, austerity, and health in Europe". In: *The Lancet* 381.9874, pp. 1323–1331.

Keeble, E. and L. Kossarova (2017). "Focus on: Emergency hospital care for children and young people". In: *Focus On Research Report. QualityWatch*, pp. 2018–10.

Kessler, R. C., M. Angermeyer, J. C. Anthony, R. De Graaf, K. Demyttenaere, I. Gasquet, G. De Girolamo, S. Gluzman, O. Gureje, J. M. Haro, et al. (2007). "Lifetime prevalence and age-of-onset distributions of mental disorders in the World Health Organization's World Mental Health Survey Initiative". In: *World Psychiatry* 6.3, p. 168.

Kieling, C., H. Baker-Henningham, M. Belfer, G. Conti, I. Ertem, O. Omigbodun, L. A. Rohde, S. Srinath, N. Ulkuer, and A. Rahman (2011). "Child and adolescent mental health worldwide: evidence for action". In: *The Lancet* 378.9801, pp. 1515–1525.

Kind, M. and J. P. Haisken DeNew (2012). "Unexpected victims: How parents' unemployment affects their children's life satisfaction". In: *Melbourne Institute of Applied Economic and Social Research*.

Knabe, A., S. Rätzel, R. Schöb, and J. Weimann (2010). "Dissatisfied with life but having a good day: time-use and well-being of the unemployed". In: *The Economic Journal* 120.547, pp. 867–889.

Koolman, X. and E. Van Doorslaer (2004). "On the interpretation of a concentration index of inequality". In: *Health Economics* 13.7, pp. 649–656.

Kossarova, L., D. Devakumar, and N. Edwards (2016). "The future of child health services: new models of care". In: *LNuffield Trust*.

Leal Filho, W., A. M. Azul, L. Brandli, A. Lange Salvia, and T. Wall (2020). "Decent work and economic growth". In: *Springer*.

Lesner, R. V. (2018). "The long-term effect of childhood poverty". In: *Journal of Population Economics* 31.3, pp. 969–1004.

Liang, K.-Y. and S. L. Zeger (1986). "Longitudinal data analysis using generalized linear models". In: *Biometrika* 73.1, pp. 13–22.

Linden, A. (2015). "Conducting interrupted time-series analysis for single-and multiple-group comparisons". In: *The Stata Journal* 15.2, pp. 480–500.

MacLeavy, J. (2011). "Reconfiguring work and welfare in the UK's 'New Economy': regulatory geographies of welfare-to-work at the local level". In: *Gender, Place & Culture* 18.5, pp. 611–633.

Maheswaran, H., E. Kupek, and S. Petrou (2015). "Self-reported health and socio-economic inequalities in England, 1996–2009: Repeated national cross-sectional study". In: *Social Science & Medicine* 136, pp. 135–146.

McInerney, M. and J. M. Mellor (2012). "Recessions and seniors' health, health behaviors, and healthcare use: Analysis of the Medicare Current Beneficiary Survey". In: *Journal of Health Economics* 31.5, pp. 744–751.

Midanik, L. T., K. Soghikian, L. J. Ransom, and I. S. Tekawa (1995). "The effect of retirement on mental health and health behaviors: The Kaiser Permanente Retirement Study". In: *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences* 50.1, S59–S61.

Minds, Y. (2018). "A new era for young people's mental health". In: *Young Minds, London*.

Minkler, M. (1981). "Research on the health effects of retirement: an uncertain legacy". In: *Journal of Health and Social Behavior*, pp. 117–130.

Modrek, S., D. Stuckler, M. McKee, M. R. Cullen, and S. Basu (2013). "A review of health consequences of recessions internationally and a synthesis of the US response during the Great Recession". In: *Public Health Reviews* 35.1, pp. 1–33.

Molcho, M., S. N. Gabhainn, C. Kelly, S. Friel, and C. Kelleher (2007). "Food poverty and health among schoolchildren in Ireland: findings from the Health Behaviour in School-aged Children (HBSC) study". In: *Public Health Nutrition* 10.4, pp. 364–370.

Mooi-Reci, I., B. Bakker, M. Curry, and M. Wooden (2019). "Why Parental Unemployment Matters for Children's Educational Attainment: Empirical Evidence from The Netherlands". In: *European Sociological Review* 35.3, pp. 394–408.

Mörk, E., A. Sjögren, and H. Svaleryd (2014). "Parental unemployment and child health". In: *CESifo Economic Studies* 60.2, pp. 366–401.

