



Doctoral Thesis

Health at the Crossroads of Generations: Exploring the Economic Impact of Family Health

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Abstract

Title: Health at the Crossroads of Generations: Exploring the Economic Impact of Family Health

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This thesis analyses the relationship between health and socioeconomic outcomes across generations. It contains three applied microeconomic studies that each use large, nationally representative datasets (from Pakistan, the Republic of Ireland, and England) and several econometric approaches. Chapter 1 presents the introduction. Chapter 5 concludes the thesis by summarising key findings, discussing limitations, and offering policy recommendations.

Chapter 2 investigates the effects of a caesarean birth on symptoms of acute respiratory illness (ARI) and diarrhoea in Pakistani children, using Pakistan Demographic and Health Survey (DHS) data. Mother-fixed effects control for environmental and genetic factors. Heterogeneity by child gender is studied, as female children are more resilient to infections. Additionally, an Instrumental variable approach is employed using the mode of delivery of the older sibling of the study child as an instrumental variable (IV) for the study child's mode of delivery. Results show that caesarean section, particularly planned caesarean, increases diarrhoea risk, especially for male children, but has no effect on the risk of respiratory illness.

Chapter 3 examines the effect of childhood illness on parental employment, using the Growing Up in Ireland study. A longstanding child health condition reduces single mothers' likelihood of working by nearly five percentage points. However, conditional on employment, maternal work hours remain unchanged. In contrast, fathers of children with health conditions are more likely to work but work fewer hours if employed.

Chapter 4 presents evidence on the impact of parental health on GCSE attainment, using the Millennium Cohort Study (MCS) data. While no direct effect is found on

educational outcomes, poor parental health increases the risk of adolescent emotional and behavioural problems, as well as school absences, between the ages of 14 and 16.

Findings from this thesis can inform targeted investments to reduce health and socioeconomic inequalities by identifying populations most vulnerable to the consequences of poor health.

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Author's Declaration

I, Rubab Ahmed, declare that the work presented in this thesis titled “**Health at the Crossroads of Generations: Exploring the Economic Impact of Family Health**” is original and my own to the best of my knowledge and belief. The material has not been submitted in any other form for the award of a higher degree at this or any other university.

The thesis does not exceed the maximum permitted word length of 80,000 words including appendices, footnotes and the bibliography.

Chapter 2, titled “Child health and parental labour supply: Evidence from the Growing Up in Ireland (GUI) cohort study”, is a collaborative work by Vincent O’Sullivan, Kevin Denny, and myself. A signed declaration of joint authorship is available in Appendix B.

Rubab Ahmed

Notes

This PhD has been funded by the Economic and Social Research Council’s North West Social Sciences Doctoral Training Partnership (ESRC NWSSDTP) and the Department of Economics at Lancaster University.

Each chapter of this thesis includes its own literature review. This thesis employs multiple econometric methods, which are explained within each chapter. The references for all chapters are compiled and listed at the end of this thesis.

Chapters presented at conferences and seminars

I have presented chapters of this thesis at several conferences and seminars. I presented Chapter 2, titled "Chapter 2: The Relationship Between the Mode of Delivery and Childhood Illness: Evidence from the Demographic Health Survey (DHS) Pakistan", at the NWSSDTP PhD conference 2024. This chapter was also presented at the 2024 Liverpool Mock Job Market Talks. Lastly, I presented this chapter at the PhD EVS seminar series. It has received helpful comments from members of the Economics department at the University of Liverpool. It has received valuable suggestions from Dr Zubaria Andlib, Dr Saurabh Singhal and Prof Ian Walker.

Chapter 3 titled “Child Health and Parental Labour Supply: Evidence from the Growing Up in Ireland (GUI) Cohort Study” has been presented at: The PhD seminar series at Lancaster University (2021), the NWSSDTP PhD conference (2022), the European Health Economics Association (EUHEA) PhD conference (2022), The Centre for Health Economics UCL Brown Bag Seminar series (2023), and the Scottish Economics Society (SES) Conference (2025). It has received suggestions from Marco Alfano.

Data availability

Chapter 2 uses data from the Pakistan Demographic Health Surveys (PDHS), available from the DHS program website (<https://dhsprogram.com/data/available-datasets.cfm>). This study is managed by the United States Agency for International

Development (USAID), ICF International, the Pakistan Bureau of Statistics (PBS), and the National Institute of Population Studies (NIPS)

Chapter 3 uses the Growing Up in Ireland Infant Cohort Study dataset. This was accessed by sending an application to the Irish Social Science Data Archive (www.ucd.ie/issda). This study is managed by the Department of Children and Youth Affairs, the Department of Social Protection, the Central Statistics Office (CSO) and Trinity College Dublin.

Chapter 4 uses Secure Access data awarded by the UK Data Service, with project number 242505, and accessed through Secure Lab — a secure virtual private network in a safe environment approved by the UK Data Service. To have access to this data, I successfully completed a Safe Researcher Training course and gained Accredited Researcher Status. The full data citation is: University College London, UCL Institute of Education, Centre for Longitudinal Studies, Department of Education. (2024). Millennium Cohort Study: Linked Education Administrative Datasets (National Pupil Database), England: Secure Access. [data collection]. 3rd Edition. UK Data Service. SN: 8481, DOI:<http://doi.org/10.5255/UKDA-SN-8481-3>.

The results shown in Chapter 4 have been subjected to Statistical Disclosure Control (SDC) check and approved for disclosure by trained staff. The datasets used may not exactly reproduce National Statistics aggregates.

The use of these data does not imply the endorsement of the data owner in relation to the interpretation or analysis of the data.

Chapter 1: Introduction

Health, traditionally viewed as the domain of medicine, is now widely acknowledged as a form of human capital (Grossman, 1972; Wagstaff, 1986). Economic theory (e.g. the Ben-Porath model) and evidence show that human capital investments, including in health, should be made from the very beginning of life and can help shape educational attainment, economic productivity, and intergenerational mobility (Ben-Porath, 1967; Kalemli-Ozcan, Ryder and Weil, 2000; Behrman et al., 2009; Lucas, 2010). An increasing body of evidence in economics highlights the critical importance of early childhood, in particular, as a sensitive period for the formation of skills, capabilities, and health trajectories that persist throughout the life course (Heckman, 2006; Doyle et al., 2009; Currie and Almond, 2011; Heckman and Mosso, 2014). Additionally, there is a vast body of evidence on the role of income and socioeconomic factors in the formation of health and health inequalities for individuals (Wilkinson and Marmot, 2003), and their children (Case and Paxson, 2006; Currie, Shields and Price, 2007; Doyle, Harmon and Walker, 2007).

“A prime way of giving children a good start in life is to help their parents. ”

– (Marmot, 2005)

In this context, the family unit stands out as a key environment where health and economic outcomes intersect. Parents and children are connected not only biologically, but also behaviourally and economically. Therefore, while parental outcomes, health and behaviours influence children's outcomes, children's health challenges can also have repercussions for parental economic behaviour, through additional caregiving needs and financial pressures (Becker, 1965; Beagan et al., 2008). The primary focus of this thesis is to contribute to the literature on the determinants of socioeconomic and health outcomes by recognising that individuals are affected by the caregiving responsibilities and health decisions of their parents and children. These intra-household dynamics carry significant implications for public policy, particularly in designing health, education, and social

interventions to compensate for the risks and disadvantages individuals face due to their family life.

It is arguably more important now than ever to investigate the causes and consequences of health problems. Rates of chronic illnesses and health conditions, among both children and adults, are rising globally (Ward and Goldie, 2024; Chen et al., 2025), resulting in new and growing pressures on public health systems and labour markets (Barnett et al., 2012; Cribb, Waters and Karjalainen, 2022; Office for National Statistics, 2023). An increasing number of families face difficult decisions in balancing their work or education with caregiving responsibilities (Kossek and Lee, 2017; Cattaneo et al., 2025). Alongside this, income and health inequalities, including inequalities in access to and use of healthcare, are also growing on the national and global level (Barber et al., 2017; Marmot et al., 2020; Chancel et al., 2022). It is imperative to investigate the factors that contribute to socioeconomic and health inequalities beyond one's own health. If health outcomes constrain educational attainment or labour supply within families, their socioeconomic effects may contribute to significant inequalities across generations. Understanding the causes and consequences of health at key stages of childhood development can help direct health investments and interventions to specific groups and people where it can have the most significant economic impact.

The unifying theme across all three chapters is a focus on health as both a consequence and a driver of socioeconomic inequality. Using applied microeconomics, this thesis empirically investigates the relationship between health and socioeconomic outcomes of parents and children at three crucial stages of childhood. Each chapter of this thesis investigates a distinct phase of childhood, beginning with the impact of the decision of birth delivery method on childhood illness, moving to the economic consequences of childhood health conditions or illness, and concluding with the educational impacts of parental health in adolescence. By analysing these three pathways, this thesis demonstrates that preventable illness and intergenerational health shocks are key drivers of unequal life chances. Using nationally representative survey data from Pakistan, the Republic of

Ireland, and the UK, this thesis employs multiple econometric techniques attempting to support causal inference, since causality is central to economic research (Hoover, 2006; Heckman, 2008). From a methodological perspective, the thesis makes use of fixed effects models, Instrumental Variable (IV) model, selection bias correction techniques, and rich longitudinal survey data to improve causal identification. Collectively, these chapters contribute new evidence from high-income and low-income countries on how health shapes critical life outcomes within the family unit.

The chapters in this thesis make the following contributions:

(1) To estimate the role of rising caesarean section rates on the incidence of childhood illness. This research highlights policy recommendations that support Sustainable Development Goal (SDG) 3.2, to reduce preventable childhood deaths globally. By utilising detailed information on birth history and demographic characteristics of mothers from the Pakistani Demographic Health Survey (PDHS), the chapter employs mother fixed effects and Instrumental Variable (IV) regression to establish causality. This research contributes to the understanding of health inequalities resulting from differences in the health and healthcare utilisation of mothers.

(2) To estimate the effects of longstanding childhood health conditions/illnesses on parental economic behaviours, contributing to research on the barriers that mothers face in entering the workforce. The Heckman selection model is used to correct for selection bias in mothers who are employed and use the Growing Up in Ireland (GUI) infant cohort dataset.

(3) To contribute to the literature on the intergenerational effects of poor parental health, focusing on the educational, emotional, and behavioural outcomes of teenagers in England using data from the Millennium Cohort Study (MCS) and National Pupil Database (NPD). If differences in parental health

lead to different outcomes in adolescence, this means that education is not a level playing field and more support is needed for affected children.

Specifically, chapter 2 examines the impact of the mode of delivery at birth on the incidence of illness in childhood. Using survey data on Pakistani mothers and children, this chapter evaluates whether caesarean section delivery, often performed unnecessarily in developing countries, is associated with a higher risk of preventable illness in early childhood. While caesarean section can be a lifesaving procedure when necessary, the rising rates of caesarean delivery are not solely accounted for by changes in the demographic health characteristics and clinical needs for such procedures (Betran et al., 2021). Non-medical factors contributing to the caesarean rates include maternal demand to avoid the pain of childbirth, and physician supply of it for their convenience or financial gain (Kozhimannil, Law and Virnig, 2013). In fact, at the population level, caesarean section rates exceeding 10% are not linked to reductions in maternal and newborn mortality rates (Victora and Barros, 2006; Hyde and Modi, 2012), and further research is needed to understand the costs of unnecessary caesareans. Using mother fixed effects and an instrumental variable approach based on the delivery mode of older siblings, the analysis shows that caesarean births, particularly planned ones, are associated with increased rates of diarrhoea, a major cause of childhood morbidity and mortality in this context. These findings suggest that health behaviours and maternal decision-making shape early morbidity and highlight them as a source of health inequality rooted in parental medical decision-making as early as birth. Targeted interventions can help support mothers and health practitioners to improve maternal care coordination and patient education in order to reduce preventable childhood illnesses.

Chapter 3 moves from child health outcomes to their effects on household economic behaviour. Specifically, it investigates how having a child with a longstanding illness affects parental labour supply in Ireland, using panel data from the Growing Up in Ireland (GUI) study. Poor child health can create additional caregiving responsibilities that may reduce

parental labour market participation, particularly for mothers. On the other hand, these conditions can increase a parent's incentive to work for additional income if the child requires costly care. Understanding these trade-offs is crucial for designing work-family policies and targeted supports for households with children experiencing health challenges. While prior literature has primarily explored this trade-off in US contexts, this chapter offers new evidence from Ireland, a country with relatively generous welfare support but higher costs of childcare and medical care compared to other European countries. Panel data models are estimated using four waves of the GUI data to control for possible unobserved heterogeneity and to estimate models that account for truncation of hours worked. The results show that having a child with a long-term condition reduces single mothers' likelihood of employment by approximately five percentage points. Conversely, fathers are slightly more likely to work, possibly due to increased financial need. These findings suggest a gendered division of caregiving responsibilities and support the need for targeted health and employment policies that acknowledge caregiving demands as an economic issue and a labour market barrier for mothers.

Chapter 4 investigates the intergenerational effects of poor parental health, focusing on its impact on educational attainment during adolescence. Parents who suffer from poor health may be more likely to miss school events, teacher meetings, and limit their involvement in their children's education, financially and emotionally. Additionally, children of parents with health issues may experience anxiety, stress, and caregiving burden, thus affecting their academic performance. This chapter focuses on GCSE performance, a key educational milestone in the UK context. Using data from the Millennium Cohort Study in the UK, this study explores whether exposure to poor parental health in early or mid-childhood influences GCSE outcomes, a key measure of educational attainment at the end of secondary school. Using school fixed effects to control for unobserved heterogeneity, no significant impact on academic attainment is found. However, further analysis shows that poor parental health adversely impacts child emotional and behavioural problems (EBPs) outcomes, and absences in school at ages 14-

16. This chapter should provide insight into how policymakers should invest in parents with poor health and young carers to ensure that education is a level playing field.

In summary, these chapters offer a comprehensive view of how child and parental health can drive socioeconomic outcomes across the life course, reinforcing or alleviating existing inequalities.

By highlighting the risk factors affecting child and parental outcomes across these areas, this thesis emphasises the importance of targeted health investments to create a fairer society and to develop work and education policies that address additional barriers caused by health.

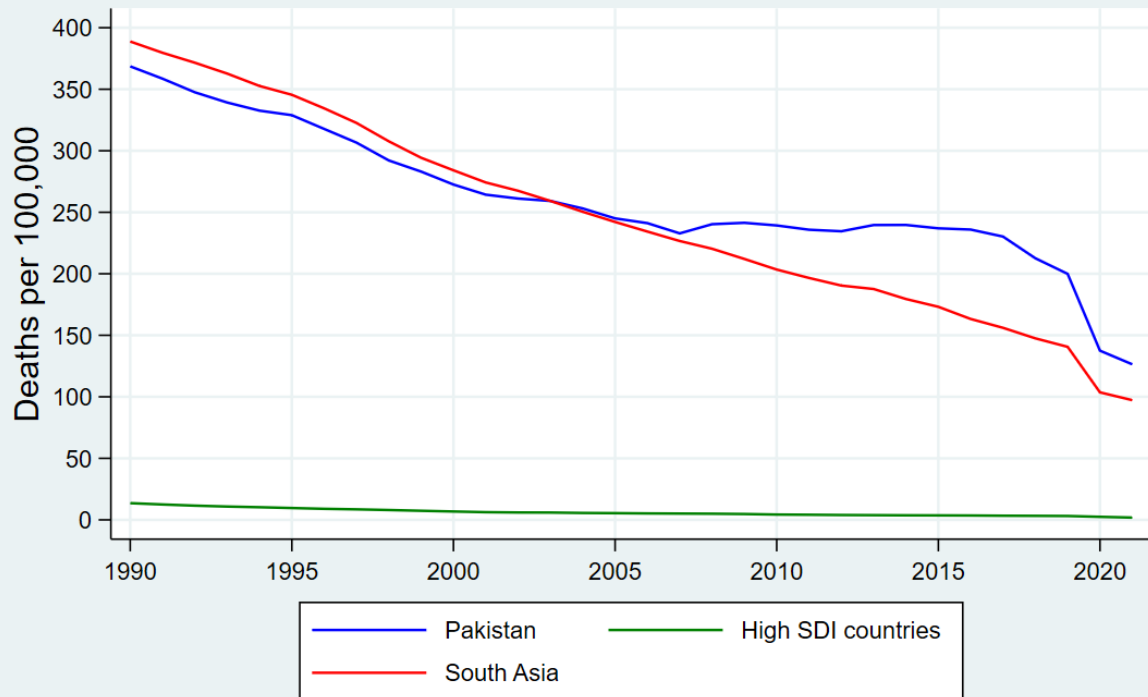
Chapter 2: The Relationship Between the Mode of Delivery and Childhood Illness: Evidence from the Demographic Health Survey (DHS) Pakistan

2.1 Introduction

Acute respiratory infections (ARIs) and diarrheal diseases significantly contribute to global childhood morbidity and mortality. ARIs, including both upper and lower respiratory tract infections, account for one-third of deaths among children under five in lower-income countries. South Asia alone has the highest number of deaths from preventable respiratory infections than any other part of the world (UNICEF, 2021). ARIs such as the common cold, influenza, pneumonia, asthma, and bronchitis are characterised by coughing, a tight feeling in the chest, shortness of breath, and fever (Alam and Bastakoti, 2015). Diarrhoea is also a leading cause of death among children, accounting for about 1 in 12 of all deaths in children under five worldwide. An estimated one-third of these deaths occur in South Asia (UN IGME, 2019).

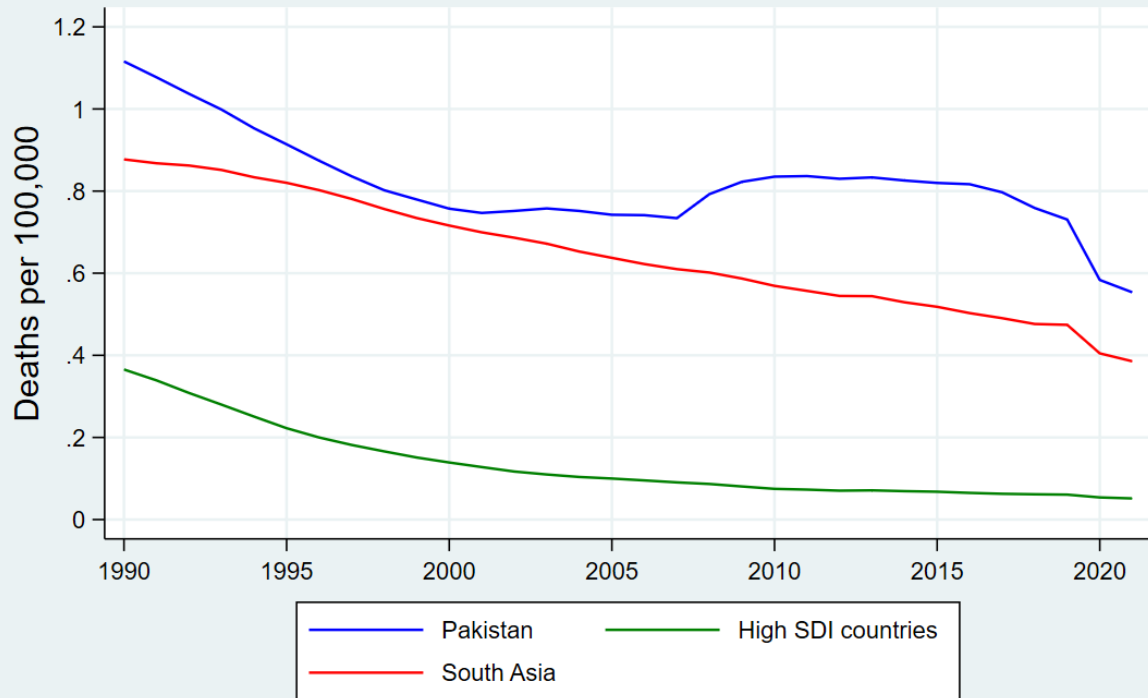
Understanding the factors that contribute to the development of these illnesses in children, including the method of delivery at birth, supports the World Health Organisation's Sustainable Development Goal (SDG) 3.2; to reduce mortality in children under five to 25 deaths per 1,000 live births through ending preventable deaths by 2030 (World Health Organisation, 2022). Diarrhoea and respiratory illnesses are recognised as two of the four key child survival issues that have stalled progress towards achieving this goal. Figures 2.1, 2.2, and 2.3 show the burden of these illnesses in Pakistan in terms of the death rates for children under five. As shown, Pakistan has a higher burden than similar South Asian countries (Global Burden of Disease Collaborative Network, 2021).

Figure 2.1: Deaths per 100,000 from Lower Respiratory Infections
Children under five

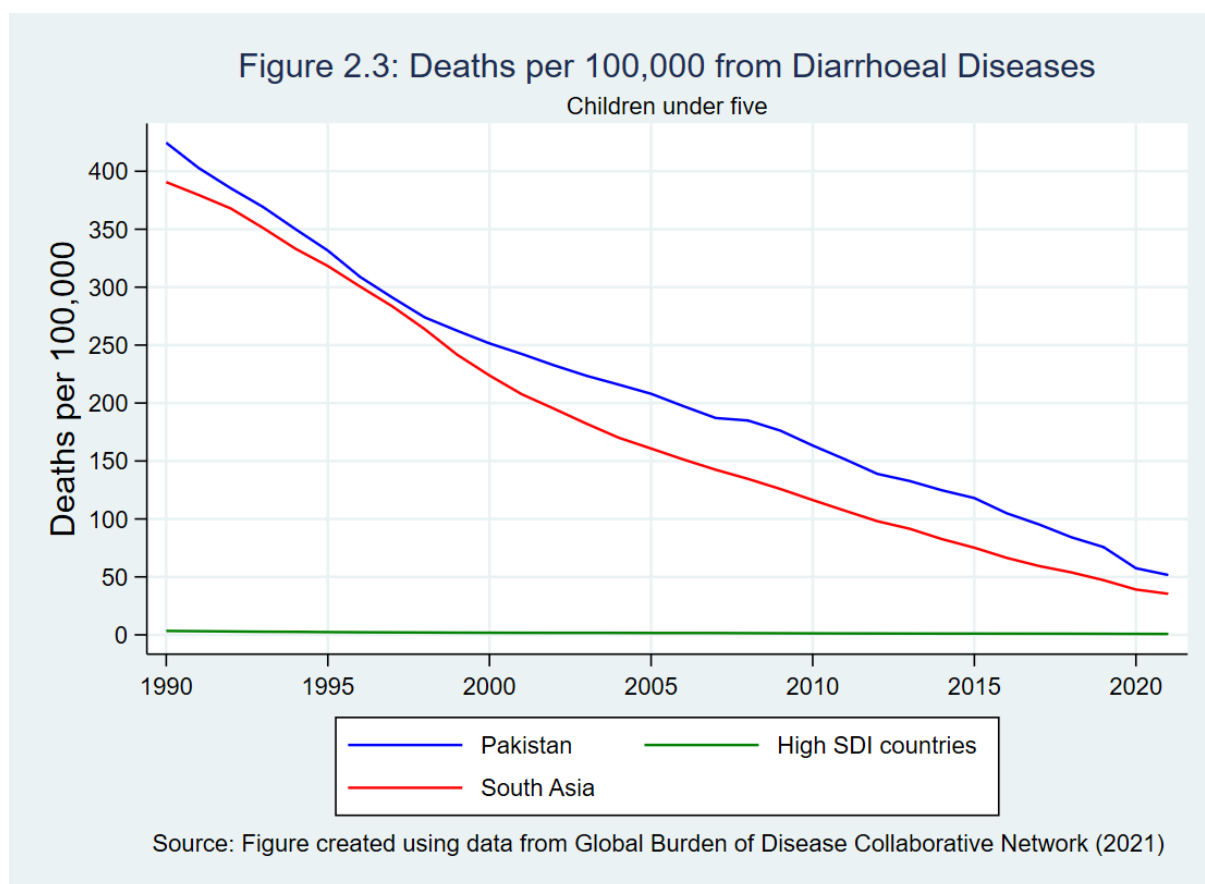


Source: Figure created using data from Global Burden of Disease Collaborative Network (2021)

Figure 2.2: Deaths per 100,000 from Upper Respiratory Infections
Children under five



Source: Figure created using data from Global Burden of Disease Collaborative Network (2021)



Pakistan is an important country to study for this issue because of its high population and high infant and child mortality rates, including a high proportion of child deaths due to acute respiratory infections and intestinal infections each year. In Pakistan, an estimated 20 to 30% of all deaths of children under five are due to respiratory infections (Khan, 2022), while diarrheal diseases are responsible for 16% of all child deaths (Rahmat et al., 2023). As childhood illness affects many children in Pakistan, it also poses a high economic burden for families (Hussain et al., 2008). Household expenditures such as medicines, health visits, hospitalisation, and transportation, as well as productivity losses, can result in financial challenges, particularly for low-income families (Rheingans et al., 2012). A better understanding of the factors contributing to the burden of disease is relevant for other low- and middle-income countries similar to Pakistan in South Asia that have also faced challenges in tackling childhood mortality and morbidity. These countries also face additional challenges due to high levels of pollution, climate change, and limited access to appropriate healthcare and vaccinations.