Mörk, E., A. Sjögren, and H. Svaleryd (2020). "Consequences of parental job loss on the family environment and on human capital formation-Evidence from workplace closures". In: *Labour Economics* 67, p. 101911.
Mroz, T. A. and T. H. Savage (2006). "The long-term effects of youth unemployment". In: *Journal of Human Resources* 41.2, pp. 259–293.
Mundlak, Y. (1978). "On the pooling of time series and cross section data". In: *Econometrica: Journal of the Econometric Society*, pp. 69–85.
Munford, L., S. Khavandi, C. Bambra, B. Barr, H. Davies, T. Doran, E. Kontopantelis, P. Norman, K. Pickett, M. Sutton, et al. (2021). "A year of COVID-19 in the North: Regional inequalities in health and economic outcomes". In.
Munford, L., L. Mott, H. Davies, V. McGowan, and C. Bambra (2022). "Overcoming health inequalities in 'left behind'neighbourhoods". In: *The University of Manchester publications*.
Murtin, F., J. Mackenbach, D. Jasilionis, and M. M. d'Ercole (2017). "Inequalities in longevity by education in OECD countries: Insights from new OECD estimates". In: *OECD Library*.
Neuman, K. (2008). "Quit your job and get healthier? The effect of retirement on health". In: *Journal of Labor Research* 29.2, pp. 177–201.
Neumayer, E. (2004). "Recessions lower (some) mortality rates: evidence from Germany". In: *Social Science & Medicine* 58.6, pp. 1037–1047.
Newacheck, P. W., D. C. Hughes, and J. J. Stoddard (1996). "Children's access to primary care: differences by race, income, and insurance status". In: *Pediatrics* 97.1, pp. 26–32.
Nikolova, M. and B. N. Nikolaev (2021). "Family matters: The effects of parental unemployment in early childhood and adolescence on subjective well-being later in life". In: *Journal of Economic Behavior & Organization* 181, pp. 312–331.
Noonan, R. J. (2019). "The effect of childhood deprivation on weight status and mental health in childhood and adolescence: Longitudinal findings from the Millennium Cohort Study". In: *Journal of Public Health* 41.3, pp. 456–461.
Nooyens, A. C., T. L. Visscher, A. J. Schuit, C. T. van Rossum, W. M. Verschuren, W. van Mechelen, and J. C. Seidell (2005). "Effects of retirement on lifestyle in relation to changes in weight and waist circumference in Dutch men: a prospective study". In: *Public Health Nutrition* 8.8, pp. 1266–1274.
O'Donnell, O., S. O'Neill, T. Van Ourti, and B. Walsh (2016). "Conindex: estimation of concentration indices". In: *The Stata Journal* 16.1, pp. 112–138.
OECD (2008). "OECD, glossary of statistical terms". In: *OECD website*.
OECD (2019). "Education at a Glance 2019 OECD Indicators". In: *OECD library*.
OECD (2020). "Family database: The labour market position of families." In: *OECD website*.
Ollivaud, P. and D. Turner (2014). "The effect of the global financial crisis on OECD potential output". In: *OECD library*.
Ooghe, E., E. Schokkaert, et al. (2007). "Equality of opportunity versus equality of opportunity sets". In: *Social Choice and Welfare* 28.2, pp. 209–230.
Oreopoulos, P., M. Stabile, R. Walld, and L. L. Roos (2008). "Short-, medium-, and long-term consequences of poor infant health an analysis using siblings and twins". In: *Journal of Human Resources* 43.1, pp. 88–138.
Oster, E. (2019). "Unobservable selection and coefficient stability: Theory and evidence". In: *Journal of Business & Economic Statistics* 37.2, pp. 187–204.
Page, M., A. H. Stevens, and J. Lindo (2009). "Parental Income Shocks and Outcomes of Disadvantaged Youth in the United States". In: *The Problems of Disadvantaged Youth*, pp. 213–236.

Parker, S. C. and J. C. Rougier (2007). "The retirement behaviour of the self-employed in Britain". In: *Applied Economics* 39.6, pp. 697–713.

Patton, G. C., S. M. Sawyer, J. S. Santelli, D. A. Ross, R. Afifi, N. B. Allen, M. Arora, P. Azzopardi, W. Baldwin, C. Bonell, et al. (2016). "Our future: a Lancet commission on adolescent health and wellbeing". In: *The Lancet* 387.10036, pp. 2423–2478.