This chapter estimates the extent to which caesarean section delivery is a contributing factor to the incidence of childhood illness in Pakistan, since the use of caesarean section delivery has increased in Pakistan in recent years. While this mode of delivery can be a lifesaving procedure when necessary, there may be externalities, such as an increased risk of childhood illness. The medical literature discusses how forgoing a natural delivery means that pressure is not placed on the baby’s chest to support expelling lung fluid and mucus and promote healthy lung development (Jain and Eaton, 2006). Additionally, a caesarean delivery alters the gut microbiome of the baby due to a lack of exposure to vaginal and faecal microbiota and increases the risk of respiratory issues (Ríos-Covian, Langella and Martín, 2021). Caesarean section can also increase the risk of having diarrhoea through this same mechanism (Neu and Rushing, 2011). The composition of an infant’s gut microbiome during the first critical months of life is believed to have a lasting influence on the child’s immunity and health trajectories (Azad et al., 2016; Isacco et al., 2019). The aim of this chapter is to contribute to the evidence available on the consequences of caesarean section on health in early childhood. This study assesses the contribution of caesarean section to the risk of ARI and diarrhoea in Pakistani children. Cost-effective interventions and educational programmes that can decrease unnecessary caesarean section deliveries may be effective in reducing the incidence of ARIs and diarrhoea, along with their economic costs.

This chapter utilises data from the Demographic Health Survey (DHS) Pakistan. We aim to estimate the effect of the mode of delivery using Ordinary Least Squares (OLS) estimation and a mother-level Fixed Effects (FE) model to study the effects within families. We explore the causal impact of being born by caesarean section on respiratory health and diarrhoea in early childhood by exploiting information on the birth delivery method of the older sibling of the study child. To do so, an Instrumental Variable (IV) approach is employed using the rich data on families from the Pakistani Demographic and Health Surveys (DHS).

The focus of this chapter is to estimate the effect of caesarean delivery on childhood illness using survey data on children under the age of 5. However, in our dataset, we do not observe the health outcomes of the 6.44% of children who are not alive at the time of the survey (passed away under the age of 5). Although our results in Section 2.6 do not find any evidence of survivorship bias, all of our results on the effect of caesarean should be interpreted as conditional on survival. Specifically, our estimates may have a downward bias because the children most at risk did not survive.

Section 2.1.1 discusses the rise of caesarean sections globally and in Pakistan and the importance of understanding the costs and benefits of this procedure. Section 2.2 discusses the existing evidence in this research area. Section 2.3 outlines the dataset used for analysis, and Section 2.4 details the empirical approach used in this chapter. Section 2.5 contains all the results from our main analysis. Section 2.6 includes any additional analysis, including robustness checks, and Section 2.7 discusses the results presented. Section 2.8 is the conclusion for this chapter.

2.1.1 Caesarean section in Pakistan

Caesarean section rates have been increasing in Pakistan in recent years. Based on the DHS data, the percentages of mothers who had at least one delivery by caesarean in the 5 years prior to each survey increased from 3.2% in 1990–91 to 22% in 2017–18 (Amjad et al., 2020). This follows a similar trend globally; the latest available data shows that approximately 21% of women give birth by caesarean section worldwide, and this is projected to increase to 28.5% by 2030 (Betran et al., 2021).

The rise in the caesarean rate can partially be attributed to several medical factors, including a higher rate of conditions that may require caesarean delivery, such as multiple gestation, maternal obesity, preterm labour, gestational diabetes, or hypertension (Sandall et al., 2018). In such cases, the use of a caesarean section can be a lifesaving procedure for the mother and child. However, evidence from the literature in health economics on small-area variation in caesarean sections finds that changes in the health distribution of pregnant women and fetuses cannot solely explain the growing trend in its usage (e.g., see

Kozhimannil, Law and Virnig, 2013). Medical factors do not fully account for the wide differences in caesarean rates observed across states and countries, and therefore may not account for the large increase in caesarean section rates recently in developing countries (e.g. see Betrán et al., 2007). Kozhimannil, Law and Virnig (2013) aim to provide evidence of the extent of variation in caesarean section rates and its causes. Using data from counties across the US, this chapter finds that caesarean section rates varied vastly across hospitals, ranging from 7.1 to 69.9 per cent. Even for women with lower-risk pregnancies, in which more limited variation might be expected due to similar clinical characteristics, caesarean rates varied fifteenfold, from 2.4 per cent to 36.5 per cent. This chapter also finds that differences in patient clinical characteristics, choices, hospital capacity, and degree of obstetric and neonatal care specialisation alone cannot explain the rising rates of caesarean sections. Therefore, non-medical determinants, such as the vast differences in medical practice patterns, are likely to be driving the costly overuse of caesarean delivery in many hospitals. Furthermore, directions for reducing these variations are noted in this study, including better coordination of maternity care, collecting and measuring more data, and enhancing patient-centred decision-making through public reporting.

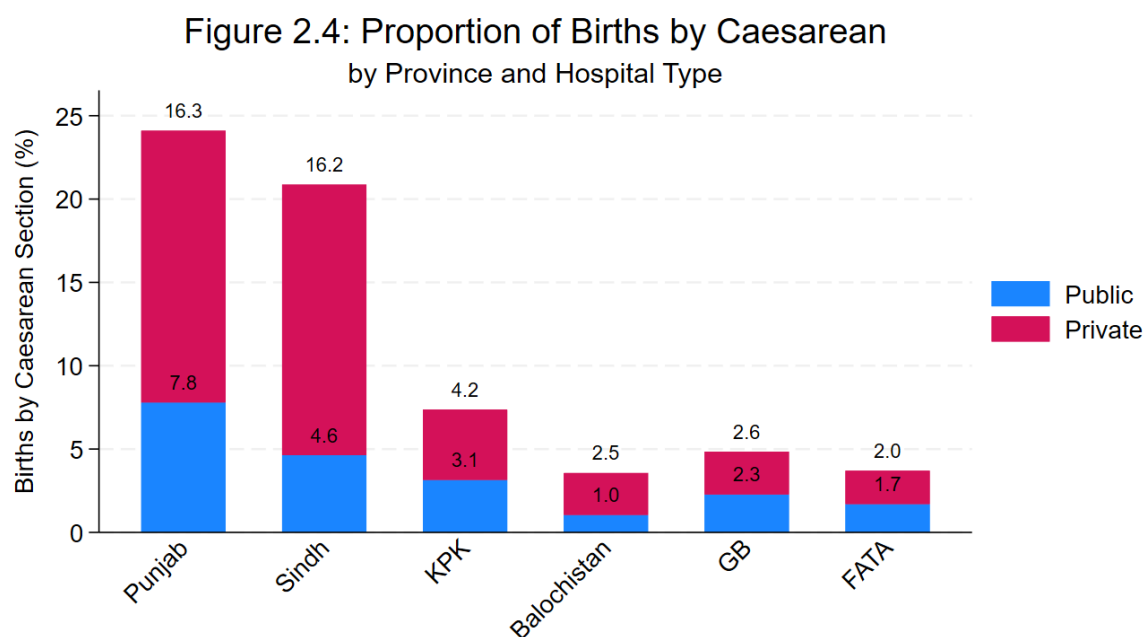
Similarly, Betrán et al. (2007) attempts to provide a global and regional comparative analysis of the rates of caesarean delivery and their correlation with other indicators of reproductive health using non-parametric regression techniques. This study finds that the rate of caesarean section births worldwide is very unevenly distributed, with a global average of 15%. For example, Latin America and the Caribbean have the highest rate (29.2%), while Africa has the lowest (3.5%). The chapter emphasises the importance of considering cultural, economic, and healthcare system factors beyond medical aspects that influence caesarean rates globally. This ‘small area variation’, as it is known in health economics literature, leads to different interventions and health outcomes for clinically similar mothers and babies. Differences in practices concerning caesarean section due to non-medical reasons can lead to health inequalities across hospitals, counties, and even countries.

Literature in medicine and economics also includes further discourse on the non-medical factors affecting the use of caesarean delivery. For one, there are supply-side factors that mean care providers may favour a caesarean delivery. Private hospitals, especially, have financial incentives to recommend caesareans due to the higher price of caesareans compared to natural (vaginal) delivery. (Gruber, Kim and Mayzlin, 1999; Grant, 2009). Another supply-side factor is the physicians' demand for leisure, given that the caesarean procedure takes less time compared to natural deliveries and can also be more time-predictable as well (Gans, Leigh and Varganova, 2007; Costa-Ramón et al., 2018). On the demand side, mothers may have preferences for elective caesarean due to fear of pain, complications, or distress to the fetus during natural labour (Dursun et al., 2011).

The evidence presented in Betrán et al. (2007) also supports that when caesarean rates rise above 15%, risks to reproductive health outcomes may begin to outweigh the benefits. Furthermore, according to data from the “United Kingdom Confidential Enquiry into Maternal Deaths”, an elective caesarean with no emergency presents a 2.84 times greater chance of maternal death than a natural birth, suggesting that, when population caesarean rates rise beyond medically necessary levels, risks may outweigh benefits (Knight and Tuffnell, 2018). This means that high caesarean rates may be an indicator of excess maternal mortality in some countries. Additionally, according to a World Health Organisation (2015) report, caesarean section rates higher than 10% were not associated with reductions in maternal and newborn mortality rates (Victora and Barros, 2006; Steer and Modi, 2009). This report also emphasises that further research and data is needed to understand the short and long-term risks of population caesarean section rates over 20%, especially when there are issues surrounding the lack of facilities or capacity to conduct the procedure safely or treat surgical complications properly, or where access to aftercare or repeat caesarean surgery in subsequent pregnancies cannot be guaranteed.

The existing evidence suggests that there may be an overuse of caesarean section, and more research is needed to understand the adverse effects of this type of delivery and evaluate whether the potential costs may outweigh the benefits. For a developing

country like Pakistan, if there is an overuse of caesarean section delivery, it is an inappropriate allocation of scarce healthcare resources, and efforts should be made to regulate the use of caesarean sections to specific cases where it is medically necessary. Information asymmetry when it comes to the decision of having a caesarean section is a concern; mothers may not be fully informed of the health risks associated with this type of birth, especially in rural areas or where the mother is uneducated. Additionally, there is no nationalised healthcare system or explicit “pro-choice” caesarean section policy in Pakistan, which may lead to supplier-induced demands in hospitals where it is more profitable to perform a caesarean section. We observe from our data that the caesarean section rate in private hospitals (30%) and the wealthier province of Punjab (24%) is much higher than the national average (15%) (see Figure 2.4). In summary, non-medical factors such as regional healthcare practices, hospital-level policies, and patient preferences contribute to the observed differences in the use of caesarean delivery across provinces and countries, and there needs to be a better understanding of its health consequences for policymakers to help mothers make a decision that will be the best choice for their own and their child’s health.



Source: DHS Pakistan 2012/13 & 2017/18

2.2 Literature Review

The impact of caesarean section on the health outcomes of children has been an area of interest in both medical and health economics research. While caesarean sections can be necessary for various medical reasons, there is growing concern about potential short and long-term health implications for children born via this method. Existing meta-analyses of cohort and case-control studies point to a positive association between caesarean section delivery and the risk of atopic diseases (Liu et al., 2024), obesity (Li, Zhou and Liu, 2013; Chiavarini et al., 2023) and type 1 diabetes (Cardwell et al., 2008; Tanoey et al., 2019). There are also studies indicating a well-established link between caesarean delivery and asthma in children (Håkansson and Källén, 2003; Salam et al., 2006; Tollånes et al., 2008; Roduit et al., 2009; Costa-Ramón et al., 2022; Keshet et al., 2022), particularly for female children (Zhong et al., 2023). However, when examining studies concerning Asian populations, there is no conclusive evidence of a higher incidence of asthma in children born by caesarean compared to children born naturally (Waqar, Shatha and Dawood, 2005; Park et al., 2010; Chen et al., 2017; Lavin, Franklin and Preen, 2017).

Table 2.1 presents the existing evidence on studies that examine the relationship between caesarean delivery and respiratory or diarrhoeal illness or infection in children. These studies mostly point to a well-established correlation between caesarean delivery and respiratory health (Moore et al., 2012; Kristensen and Henriksen, 2016; Auger et al., 2021). Studies conducted in Denmark (Kristensen and Henriksen, 2016), Eastern Canada (Auger et al., 2021), and Western Australia (Moore et al., 2012) examined infant and child hospital admissions for respiratory infections. These studies found that elective caesarean births were associated with an increased risk of admission ranging from 11% to 29%, while no heightened risk was observed for emergency caesarean deliveries. Similarly, Alterman et al. (2022) examined hospital admissions for Lower and Upper Respiratory Tract Infections (LRTIs and URTIs) during early childhood in a British cohort; they found that planned caesarean was associated with an increased risk of severe LRTIs and all caesareans were associated with a small increase in risk of URTIs. Using a logistic regression model, Menezes

et al. (2011), however, do not find evidence of an increased probability of long-term respiratory conditions in Brazilian children born by caesarean section.

Table 2. 1 Existing evidence on the relationship between caesarean birth and child health			
Paper	Data (Country)	Methods	Results
Laubereau et al. (2004)	German Infant Nutritional Intervention Programme	Multiple logistic regression analyses	17% greater risk of diarrhoea in infants (OR adj 1.46)
(Menezes et al., 2011)	International Study of Allergy & Asthma Questionnaire (Brazil)	Logistic Regression model	No evidence of association between mode of delivery and the risk of wheezing in children under 14
Moore et al., 2012	Western Australian Data Linkage System	Negative binomial regression	Elective CS increases risk of bronchiolitis/pneumonia admissions (11–29%) in children under 2; no effect from emergency CS.
(Jensen and Wüst, 2015)	Danish Administrative Registers	Fuzzy Regression Discontinuity design: Term Breech Trial as information shock	Medically necessary CS reduce doctor visits in first year of life but no significant effect on child hospitalisation until age 3
Kristensen and Henriksen, 2016	Danish National Birth Registry and the Danish National Patient Registry	Cox regression	Elective CS raises LRTI risk (HR 1.20); emergency CS has no effect in children under 14
Gondwe et al., 2020	2015–2016 India National Family Health Survey	Multivariable logistic regression	CS not associated with diarrhoea and ARI in infants under six months.
(Alterman et al., 2022)	UK MCS & linked Welsh Administrative data	Cox regression	Emergency and Planned CS increased risk of URTI (HR 1.1). Planned CS increased risk of LRTI (HR 1.39)
Costa-Ramón et al., 2022	Finnish Medical Birth Register & the Hospital Discharge Register	Day of birth as an instrument & DiD within siblings to identify CS effects	Unplanned CS increases probability of an asthma diagnosis by 1.3 to 2% for children ages 5–10
(Card, Fenizia and Silver, 2023)	Linked Cohort Data: California Office of Statewide Health Planning and Development	IV analysis: mother's distance to hospitals with high CS rate as an instrument	CS children under one more likely to visit ER for respiratory problems
(Rogvi et al., 2025)	Danish, Norwegian & Swedish Medical Birth Register (1997–2003)	Fuzzy Regression Discontinuity design: Term Breech Trial as information shock	No significant CS effect on asthma, allergies, or type 1 diabetes for breech children ages 1–12

*Notes: OR- odds ratio, CS- caesarean section, ER- emergency room, HR- hazard ratios, URTI and LRTI- upper and lower respiratory tract infections, DiD- difference-in-differences

While medical literature suggests that a caesarean section can disturb the intestinal bacteria of children for up to seven years after birth (Inchingolo et al., 2024), few studies attempt to estimate the effect this has on the likelihood of developing intestinal illnesses such as diarrhoea during childhood. The existing evidence on the effects of caesarean on intestinal illnesses is mixed. Some evidence indicates that children born via caesarean section are more likely to require hospitalisation for gastroenteritis (Laubereau et al., 2004; Auger et al., 2021) but not coeliac disease (Yang et al., 2022). Additionally, emergency caesarean sections were found to be associated with an increased risk of Crohn’s disease and ulcerative colitis, based on data from developed countries (Bager et al., 2012; Kristensen and Henriksen, 2016). Laubereau et al. (2004) report that caesarean birth was associated with a 46% increased risk of diarrhoea in German children. However, this study only included children under the age of one who had a parental history of allergy. In a study using Indian national data, Gondwe et al. (2020) find that caesarean delivery was not associated with concomitant diarrhoea or symptoms of ARI in infants, after controlling for key socioeconomic, healthcare, and maternal factors.

Overall, evidence on the effect of caesarean delivery on children's respiratory and intestinal health mainly focuses on developed countries. The lack of available data makes this relationship challenging to study; conducting randomised controlled trials is also not appropriate due to ethical constraints. Another challenge is addressing omitted variable bias due to the existence of risk factors that are not observed in birth certificates and hospital records. These risk factors, such as maternal education and family income, are correlated with both caesarean section and child outcomes. Due to this bias, we cannot interpret the association between mode of delivery and adverse health outcomes in children as a causal relationship based solely on observable factors.

Table 2.1 also outlines the studies that have exploited quasi-experimental variations to investigate the consequences of caesarean on child health outcomes. These studies have also focused on developed countries and yield varying results. Jensen and Wüst (2015) and Rogvi et al. (2025) use a fuzzy regression discontinuity by exploiting obstetricians'

knowledge regarding specific situations, like a breech presentation of the fetus, as an information shock that would lead to a medically justified caesarean. Focusing on high-risk births, the findings from these studies support the notion that caesarean sections are beneficial when there is an obvious medical necessity. Conversely, research examining births with lower risk levels indicates potential adverse health outcomes for infants (Costa-Ramón et al., 2018, 2022). This paper uses Finnish data on external factors such as the time of day of birth (preceding a weekend) to exploit exogenous variation in determining a “non-medical” caesarean. Findings from this study suggest that medically unnecessary caesareans increase the probability of an asthma diagnosis in early childhood, but do not affect the probability of developing atopic diseases, type 1 diabetes and obesity (Costa-Ramón et al., 2022). Likewise, Card, Fenizia and Silver (2023) use the mother’s distance to hospitals with a high caesarean rate as an instrument for a caesarean birth and find evidence that babies born by caesarean section are more likely to develop respiratory problems in the long run. Lastly, Pilvar and Yousefi (2021) also exploit variations in physician-induced demand for caesarean after a policy change in Iran to study the causal effects of caesarean on neonatal health. They do not find any effects on neonatal health, NICU admission, or mortality rate.

While evidence from developed countries offers valuable insights, research conducted in developing countries such as Pakistan is crucial for several reasons. Firstly, findings from developed countries may not be directly applicable to settings with different healthcare systems, environmental factors, and cultural practices. For example, Pakistani children may face additional risk factors such as limited access to clean water, exposure to pollution and extreme weather conditions, as well as limited education surrounding hygiene, nutrition and antenatal health (Asim and Nawaz, 2018; Murtaza et al., 2021; Abbas et al., 2023; Rahmat et al., 2023; Tharwani et al., 2023). As a result, children born via caesarean section in Pakistan may face an increased risk of diarrhoea and ARI compared to children in developed countries, where the risk is more effectively mitigated. This is reflected in our sample, where almost 20% of children had reported recent diarrhoea.

While two studies using Indian national data, Gondwe et al. (2018, 2020), explore this relationship in the context of a developing country and find that caesarean delivery was not associated with concomitant diarrhoea or symptoms of ARI, these papers use multivariate logistic regression and do not attempt to control for unobservable confounding factors that may affect both the probability of having a caesarean delivery and childhood illness. In comparison, this chapter uses methods such as mother-level fixed effects and Instrumental Variables (IV) regression to estimate the causal effect of caesarean section on childhood illness. Furthermore, these papers focus on short-term effects on illness in infant children only.

Therefore, we will contribute to evidence from developing countries to ensure the generalizability and applicability of research findings to these contexts. Secondly, developing countries often face unique challenges such as limited healthcare infrastructure, resource constraints, and higher levels of health inequalities. By investigating the impact of caesarean delivery in this context, we can identify specific risk factors that will inform targeted interventions. Evidence generated from developing countries can support policymaking and healthcare practices in these settings specifically, contributing to the development of effective strategies for improving child health outcomes. Lastly, understanding the impact of caesarean delivery on child health outcomes in Pakistan is not only important for addressing local health challenges but also for contributing to global health and development goals, given the significant contribution of developing countries to the global burden of disease and child mortality. By using a nationally representative survey dataset, this chapter can incorporate factors in this study that may not be available in hospital records, such as the mother's wealth and education, and observe cases of illness where the child has not visited a hospital or received any treatment.

2.3 Data

The Pakistan Demographic and Health Surveys (PDHS) are a series of cross-sectional datasets conducted periodically for the years 1990-1991, 1994-1995, 2006-2007, 2012-2013, and 2017-2018. These surveys are a collaborative effort between the Pakistan

Bureau of Statistics (PBS), the Ministry of National Health Services, Regulations and Coordination, the Institute of Population Studies (NIPS), and international organisations such as the United Nations Population Fund (UNFPA) and the Department for International Development (DFID). The primary objective of this project is to collect comprehensive data on maternal and child health, and family planning practices in Pakistani families nationwide.

The DHS in Pakistan employs rigorous methodologies, including interviews, biomarker collection, and extensive questionnaires, covering a wide range of topics. These surveys involved large-scale sampling across different regions and rural and urban areas, ensuring a representative sample that reflects the diverse demographics of Pakistan. The information collected provides an understanding of health trends, enabling researchers to identify disparities between regions, socioeconomic groups, and genders. The survey of women includes ever-married women aged 15-49 who are permanent residents of the selected households.

This chapter uses pooled child-level cross-sectional data from the 2012/13 survey and the 2017/18 survey, as these two most recent surveys are where we observe a considerable portion of women who have had a caesarean section, with an average of 15%. There were 12,695 women interviewed (who had a child) with a 94% response rate in the 2017/2018 PDHS and 13,558 women in the 2012/2013 PDHS with a 93% response rate. We use the Births' Recode (BR) dataset, which is at the child level, and each observation is every child born to an interviewed woman. This contains the full birth history of all DHS mothers for children born in the last 5 years prior to the survey. It also records data on other maternal and child characteristics including age, employment, and education of the mother, antenatal care, childhood illness, breastfeeding and area of residence. We also have data from a Community Questionnaire, which contains information about basic infrastructure in the woman's community ("cluster") of 20-40 households and access to health works, facilities, and services in that community.

Table 2. 2 Sample Selection from the PDHS	
All children from the 2012/13 survey and 2017/18 survey (born 5 years prior to the survey)	22,235
Selecting children who are alive at the time of the survey (1,435 dead)	20,800
Removing Missing Observations (0.68%)	20,657
Sample used for OLS analysis	20,657
Selecting children with at least one sibling in the survey (Within Families Analysis)	12,624
Selecting Children who have an older sibling in the survey	6,636
Sample used for IV analysis	6,636

From the sample of children born 5 years prior to the 2013 and 2018 surveys, we select our sample for analysis by removing children who were dead at the time of the survey and children who had missing responses to any of the variables used in our study. For our initial analysis, we have a sample of 20,657 children. The sample used for the within-families analysis is 12,624 because we are selecting children who have at least one sibling in the dataset. The sample used for the IV analysis is 6,636 because we are selecting children who have an older sibling in the survey (as the IV is variation in the older sibling being born by caesarean) and excluding the oldest child in each family. Table 2.2 outlines our selection of the sample used for analysis.

The DHS identifies a child experiencing Acute Respiratory Infection (ARI) by the mother's response to questions on the child's symptoms of ARI. The mother was asked whether the child had been ill in the 2 weeks preceding the survey with (1) a fever (2) a cough (3) short, rapid breathing or (4) difficulty in breathing that the mother considered to be chest related (5) difficulty in breathing that the mother considered to be nose related. In our main sample, 44.83% of children under age 5 showed at least one symptom of ARI. Figure 2.5 shows the distribution of children according to the number of symptoms of ARI they reported. The mothers were also asked if the child experienced diarrhoea in the two weeks preceding the survey. In our sample, 19.72% of children experienced diarrhoea recently.