Perry, B. L., B. Aronson, and B. A. Pescosolido (2021). "Pandemic precarity: COVID-19 is exposing and exacerbating inequalities in the American heartland". In: *Proceedings of the National Academy of Sciences* 118.8.

Pieters, J. and S. Rawlings (2020). "Parental unemployment and child health in China". In: *Review of Economics of the Household* 18.1, pp. 207–237.

Pinger, P. R. (2015). "Understanding the mechanisms behind intergenerational effects of economic distress". In: *Mimeograph: University of Bonn*.

Powdthavee, N. (2014). "What childhood characteristics predict psychological resilience to economic shocks in adulthood?" In: *Journal of Economic Psychology* 45, pp. 84–101.

Powdthavee, N. and J. Vernoit (2013). "Parental unemployment and children's happiness: A longitudinal study of young people's well-being in unemployed households". In: *Labour Economics* 24, pp. 253–263.

Pye, V., N. Taylor, R. Clay-Williams, and J. Braithwaite (2016). "When is enough, enough? Understanding and solving your sample size problems in health services research". In: *BMC research notes* 9.1, pp. 1–7.

Radloff, L. S. (1977). "A self-report depression scale for research in the general population". In: *Applied Psychology Measurements* 1, pp. 385–401.

Ramos, X. and D. Van De Gaer (2016). "Approaches to inequality of opportunity: Principles, measures and evidence". In: *Journal of Economic Surveys* 30.5, pp. 855–883.

Rau, T., M. Sarzosa, and S. Urzúa (2021). "The children of the missed pill". In: *Journal of Health Economics* 79, p. 102496.

Raudenbush, S. W. and A. S. Bryk (2002). "Hierarchical linear models: Applications and data analysis methods". In: *Sage* 1.

Reeves, A., M. McKee, S. Basu, and D. Stuckler (2014). "The political economy of austerity and healthcare: Cross-national analysis of expenditure changes in 27 European nations 1995–2011". In: *Health Policy* 115.1, pp. 1–8.

Rege, M., K. Telle, and M. Votruba (2011). "Parental job loss and children's school performance". In: *The Review of Economic Studies* 78.4, pp. 1462–1489.

Reiss, F. (2013). "Socioeconomic inequalities and mental health problems in children and adolescents: a systematic review". In: *Social Science & Medicine* 90, pp. 24–31.

Ridley, M., G. Rao, F. Schilbach, and V. Patel (2020). "Poverty, depression, and anxiety: Causal evidence and mechanisms". In: *Science* 370.6522, eaay0214.

Roemer, J. (1998). "Equality of opportunity, Harvard U". In: *Press, Cambridge*.

Roemer, J. E. (2002). "Equality of opportunity: A progress report". In: *Social Choice and Welfare*, pp. 455–471.

Roemer, J. E. and A. Trannoy (2016). "Equality of opportunity: Theory and measurement". In: *Journal of Economic Literature* 54.4, pp. 1288–1332.

Rosa Dias, P. (2009). "Inequality of opportunity in health: evidence from a UK cohort study". In: *Health Economics* 18.9, pp. 1057–1074.

Rosa Dias, P. (2010). "Modelling opportunity in health under partial observability of circumstances". In: *Health Economics* 19.3, pp. 252–264.

Rose, D., D. Pevalin, P. Elias, and J. Martin (2001). "Towards a European socio-economic classification". In: *Final Report to Eurostat of the Expert Group Retrieved* 8.04, p. 2014.

Rose, L. (2020). "Retirement and health: Evidence from England". In: *Journal of Health Economics* 73, p. 102352.

Rosenzweig, M. R. and T. P. Schultz (1983). "Estimating a household production function: Heterogeneity, the demand for health inputs, and their effects on birth weight". In: *Journal of Political Economy* 91.5, pp. 723–746.

Rougeaux, E., S. Hope, C. Law, and A. Pearce (2017). "Have health inequalities changed during childhood in the New Labour generation? Findings from the UK Millennium Cohort Study". In: *BMJ open* 7.1, e012868.

Rubin, K. H., R. J. Coplan, and J. C. Bowker (2009). "Social withdrawal in childhood". In: *Annual Review of Psychology* 60, pp. 141–171.

Ruhm, C. J. (2000). "Are recessions good for your health?" In: *The Quarterly Journal of Economics* 115.2, pp. 617–650.

Ruhm, C. J. (2015). "Recessions, healthy no more?" In: *Journal of Health Economics* 42, pp. 17–28.

Ruhm, C. J. and W. E. Black (2002). "Does drinking really decrease in bad times?" In: *Journal of Health Economics* 21.4, pp. 659–678.

Ruiz-Valenzuela, J. (2021). "The effects of parental job loss on children's outcomes". In: *Oxford Research Encyclopedia of Economics and Finance*.

Sadler, K., T. Vizard, T. Ford, F. Marchesell, N. Pearce, D. Mandalia, J. Davis, E. Brodie, N. Forbes, A. Goodman, et al. (2018). "Mental health of children and young people in England, 2017". In: *NHS Digital*.

Sawyer, S. M., R. A. Afifi, L. H. Bearinger, S. J. Blakemore, B. Dick, A. C. Ezeh, and G. C. Patton (2012). "Adolescence: a foundation for future health". In: *The Lancet* 379.9826, pp. 1630–1640.

Schaller, J. and M. Zerpa (2019). "Short-run effects of parental job loss on child health". In: *American Journal of Health Economics* 5.1, pp. 8–41.

Scheier, M. F. and M. W. Bridges (1995). "Person variables and health: personality predispositions and acute psychological states as shared determinants for disease". In: *Psychosomatic Medicine* 57.3, pp. 255–268.

Schneider, B. H., J. F. Richard, A. J. Younger, and P. Freeman (2000). "A longitudinal exploration of the continuity of children's social participation and social withdrawal across socioeconomic status levels and social settings". In: *European Journal of Social Psychology* 30.4, pp. 497–519.

Schneider, W., J. Waldfogel, and J. Brooks-Gunn (2017). "The Great Recession and risk for child abuse and neglect". In: *Children and Youth Services Review* 72, pp. 71–81.

Schofield, T. J., R. D. Conger, M. B. Donnellan, R. Jochem, K. F. Widaman, and K. J. Conger (2012). "Parent personality and positive parenting as predictors of positive adolescent personality development over time". In: *Merrill-Palmer Quarterly* 58.2, p. 255.

Shorrocks, A. F. (2013). "Decomposition procedures for distributional analysis: a unified framework based on the Shapley value". In: *Journal of Economic Inequality* 11.1, pp. 99–126.

Skalická, V., F. Van Lenthe, C. Bambra, S. Krokstad, and J. Mackenbach (2009). "Material, psychosocial, behavioural and biomedical factors in the explanation of relative socio-economic inequalities in mortality: evidence from the HUNT study". In: *International Journal of Epidemiology* 38.5, pp. 1272–1284.

Stanley, J. C. and N. L. Gage (1966). "Experimental and quasi-experimental designs for research". In: *Chicago: R. McNally*.

Starfield, B., A. W. Riley, W. P. Witt, and J. Robertson (2002). "Social class gradients in health during adolescence". In: *Journal of Epidemiology & Community Health* 56.5, pp. 354–361.

StataCorp, L. (2017). "Mata Reference Manual". In: *The Stata Journal*.

Steptoe, A., E. Breeze, J. Banks, and J. Nazroo (2012). "Cohort profile: the English longitudinal study of ageing". In: *International Journal of Epidemiology* 42.6, pp. 1640–1648.

Stevens, A. H., D. L. Miller, M. E. Page, and M. Filipski (2015). "The best of times, the worst of times: understanding pro-cyclical mortality". In: *American Economic Journal: Economic Policy* 7.4, pp. 279–311.

Stuart, E. A., H. A. Huskamp, K. Duckworth, J. Simmons, Z. Song, M. E. Chernew, and C. L. Barry (2014). "Using propensity scores in difference-in-differences models to estimate the effects of a policy change". In: *Health Services and Outcomes Research Methodology* 14.4, pp. 166–182.

Stuart, E. A., G. King, K. Imai, and D. Ho (2011). "MatchIt: nonparametric preprocessing for parametric causal inference". In: *Journal of Statistical Software*.

Sugisawa, A., H. Sugisawa, Y. Nakatani, and H. Shibata (1997). "Effect of retirement on mental health and social well-being among elderly Japanese". In: *Japanese Journal of Public Health* 44.2, pp. 123–130.

Sullivan, D. and T. Von Wachter (2009). "Job displacement and mortality: An analysis using administrative data". In: *The Quarterly Journal of Economics* 124.3, pp. 1265–1306.

Taylor, M. F., J. Brice, N. Buck, and E. Prentice-Lane (1993). "British Household Panel Survey user manual: Volume A: Introduction, technical report and appendices". In: *University of Essex Colchester*.