Figure 2.5: Number of ARI symptoms in Children

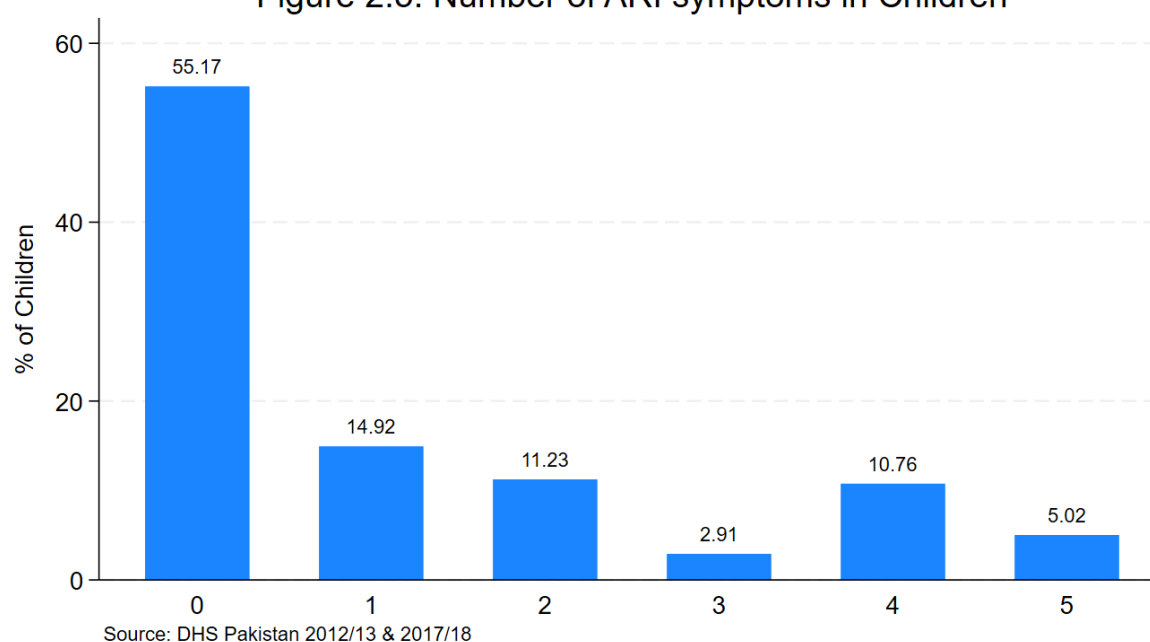
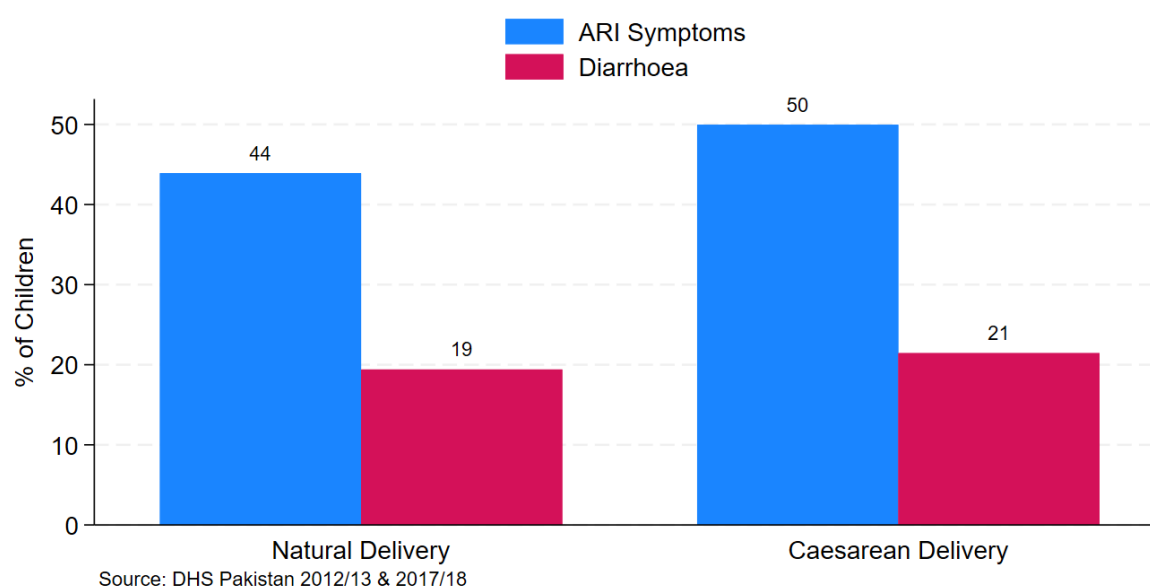


Figure 2.6: Proportion of Children with ARI Symptoms and Diarrhoea by Caesarean Delivery Status



We can identify children who were born by caesarean section in both survey years. In the 2017/2018 survey only, we can also identify if this was a planned or unplanned caesarean section by observing if the decision to have a caesarean section was made before or after the onset of labour pains. For 2017/2018, we observe that 16.76% of the total number of births in the 5 years preceding the survey were delivered by caesarean section and for 12.67% of the total number of births, the decision to deliver by caesarean was made

before the onset of labour pains (an elective or planned surgery). Figure 2.6 shows that children born by caesarean are more likely to have symptoms of ARI (50% and 44%) and slightly more likely to have diarrhoea (21% and 19%).

We also observe that the caesarean delivery rate is higher for births in private facilities (69.7%) than in public facilities (30.2%). Furthermore, Figure 2.7 shows that mothers in urban areas are twice as likely to give birth via caesarean than women in rural areas (21% and 11%). Among mothers with at least a primary level of education, 25% give birth by caesarean, compared to only 7% of births to women with no education. Women in the highest wealth quintile have a higher likelihood of delivering babies via caesarean (34%) compared to those in the lowest quintile (4%). Caesarean deliveries account for less than 5% of births in GB, Baluchistan, and Sindh, compared to 24% and 20.8% in Pakistan's wealthiest provinces, Punjab and Sindh, respectively. (Figure 2.4).

Figure 2.7: Percentage of Caesarean Births

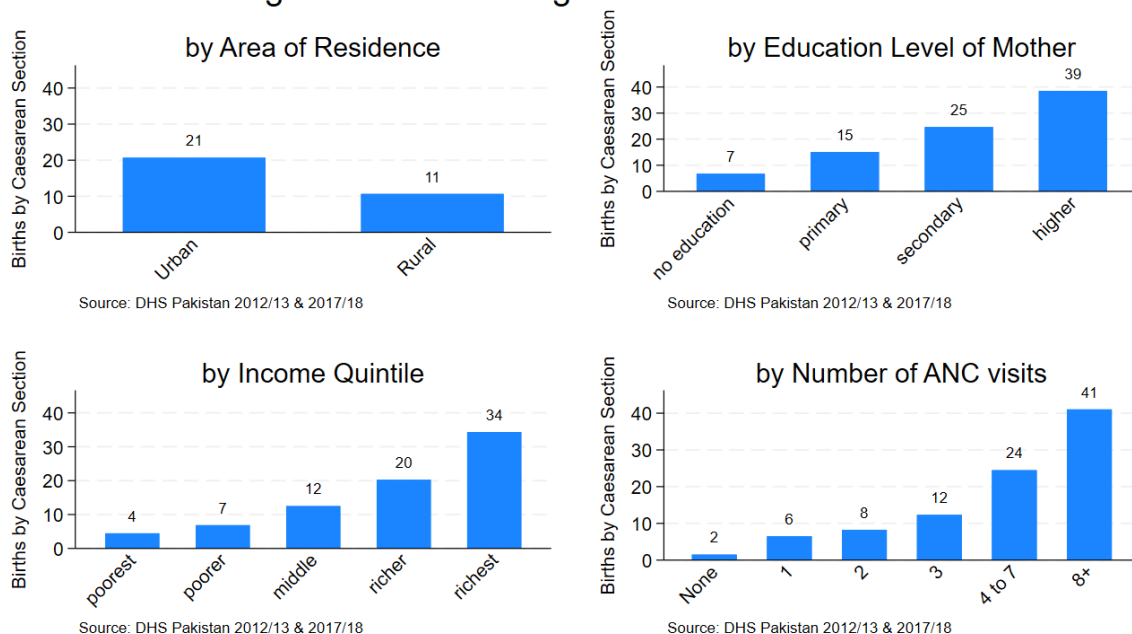


Table 2. 3 Variables used for analysis	
Variable	Description
Caesarean Birth	Binary: Child was delivered by caesarean
Gender of the Child	Binary: Child is female
Birth Order	Categorical: Birth order number of the child
Mother's Age at Birth	Categorical: Mother's age at birth of child
Wealth Quintile	Categorical: poorest, poorer, middle, richer, and richest
Maternal Education	Binary: Mother has at least a primary school level of education
Maternal Employment	Binary: Mother is currently working
Maternal Health Behaviours	Binary: Mother smokes or uses tobacco Numerical: Antenatal Care Visits Binary: whether child was ever breastfed
Province	Categorical: Punjab, Sindh, Khyber Pakhtunkhwa, Baluchistan, Gilgit-Baltistan, FATA
Time variables	Year of the child's birth Year of interview Month of Interview
IV Variable	Binary: Older Sibling was born by Caesarean Delivery

In the models estimated in this chapter, we control for factors potentially correlated with child health outcomes and caesarean section usage. These factors are the age of the child and mother (at the time of birth), gender and birth order of the child, province of residence, mother's education, employment status, income quintile, breastfeeding, and parent health behaviours. Table 2.3 outlines the variables used in this study.

2.3.1 Descriptive Statistics

Table 2.4 shows the descriptive statistics of key variables included in the analysis. In our sample, 15% of children are born by caesarean section. Column (1) shows the mean and standard deviations of the variables in the full sample of all children used for the OLS analysis. Fewer than half of the mothers in our sample have a primary level of education or live in an urban area. The average number of antenatal visits during the pregnancy for the study child is 3.69 (compared to the WHO recommendation of at least eight visits and the NHS England protocol of up to ten visits) (World Health Organization, 2016; National Health Service, 2020). The sample only includes children under five years old, and the average age in the sample is 2.02 years. Only 15% of mothers in our sample are employed. This is not unexpected, given that Pakistan has one of the lowest female employment rates

globally (Amber and Chichaibelu, 2023). These statistics help build a picture to understand the context of the country which is being studied for this chapter.

Table 2. 4 Balance table of covariates by mode of birth of the child

	(1) Full sample	(2) Natural Delivery	(3) CS delivery	(4) Difference (2)-(3)
Age of the Child	2.02 (1.42)	2.06 (1.42)	1.83 (1.41)	0.23***
Female Child	0.49 (0.50)	0.50 (0.50)	0.46 (0.50)	0.03***
Birth Order: 1	0.23 (0.42)	0.21 (0.41)	0.35 (0.48)	-0.14***
2 to 3	0.38 (0.48)	0.36 (0.48)	0.45 (0.50)	-0.09***
4 to 5	0.22 (0.41)	0.23 (0.42)	0.14 (0.35)	0.09***
6+	0.17 (0.38)	0.19 (0.39)	0.06 (0.23)	0.14***
Mother's age at birth: <20	0.10 (0.30)	0.10 (0.30)	0.07 (0.26)	0.03***
20 to 34	0.79 (0.41)	0.78 (0.41)	0.85 (0.36)	-0.07***
35 to 49	0.11 (0.32)	0.12 (0.32)	0.08 (0.27)	0.04***
Mother is employed	0.15 (0.36)	0.16 (0.36)	0.13 (0.34)	0.03***
Wealth Index: Poorest	0.23 (0.42)	0.26 (0.44)	0.07 (0.25)	0.19***
Poorer	0.20 (0.40)	0.22 (0.42)	0.09 (0.29)	0.13***
Middle	0.19 (0.39)	0.20 (0.40)	0.16 (0.37)	0.04***
Richer	0.19 (0.39)	0.18 (0.38)	0.25 (0.43)	-0.08***
Richest	0.19 (0.39)	0.15 (0.35)	0.43 (0.49)	-0.28***
Mother has primary education	0.44 (0.50)	0.39 (0.49)	0.75 (0.43)	-0.36***
Child ever breastfed	0.97 (0.17)	0.97 (0.16)	0.95 (0.23)	0.03***
Mother smokes/tobacco	0.08 (0.27)	0.08 (0.28)	0.04 (0.19)	0.04***
Punjab	0.34 (0.47)	0.30 (0.46)	0.54 (0.50)	-0.24***
Sindh	0.22 (0.41)	0.20 (0.40)	0.30 (0.46)	-0.10***

KPK	0.20 (0.40)	0.22 (0.41)	0.10 (0.30)	0.12***
Baluchistan	0.15 (0.36)	0.17 (0.38)	0.04 (0.18)	0.13***
Gilgit Baltistan	0.05 (0.22)	0.05 (0.23)	0.02 (0.12)	0.04***
FATA	0.05 (0.21)	0.05 (0.23)	0.01 (0.11)	0.04***
Urban Area	0.44 (0.50)	0.41 (0.49)	0.60 (0.49)	-0.19***
Number of ANC visits	3.66 (3.38)	3.14 (3.08)	6.30 (3.61)	-3.15***
Observations	20657	17543	3114	20657

*, **, *** indicate significance at 10%, 5%, and 1% levels. Columns 1-3 display the means with standard deviations in parentheses

Columns (2) to (4) of Table 2.4 illustrate that women who have had a caesarean birth are less likely to be employed, less likely to be in poverty, less likely to come from poorer provinces (KPK, Baluchistan, GB), and less likely to be tobacco users. Women who had a caesarean are also more likely to be rich, more likely to come from the richer provinces (Punjab and Sindh), and more likely to be primary school educated. They are more likely to be from an urban area and have a higher number of ANC visits on average.

Table 2.5 presents a balance table showing the incidence of respiratory symptoms in samples of children born via caesarean section and those born naturally. This shows some patterns in the data; there are differences in the prevalence of ARI symptoms across the types of birth delivery methods. For instance, children born through caesarean are more likely to have a fever or cough compared to those born naturally. Children born by caesarean are also more likely to have had diarrhoea. Further analysis is needed to control for variations in other variables to study this relationship.

Table 2. 5 Balance table: Reported illness by mode of birth of the child

	(1) Full sample	(2) Natural Delivery	(3) CS Delivery	(4) Difference (2)-(3)
Any symptoms of ARI	0.45 (0.50)	0.44 (0.50)	0.50 (0.50)	-0.06***
Any two symptoms of ARI	0.30 (0.46)	0.29 (0.46)	0.33 (0.47)	-0.03***
Fever in the last two weeks	0.36 (0.48)	0.36 (0.48)	0.38 (0.49)	-0.03**
Cough in the last two weeks	0.35 (0.48)	0.34 (0.47)	0.39 (0.49)	-0.05***
Short, rapid breaths	0.19 (0.39)	0.19 (0.39)	0.19 (0.40)	-0.01
Problems with the chest only	0.15 (0.35)	0.15 (0.35)	0.14 (0.34)	0.01
Problems with the nose only	0.10 (0.30)	0.10 (0.30)	0.10 (0.31)	-0.00
Problems with nose & chest	0.06 (0.24)	0.06 (0.24)	0.05 (0.22)	0.01*
Diarrhoea in last two weeks	0.20 (0.40)	0.19 (0.40)	0.21 (0.41)	-0.02**
Observations	20657	17543	3114	20657

*, **, *** indicate significance at 10%, 5%, and 1% levels. Columns 1-3 display the means with standard deviations in parentheses

For our within-families model we are essentially comparing the outcomes of siblings and including mother fixed effects. Therefore, the sample used for this analysis consists of children with at least one sibling in the survey. That is, “singleton” children are dropped from the analysis because they do not help identify variation within families. Appendix Table 2.1 shows the balance table for the sample of singleton children and the sample of children used for the within-families analysis. One of the drawbacks of using a mother-fixed effects analysis is that, while it enhances internal validity by controlling for mother-specific factors, it is unable to estimate the effects for the full sample of children, thereby reducing external validity. It is important to note that in this case, the singleton children in our sample are not necessarily only children without siblings. In fact, 64.83% of singleton children in our sample have one or more siblings, but the siblings are five years old or more and therefore not observed in our dataset. However, due to this sample selection, we are selecting children of mothers who have had at least two births in the past 5 years (i.e.,

more fertile women) for our within-families analysis. The balance table shows that compared to singleton children, children with at least one sibling under the age of 5 are less likely to have symptoms of ARI, less likely to have diarrhoea, less likely to be born by caesarean delivery, and less likely to live in an urban area. They are more likely to be female and more likely to be from the poorest families. The mothers of such children are less likely to have completed primary school.

Table 2.6 shows the descriptive statistics for the sample used in the IV regression analysis in column (1). This sample includes children with an older sibling in the survey, allowing us to observe the older siblings' mode of delivery and study the causal effect of a caesarean birth on the outcomes for the younger sibling. Compared to the sample used in the main model, the average age of the children studied is lower (around 1 year old in this sample, compared to 2 years old in the previous sample) due to the study design. All other average characteristics of this sample are similar to those shown in the sample used for our OLS analysis. In this sample, 11.87% of children had an older sibling who was born by caesarean delivery.

Table 2. 6 Balance table by older siblings' mode of birth (IV sample)

	(1) Full sample	(2) Older Sibling Natural	(3) Older Sibling Caesarean	(4) Difference (3)- (2)
Any symptoms of ARI	0.46 (0.50)	0.45 (0.50)	0.52 (0.50)	-0.07***
Diarrhoea	0.25 (0.43)	0.25 (0.43)	0.25 (0.43)	-0.01
CS delivery	0.13 (0.34)	0.03 (0.17)	0.89 (0.32)	-0.86***
Age of the Child	0.99 (0.95)	1.00 (0.95)	0.95 (0.96)	0.05
Female Child	0.49 (0.50)	0.49 (0.50)	0.49 (0.50)	0.00
Birth Order: 1	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00
2 to 3	0.53 (0.50)	0.49 (0.50)	0.78 (0.41)	-0.29***
4 to 5	0.27 (0.44)	0.28 (0.45)	0.19 (0.39)	0.09***
6+	0.20 (0.40)	0.23 (0.42)	0.03 (0.17)	0.20***
Mother's age at birth:<20	0.05	0.05	0.04	0.00

	(0.21)	(0.21)	(0.20)	
20 to 34	0.85	0.84	0.91	-0.07***
	(0.36)	(0.37)	(0.28)	
35 to 49	0.11	0.11	0.05	0.07***
	(0.31)	(0.32)	(0.21)	
Mother is employed	0.16	0.16	0.12	0.05***
	(0.36)	(0.37)	(0.32)	
Wealth Index: Poorest	0.25	0.28	0.07	0.20***
	(0.43)	(0.45)	(0.26)	
Poorer	0.21	0.22	0.09	0.13***
	(0.40)	(0.41)	(0.29)	
Middle	0.20	0.20	0.17	0.03
	(0.40)	(0.40)	(0.38)	
Richer	0.18	0.17	0.24	-0.07***
	(0.39)	(0.38)	(0.43)	
Richest	0.16	0.13	0.42	-0.29***
	(0.37)	(0.34)	(0.49)	
Mother has primary education	0.42	0.38	0.74	-0.37***
	(0.49)	(0.48)	(0.44)	
Child ever breastfed	0.98	0.98	0.96	0.02***
	(0.15)	(0.14)	(0.19)	
Mother is a smoker/tobacco	0.08	0.09	0.04	0.05***
	(0.28)	(0.29)	(0.20)	
Punjab	0.35	0.32	0.56	-0.25***
	(0.48)	(0.47)	(0.50)	
Sindh	0.22	0.21	0.31	-0.10***
	(0.41)	(0.41)	(0.46)	
KPK	0.19	0.20	0.08	0.12***
	(0.39)	(0.40)	(0.27)	
Baluchistan	0.15	0.17	0.03	0.14***
	(0.36)	(0.37)	(0.17)	
Gilgit Baltistan	0.05	0.05	0.01	0.04***
	(0.21)	(0.22)	(0.11)	
FATA	0.05	0.05	0.01	0.05***
	(0.22)	(0.23)	(0.09)	
Urban Area	0.42	0.40	0.58	-0.18***
	(0.49)	(0.49)	(0.49)	
Number of ANC visits	3.24	2.90	5.72	-2.82***
	(3.11)	(2.91)	(3.37)	
Observations	6636	5848	788	6636

*, **, *** indicate significance at 10%, 5%, and 1% levels. Columns 1-3 report the means and standard deviations in parentheses.

Table 2.6 also shows the differences in our variables of interest by the type of delivery of the older sibling, and the t-test of the differences in the two groups. This table

shows that 89% of children in our sample were born by caesarean delivery if their older sibling was born by caesarean, while only 3.15% of children were born naturally if their older sibling was born by caesarean.

2.4 Empirical Approach

2.4.1 OLS and Within-Families effects

Firstly, we present the estimates from our OLS analysis, which includes fixed effects for year of birth and region-year of survey trends. We also control for the month of the survey. This is because the outcome variables, symptoms of ARI and diarrhoea, concern the presence of any symptoms 2 weeks prior to the survey. The families are surveyed in different months, which may impact whether they are experiencing any symptoms. We control for region-trend effects, which is the interaction between the region of residence and the year of survey. There may be trends in pollution, healthcare availability, weather, and security in a particular region during a specific year that could influence one or more of these variables. The year of birth fixed effects ensure we are comparing children of the same age. Therefore, we estimate following equation:

$$Y_{itk} = \delta_t + \lambda_k + \beta_0 + \beta_1 X_{1itk} + \beta_2 X_{2itk} + \varepsilon_{itk} \quad (2.1)$$

Where Y_{itk} is the outcome for child i , from region- survey year k , and born in the year t . X_1 is a binary variable for whether the child was born by caesarean section, X_2 is the vector of child and mother's individual characteristics, including child's gender, birth order, mother's age at birth, wealth index, education, employment status, whether the mother smokes, if the child was ever breastfed, and the number of antenatal care visits the child had. δ_t and λ_k represent the year of birth and region-trend fixed effects.

In addition to this, we estimate the effects of a mother-fixed effects model. By including the mother's fixed effects, we control for unobserved time-invariant characteristics of the mother, such as genetic or environmental factors that could affect whether she has

a caesarean section or whether the child develops an illness, and examine the average effect of having a caesarean section between siblings. We refer to this strategy as the “within-families” analysis in this chapter. This empirical strategy builds on numerous studies that have used mother fixed effects to estimate the impact of health shocks on children (for example, Almqvist et al., 2012; Aizer, Stroud and Buka, 2016). For this model, we rely on the mother and year of birth fixed effects. Therefore, we estimate the following equation:

$$Y_{ijt} = \mu_j + \delta_t + \beta_0 + \beta_1 X_{1ijt} + \beta_2 X_{2ijt} + \varepsilon_{ijt} \quad (2.2)$$

Where Y_{ijk} is the outcome for child i , born to mother j , in the year t . X_2 is a vector of the child’s individual characteristics, including birth order, number of ANC visits, whether ever breastfed, gender, and mother’s age at birth. μ_j represents the mother fixed effects.

Additionally, for the 2017/2018 sample only, we have information on whether the caesarean section was planned or unplanned/emergency (based on whether the decision to have a caesarean section was made before or after the onset of labour pains). For this analysis, we will split the main independent variable of Caesarean Section (X_1) to capture the effect of planned and unplanned caesarean. Thus, estimating the following equation:

$$Y_{itk} = \delta_t + \alpha_k + \beta_0 + \beta_1 \text{Unplanned}_{itk} + \beta_2 \text{Planned}_{itk} + \beta_3 X_{3itk} + \varepsilon_{itk} \quad (2.3)$$

Where δ_t and α_k represent the year of birth, and region fixed effects. Lastly, we repeat this analysis in equation 2.3 using the within-families model:

$$Y_{ijt} = \mu_j + \delta_t + \beta_0 + \beta_1 \text{Unplanned}_{ijt} + \beta_2 \text{Planned}_{ijt} + \beta_3 X_{3ijt} + \varepsilon_{ijt} \quad (2.4)$$

Where μ_j and δ_t represent the mother and year of birth fixed effects

2.4.2 Instrumental Variables Model

This chapter also uses an Instrumental Variables (IV) approach to estimate the causal effects of a caesarean section delivery on childhood illness. When looking at the correlation between a caesarean birth and childhood illness, the results are likely to be biased due to unobserved factors that may affect both the treatment and the outcome. An IV approach can overcome endogeneity concerns in this relationship when a valid and relevant instrument is used. For an instrument to be valid, it should only affect the outcome variable through exogenous variation of the treatment variable. For an instrument to be relevant, it should have sufficiently large explanatory power of the treatment variable. One can use a two-stage least squares (2SLS) approach to estimate a Local Average Treatment Effect (LATE) for the effect of caesarean delivery on illness outcomes by employing a valid and relevant instrument.

We created a variable indicating whether the previous birth of the mother of the study child was via caesarean and used that as an instrumental variable for whether the study child was born via caesarean. For this analysis, we exclude children who do not have an older sibling. There are 6,636 observations.