Taylor-Robinson, D. C., E. T. Lai, M. Whitehead, and B. Barr (2019). "Child health unravelling in UK". In: *Bmj* 364.

Tekin, E., C. McClellan, and K. J. Minyard (2013). "Health and health behaviors during the worst of times". In: *National Bureau of Economic Research*.

Thompson, K., J. van Ophem, and A. Wagemakers (2019). "Studying the impact of the Eurozone's great recession on health: methodological choices and challenges". In: *Economics & Human Biology* 35, pp. 162–184.

UNICEF (2021). "Preventing a lost Decade". In: *UNICEF: United Nations Children's Fund*.

University College London, I. E. (2022). "SN8681 Next Steps: Linked Health Administrative Datasets (Hospital Episode Statistics), England, 1997-2017: Secure Access. [data collection]." In: *UCL Institute of Education, Centre for Longitudinal Studies, NHS Digital, UK Data Service. SN:8681,* http://doi.org/10.5255/UKDA-SN-8681-1..

Van De Gaer, D. (1995). "Equality of opportunity and investment in human capital." In: *Science Index Library*.

Van Den Berg, G. J., M. Lindeboom, and F. Portrait (2006). "Economic conditions early in life and individual mortality". In: *The American Economic Review* 96.1, pp. 290–302.

Viner, R. M., E. K. Arkell, M. Ashe, and M. Simpson (2017). "Responding to the changing burden of disease for children and adolescents in modern Britain: the RCPCH State of Child Health Report 2017". In: *BMJ Paediatrics Open* 1.1.

Viner, R. M., E. M. Ozer, S. Denny, M. Marmot, M. Resnick, A. Fatusi, and C. Currie (2012). "Adolescence and the social determinants of health". In: *The Lancet* 379.9826, pp. 1641–1652.

Wagstaff, A. (2005). "The bounds of the concentration index when the variable of interest is binary, with an application to immunization inequality". In: *Health Economics* 14.4, pp. 429–432.

Wagstaff, A., P. Paci, and E. Van Doorslaer (1991). "On the measurement of inequalities in health". In: *Social Science & Medicine* 33.5, pp. 545–557.

Wardle, J., K. Robb, and F. Johnson (2002). "Assessing socioeconomic status in adolescents: the validity of a home affluence scale". In: *Journal of Epidemiology & Community Health* 56.8, pp. 595–599.

West, P. and H. Sweeting (2004). "Evidence on equalisation in health in youth from the West of Scotland". In: *Social Science & Medicine* 59.1, pp. 13–27.

Whitehead, M., B. Burström, and F. Diderichsen (2000). "Social policies and the pathways to inequalities in health: a comparative analysis of lone mothers in Britain and Sweden". In: *Social Science & Medicine* 50.2, pp. 255–270.

WHO (2008). "Closing the gap in a generation: health equity through action on the social determinants of health: Commission on Social Determinants of Health final report". In: *World Health Organization library*.

Wiggins, J. S. (1996). "The five-factor model of personality: Theoretical perspectives". In: *Guilford Press*.

Woodward, A. and I. Kawachi (2000). "Why reduce health inequalities?" In: *Journal of Epidemiology & Community Health* 54.12, pp. 923–929.

Wooldridge, J. M. (2019). "Correlated random effects models with unbalanced panels". In: *Journal of Econometrics* 211.1, pp. 137–150.

Yi, J., J. J. Heckman, J. Zhang, and G. Conti (2015). "Early health shocks, intra-household resource allocation and child outcomes". In: *The Economic Journal* 125.588, F347–F371.

Zhang, Q. and Y. Wang (2004). "Socioeconomic inequality of obesity in the United States: do gender, age, and ethnicity matter?" In: *Social Science & Medicine* 58.6, pp. 1171–1180.

Zilanawala, A., L. Bécares, and A. Benner (2019). "Race/ethnic inequalities in early adolescent development in the United Kingdom and United States". In: *Demographic Research* 40, pp. 121–154.

Zins, M., A. Guéguen, M. Kivimaki, A. Singh-Manoux, A. Leclerc, J. Vahtera, H. Westerlund, J. E. Ferrie, and M. Goldberg (2011). "Effect of retirement on alcohol consumption: longitudinal evidence from the French Gazel cohort study". In: *PLoS One* 6.10, e26531.

Zwier, D., M. Damman, and S. G. Van Den Heuvel (2020). "Explaining differences in retirement timing preferences between the solo self-employed and employees". In: *International Journal of Manpower*.