Our estimates were computed using a two-stage least squares regression (Equations 2.5 and 2.6) (Wooldridge, 2002; Angrist and Pischke, 2009). Equation 2.5 shows the first stage, which estimates the correlation between the older sibling being born by Caesarean ($\mathbf{Z}_{itk}$) and the study child being born by caesarean (Caesarean_{itk}). This exogenous variation in birth delivery method is exploited to estimate the causal effect of a caesarean section ($\widehat{\text{Caesarean}}_{itk}$) on a child's illness (Y_{itk}) (see Equation 2.6). The following two equations are estimated for the IV analysis:

$$\text{Caesarean}_{itk} = \gamma_0 + \gamma_1 \mathbf{Z}_{itk} + \gamma_2 X_{itk} + \delta_t + \alpha_k + u_{itk} \quad (2.5)$$

$$Y_{itk} = \beta_0 + \beta_1 \widehat{\text{Caesarean}}_{itk} + \beta_2 X_{itk} + \delta_t + \alpha_k + e_{itk} \quad (2.6)$$

In both equations, we include a set of controls X_{itk} for the study child’s gender, birth order, mother’s age at birth, education, employment, household income, and number of neonatal visits. We also include δ_t and α_k , the year of birth and region-survey year fixed effects.

The covariates in the model are the child’s gender, birth order, mother’s level of education, employment status, wealth quantile, age at birth, breastfeeding, region, age at delivery, and number of ANC visits.

2.5 Main Results

In this section, we present the OLS estimates, and the within-families model estimates. We also present the estimates of our IV sample.

2.5.1 OLS estimates

The first coefficient in each panel shows the estimates with no additional controls included in the regression. We subsequently add a set of controls that are used in literature on the relationship between caesarean delivery and child health outcomes from papers cited in the following meta-analyses: Bager, Wohlfahrt and Westergaard, 2008; Cardwell et al., 2008; Thavagnanam et al., 2008; Li, Zhou and Liu, 2013; Keag, Norman and Stock, 2018; Darabi et al., 2019. This includes the child’s sex, birth order, mother’s age at birth, employment status, whether the mother has at least a primary level education, and wealth index. In the third column, we add a set of controls for the mother’s health behaviours that are less frequently included in the literature: whether the child was ever breastfed, the mother’s smoking, and the number of neonatal visits. The fourth column also contains the full set of covariates and the region-year fixed effects.

Table 2. 7. OLS estimation: Any symptoms of Acute Respiratory Illness

	(1) No Controls	(2) Child & Maternal Controls	(3) All Controls	(4) All Controls	(5) All Controls + Female Interaction
Births delivered by Caesarean	0.043*** (0.015)	0.029* (0.015)	0.032** (0.015)	0.029* (0.015)	0.037** (0.018)
Caesarean*Female					-0.017 (0.025)
Main+ additional effect					0.02
Observations	20657	20657	20657	20657	20657
R-squared	0.021	0.026	0.033	0.037	0.037
Mean of Dep. Variable	0.467	0.467	0.467	0.467	0.467
Region FE	Yes	Yes	Yes	No	No
Region-year FE	No	No	No	Yes	Yes

Standard errors in parentheses

All regressions include year of birth and month of survey fixed effects. The standard errors are clustered at the community level.

Child and Maternal controls include child sex, birth order, mother's age at birth, household income quintile, maternal education, and maternal employment. All controls additionally include maternal health behaviors: breastfeeding, number of antenatal care visits, and smoking behaviour.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7 presents the OLS estimates of equation (2.1) on the first outcome: having any symptoms of ARI. The key finding in this model is the small but statistically significant and positive estimates of the effect of caesarean delivery on the likelihood of children experiencing any symptoms of ARI across all model specifications (panel one in columns 1-4). These estimates suggest a slightly higher likelihood of having symptoms of ARI for children born by caesarean delivery. In column 1, the model is estimated without any additional controls, and the likelihood of presenting any symptoms of ARI is 4.3 percentage points higher and statistically significant at the 1% level. When controls are subsequently added to the model, this likelihood decreases in magnitude but remains statistically significant at the 10% level. In the model with the complete set of controls (column 4), the increase in likelihood of symptoms of ARI is 2.9 percentage points for children born by caesarean.

In column 5, the additional effect of caesarean section birth for female children is studied. This is because male children tend to have less resistance and a weaker immune

response to infections than female children (Muenchhoff and Goulder, 2014). The coefficient in the first panel of column 5 is the effect of caesarean section on the outcome variable for male children. This is slightly higher in magnitude and significance than for the overall sample. The second panel is the additional effect of caesarean section for female children. This coefficient is negative, meaning that the estimated effect for girls is lower than for boys. However, this effect is not statistically significant. A joint test of the main effect with the interaction shows that the effect for female children is not statistically significant. This suggests that the effect of caesarean delivery on ARI may be driven more by the effect on male children.

Next, we present the OLS estimates of caesarean section on having Diarrhoea in Table 2.8. The key finding in this model is the statistically significant and positive estimates of the effect of caesarean delivery on the likelihood of children experiencing diarrhoea across all model specifications (panel one in columns 1-4). These estimates suggest a higher likelihood of having diarrhoea for children born by caesarean delivery. In column 1, the model is estimated without any additional controls, and the likelihood of presenting any symptoms of ARI is 2.6 percentage points higher for children born by caesarean and statistically significant at the 5% level. When controls are subsequently added to the model, this estimated effect increases in magnitude and significance. In the model with the complete set of controls (column 4), the increase in likelihood of diarrhoea is 3.5 percentage points for children born by caesarean ($p < 0.01$). In column 5, the additional effect for female children is studied. The coefficient in the first panel of column 5 is the effect of caesarean section on the outcome variable for male children. This shows that the estimated effect of caesarean on a male child having diarrhoea is larger in magnitude and significance (5.3 percentage points, $p < 0.01$). The second panel is the additional effect of caesarean section for female children. This coefficient is negative, which means that the estimated effect for girls is lower than for boys, but still positive (1.5 percentage points). However, a joint test of the main effect with the interaction shows that the effect on female children is not statistically significant. This suggests that the risk of diarrhoea is also significantly higher

for male children born by caesarean, but we do not find any evidence of a statistically significant effect for female children.

Table 2. 8 OLS estimation: Diarrhoea

	(1)	(2)	(3)	(4)	(5)
	No Controls	Child & Maternal Controls	All Controls	All Controls	All Controls + Female Interaction
Births delivered by Caesarean	0.026** (0.012)	0.035*** (0.012)	0.036*** (0.012)	0.035*** (0.012)	0.053*** (0.015)
Caesarean*Female					-0.037* (0.020)
Main + additional effect					0.016
Observations	20657	20657	20657	20657	20657
R-squared	0.043	0.045	0.048	0.052	0.053
Mean of Dep. Variable	0.209	0.209	0.209	0.209	0.209
Region FE	Yes	Yes	Yes	No	No
Region-year FE	No	No	No	Yes	Yes

Standard errors in parentheses

All regressions include year of birth and month of survey fixed effects. The standard errors are clustered at the community level.

Child and Maternal controls include child sex, birth order, mother's age at birth, household income quintile, maternal education, and maternal employment. All controls additionally include maternal health behaviours: breastfeeding, number of antenatal care visits, and smoking behaviour.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.5.2 Within-Families estimates

Appendix Table 2.2 shows the results of the previous OLS estimates conducted on the sample used for the within-families analysis. These estimates are similar in direction and magnitude to those obtained from the full sample, albeit with reduced statistical power.

Table 2.9 shows the estimated effects on having any symptoms of ARI within families. Column 1 presents the estimates with mother-level fixed effects, but no additional controls. Column 2 includes mother-level fixed effects and a set of controls for the child's characteristics. In column 3, we include the controls and indicators for the child's year of birth fixed effect. Lastly, column 4 presents the estimated effects of the model with the complete set of controls and an interaction for the child's gender. Compared to the previous

OLS results, examining within-families effects with the full set of controls reveals that the magnitude of the positive effect of caesarean section on experiencing symptoms of ARI within families is larger but not statistically significant. For column 5, there is no significant effect of a caesarean birth for male children. A joint test of significance shows that the effect of caesarean on female children is also not significant.

Table 2. 9 Within Families Analysis: Any symptoms of Acute Respiratory Illness

	(1) No Controls	(2) All Controls	(3) All Controls	(4) All Controls + Female Interaction
Births delivered by Caesarean	0.112** (0.046)	0.065 (0.047)	0.055 (0.047)	0.056 (0.051)
Female Child		-0.016 (0.013)	-0.016 (0.013)	-0.015 (0.014)
Caesarean*Female				-0.003 (0.035)
Main+additional effect				0.053
Observations	12624	12624	12624	12624
R-squared	0.650	0.667	0.671	0.671
Mean of Dep. Variable	0.433	0.433	0.433	0.433
Year of Birth FE	No	No	Yes	Yes

Standard errors in parentheses

All regressions include mother fixed effects. The standard errors are clustered at the community level.

Child-level controls include child sex, birth order, mother's age at birth, breastfeeding, and number of antenatal care visits.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Compared to previous studies, the results of this paper are similar to those of other developing countries ((Menezes *et al.*, 2011 (Brazil); Gondwe *et al.*, 2018, 2020 (India)) that found no evidence of an effect of caesarean birth on the incidence of ARI in children. In comparison, research on developed countries ((Laubereau *et al.*, 2004 (Germany); Moore *et al.*, 2012 (Australia); Kristensen and Henriksen, 2016 (Denmark)) finds evidence that a caesarean birth increases the risk of ARI. One possible explanation for this is that in developing countries, including Pakistan, mothers with a higher socio-economic status (SES) are more likely to have a caesarean section (see Figure 2.7). In contrast, in many developed countries, mothers from a more disadvantaged SES group have a higher

caesarean birth rate (Smith *et al.*, 2023). Mothers with a higher SES may also access other healthcare and additional resources that mitigate the increased risk of ARI after a caesarean birth which may be why we find no effect of caesarean birth on ARI. Further research could focus on studying the use of healthcare, community support, and education as mediating factors. This may require rich longitudinal data on the health and behaviours of mothers and children, which is currently not available on Pakistan.

Table 2.10 shows the estimated effects on having diarrhoea within families, controlling for mother-level effects. Compared to the previous results, looking at within-family effects with the complete set of controls, we find large and statistically significant effects of a caesarean birth on the child having diarrhoea (9.4 percentage points, $p < 0.01$). In column 5, we find that for male children, caesarean delivery is associated with an 11.9 percentage point ($p < 0.01$) increase in diarrhoea incidence. The effect for female children is smaller (6.3 percentage points) and not statistically significant ($p > 0.1$).

Table 2. 10 Within Families Analysis: Diarrhoea

	(1) No Controls	(2) All Controls	(3) All Controls	(4) All Controls + Female Interaction
Births delivered by Caesarean	0.158*** (0.035)	0.100*** (0.033)	0.094*** (0.034)	0.119*** (0.039)
Female Child		-0.023* (0.012)	-0.024** (0.012)	-0.015 (0.013)
Caesarean*Female				-0.056 (0.034)
Main+additional effect				0.063
Observations	12624	12624	12624	12624
R-squared	0.558	0.597	0.603	0.603
Mean of Dep. Variable	0.196	0.196	0.196	0.196
Year of Birth FE	No	No	Yes	Yes

Standard errors in parentheses

All regressions include mother fixed effects. The standard errors are clustered at the community level.

Child level controls include child sex, birth order, mother's age at birth, breastfeeding, and number of antenatal care visits.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.5.3 IV results

Appendix Table 2.3 shows the results of the previous OLS estimates conducted on the sample used for IV analysis. The estimates for symptoms of ARI are similar in direction and magnitude to those conducted on the full sample, albeit with less statistical power. The estimates on the effects of having diarrhoea are larger than those from the full sample (4.8 percentage points, $p < 0.05$).

Tables 2.11 and 2.12 present the results of the 2SLS IV model for the ARI and diarrhoea outcomes, respectively. The strength and relevance of the instrument in the IV model is evaluated by the statistical significance in the first stage, and on its Kleibergen-Paap rk Wald F statistic, which is 2300, well above the widely accepted threshold (Lee et al., 2022; Keane and Neal, 2023). The coefficient on the instrument in the first stage is large in magnitude and statistically significant at the 1% level.

Table 2. 11. IV analysis (older sibling born by caesarean): Any Symptoms of Respiratory Illness

	(1) No Controls	(2) Child & Maternal Controls	(3) All controls	(4) + Region-trend
Births delivered by Caesarean	0.0369 (0.032)	0.0226 (0.035)	0.0262 (0.035)	0.0239 (0.035)
Observations	6636	6636	6636	6636
R-squared	0.0009	0.0054	0.0102	0.0097
First stage Coef.	0.8490 (0.0161)	0.8300 (0.0164)	0.8280 (0.0165)	0.8280 (0.0165)
Kleibergen-Paap rk Wald F statistic	2528.9540	2350.0010	2326.6490	2303.4960

Standard errors in parentheses are clustered at the community level.

Dependent Variable in the Second Stage is Any Symptoms of Respiratory Illness

First stage regresses the instrument on Births by Caesarean

All regressions include year of birth, month of survey and region fixed effects. Child and maternal controls include child sex, birth order, mother's age at birth, household income quintile, maternal education, and maternal employment. All controls additionally include maternal health behaviours: breastfeeding, number of antenatal visits, and smoking behaviour

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2. 12. IV analysis (older sibling born by caesarean): Diarrhoea

	(1) No Controls	(2) Child & Maternal Controls	(3) All controls	(4) + Region-trend
Births delivered by Caesarean	0.0165 (0.029)	0.0309 (0.030)	0.0312 (0.031)	0.0318 (0.031)
Observations	6636	6636	6636	6636
R-squared	0.0006	0.0037	0.0047	0.0047
First stage Coef.	0.8490 0.0161	0.8300 0.0164	0.8280 0.0165	0.8280 0.0165
Kleibergen-Paap rk Wald F statistic	2528.9540	2350.0010	2326.6490	2303.4960

Standard errors in parentheses are clustered at the community level.

Dependent Variable in the Second Stage is the child having diarrhoea

First stage regresses the instrument on Births by Caesarean

All regressions include year of birth, month of survey and region fixed effects. Child and maternal controls include child sex, birth order, mother's age at birth, household income quintile, maternal education, and maternal employment. All controls additionally include maternal health behaviours: breastfeeding, number of antenatal visits, and smoking behaviour

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results of the second stage estimates show that a caesarean birth has a small, positive and statistically insignificant effect on the presence of symptoms of respiratory illness in children. Similarly, caesarean birth has a small and insignificant effect on the presence of diarrhoea in children. The magnitude of the estimated effects closely matches that of our OLS estimates.

In Appendix Table 2.4, we present a robustness check of our IV model, controlling for whether the older sibling has any symptoms of ARI or diarrhoea. The assumption in the IV model shown in Tables 2.11 and 2.12 is that an older sibling being born by a caesarean section generates a variation in the decision for the mode of birth of the younger child but has no direct effect on the younger child's incidence of illness. This is a reasonable assumption, but since respiratory health and diarrhoea are communicable illnesses, an older sibling born by caesarean section could affect the health of the older sibling and, therefore, also the younger sibling, as they live in the same household and can pass on the illness. In

Appendix Table 2.5, the coefficient on the instrument in the first stage remains large in magnitude and statistically significant at the 1% level, with a Kleibergen-Paap rk Wald F statistic that exceeds the accepted threshold. We find that, compared to the IV estimates in Table 2.11 and Table 2.12, the magnitude of the estimated effect on having any symptoms of ARI is significantly reduced, and the estimated effect on diarrhoea is slightly reduced. Both estimates are not statistically significant.

2.6 Additional Analysis

In this section, we present additional analysis for this chapter, including robustness checks. Firstly, in section 2.6.1, by utilising data from the 2017/2018 survey on the timing of the decision of caesarean, we estimate the effects of a planned caesarean and an emergency caesarean separately. Next, in section 2.6.2, we conduct a subgroup analysis using OLS and the within-families model to see if there is a difference in the estimated effect for infants (under 12 months) and older children. In section 2.6.3, we repeat our main analysis with a focus on other measures of ARI as a robustness check; incidence of just fever, fever and cough or any two symptoms of ARI. Section 2.6.4 presents the average marginal effects of our estimates using a probit specification and a negative binomial model as a robustness check. Lastly, we present the results of an Oster test to examine the sensitivity of our estimates to omitted variables bias in section 2.6.5, and address survival bias in our study by performing exploratory survival analysis in section 2.6.6.

2.6.1 Timing of the Decision

We conducted additional analysis to understand the effect of the timing of the decision to have a caesarean (unplanned or planned caesarean) by estimating equation 2.4. This additional analysis is conducted on the sample of children whose mothers participated in the 2017/2018 survey, as this was the only PDHS survey that reports the timing of the decision to have a caesarean. In Appendix Table 2.5, we compare the descriptive characteristics of the 2017/18 sample with the 2012/13 sample and the full sample. We find that the 2017/18 sample has a greater proportion of children who report ARIs but

fewer who report diarrhoea. The proportion of women who had a caesarean section is 18% in this sample (N=1770), compared to 12% in the 2012/2013 sample. Amongst these caesarean births, 29% of them were an unplanned caesarean (N=513) while the remaining 71% were planned caesarean births (N=1257). This sample also has a smaller proportion of employed mothers and a greater proportion of mothers who smoke.

Table 2. 13. OLS estimation; Timing of decision distinction

	(1)	(2)
	Any Symptoms of ARI	Diarrhoea
Planned Caesarean	0.011 (0.024)	0.038** (0.019)
Unplanned Caesarean	0.021 (0.034)	0.041 (0.028)
Observations	9834	9834
R-squared	0.042	0.048
Mean of Dep. Variable	0.477	0.191
Region FE	No	No
Region-year FE	Yes	Yes

Standard errors in parentheses are clustered at the community level.

All regressions include year of birth and month of survey and region-trend fixed effects.

All controls included : child sex, birth order, mother's age at birth, household income quintile, maternal education, and maternal employment, breastfeeding, number of antenatal care visits, and smoking behaviour.

* p < 0.10, ** p < 0.05, *** p < 0.01

Table 2.13 presents the estimated effects of a planned and unplanned caesarean separately on having symptoms of ARI (column 1) and Diarrhoea (column 2). The results show no significant effect of planned or unplanned caesarean on the likelihood of having symptoms of ARI. We do find that a planned caesarean has a significant, positive effect on the likelihood of having diarrhoea (3.8 percentage points, $p < 0.05$) while the estimated effect of an unplanned caesarean is insignificant.

Table 2.14 presents the estimated effects of a planned and unplanned caesarean separately on having symptoms of ARI (column 1) and Diarrhoea (column 2) using the within-families model. We find that there is no significant effect of planned or unplanned caesarean birth on having symptoms of ARI. In column 2, we show that planned caesarean has a large negative effect on the likelihood of having diarrhoea, and this is statistically

significant (13.1 percentage points, $p < 0.05$). However, an unplanned caesarean section does not have a significant estimated effect on the likelihood of diarrhoea.

In these results, our estimate of the effect of unplanned caesarean on diarrhea and ARI may not be significant due to the small sample of unplanned caesarean births (513 births are by unplanned caesarean). However, from a policy perspective, unplanned caesareans (defined as emergency caesareans where the decision to have a caesarean is taken after the onset of labour pains) may be a life-saving procedure and we are interested in studying the consequences of unnecessary planned caesareans. However, due to the absence of detailed data on the reason for the unplanned caesarean or complications during pregnancy, we are unable to identify how many of these planned caesareans were medically necessary. Nevertheless, these results are interesting as they encourage the collection of more detailed data during pregnancy in developing countries and further investigation into the causes and consequences of planned caesareans.

Table 2. 14. Within Families Analysis; Timing of decision distinction

	(1) Any Symptoms of ARI	(2) Diarrhoea
Planned Caesarean	0.045 (0.068)	0.131** (0.062)
Unplanned Caesarean	0.016 (0.073)	0.105 (0.076)
Observations	5965	5965
R-squared	0.685	0.603
Mean of Dep. Variable	0.442	0.178
Year of Birth FE	Yes	Yes

Standard errors in parentheses are clustered at the community level

All regressions include mother fixed effects and child controls: child sex, birth order, mother's age at birth, breastfeeding, and number of antenatal care visits.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.6.2 Heterogeneity: the age of the child

We are interested in looking at whether the effect of caesarean on symptoms of ARI and diarrhoea varies between infants and children over 12 months old.

Table 2.15 shows that caesarean delivery is associated with a higher likelihood of ARI symptoms among children under 12 months in both the OLS (4.7 pp) and within-families (10.8 pp) specifications; however, these estimates are only weakly significant at the 10% level. The additional effect for children over 12 months is negative and statistically insignificant in both models. Joint tests of significance confirm that the effect of caesarean on symptoms of ARI is not statistically significant for children over 12 months.

Table 2.16 shows that, in the OLS estimates, caesarean delivery is associated with a small and weakly significant increase in diarrhoea incidence among children under 12 months of age (3.5 pp, $p < 0.1$). A joint test of significance reveals that the effect for older children remains weakly significant but larger in magnitude for older children (>12 months).

Table 2. 15. Any symptoms of ARI: The role of the child's age

	(1) OLS	(2) Within Families Model
Caesarean Delivery	0.047*	0.108*
Ref Category: Child is under 1	(0.027)	(0.061)
Child is over 12 months old	0.011 (0.014)	0.053*** (0.021)
Caesarean Delivery # Child is over 12 months old	-0.019 (0.031)	-0.057 (0.042)
Main+additional effect	0.028	0.051
Observations	20657	12624
R-squared	0.032	0.668
Mean of Dep. Variable	0.467	0.433
Month of Survey FE	Yes	No
Mother FE	No	Yes
Region-trend	Yes	Yes

Standard errors in parentheses are clustered at the community level.

The within-families model controls include child sex, age, birth order, mother's age at birth, breastfeeding, and number of antenatal care visits. OLS model additionally controls for mother's smoking, education, employment and wealth quintile

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the within-families model, caesarean delivery is associated with a large, statistically significant increase in diarrhoea incidence for infants (10.6 pp, $p < 0.01$). A joint test of significance reveals that the effect is similar and statistically significant for children aged over 12 months born by caesarean (10.3 pp, $p < 0.001$). There is no evidence that the effect of caesarean differs between infants and older children. Therefore, infants and older children born by caesarean are both at risk of diarrhoea. These results suggest that a caesarean birth can have significant short and long-term risks.

Table 2. 16. Diarrhoea: The role of the child's age

	(1) OLS	(2) Within Families Model
Caesarean delivery	0.035*	0.106***
Ref Category: Child is under 1	(0.020)	(0.039)
Child is over 12 months old=1	-0.051*** (0.011)	0.061*** (0.018)
Caesarean Delivery # Child is over 12 months old=1	0.008 (0.022)	-0.003 (0.038)
Main+additional effect	0.043*	0.103***
Observations	20657	12624
R-squared	0.036	0.598
Mean of Dep. Variable	0.209	0.196
Month of Survey FE	Yes	No
Mother FE	No	Yes
Region-trend	Yes	Yes

Standard errors in parentheses are clustered at the community level.

The within-families model controls include child sex, age, birth order, mother's age at birth, breastfeeding, and number of antenatal care visits. OLS model additionally controls for mother's smoking, education, employment and wealth quintile

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.6.3 Measures of Outcome

We present the effect of a caesarean delivery on illness using different measures of illness: whether the child has at least two symptoms of respiratory illness, whether they

had a fever two weeks preceding the survey, and whether they had just a fever and cough in the past 2 weeks. Tables 2.17 and 2.18 present the estimates obtained using OLS and the within-families model for these outcomes. We do not find any significant effects; therefore, our estimates on the effects of caesarean delivery on having ARI are not robust.

Table 2. 17. OLS estimation: Other measures of the outcome variable

	(1)	(2)	(3)
	Any two symptoms	Fever only	Fever and cough
Births delivered by Caesarean	0.008	0.010	-0.003
	(0.014)	(0.014)	(0.012)
Observations	20657	20657	20657
R-squared	0.033	0.031	0.031
Mean of Dep. Variable	0.316	0.376	0.275
Region-year FE	Yes	Yes	Yes

Standard errors in parentheses are clustered at the community level.

All regressions include year of birth and month of survey fixed effects.

Child and Maternal controls include child sex, birth order, mother's age at birth, household income quintile, maternal education, and maternal employment. All controls additionally include maternal health behaviours: breastfeeding, number of antenatal care visits, and smoking behaviour.

* p < 0.10, ** p < 0.05, *** p < 0.01

Table 2. 18. Within Families: Other measures of the outcome variable

	(1)	(2)	(3)
	Any two symptoms	Fever only	Fever and cough
Births delivered by Caesarean	0.048	0.057	0.040
	(0.040)	(0.045)	(0.036)
Observations	12624	12621	12624
R-squared	0.691	0.651	0.675
Mean of Dep. Variable	0.288	0.347	0.249
Year of Birth FE	Yes	Yes	Yes

Standard errors in parentheses are clustered at the community level.

All regressions include mother fixed effects.

Child level controls include child sex, birth order, mother's age at birth, breastfeeding, and number of antenatal care visits.

* p < 0.10, ** p < 0.05, *** p < 0.01

2.6.4 Specification Check

The probit model is a type of regression analysis used when the dependent variable is binary. Since our main outcome variables of interest are binary variables for whether the child has symptoms of respiratory illness and whether the child has diarrhoea, probit

regression can estimate the probability of the outcome occurring using maximum likelihood estimation. Average marginal effects are computed to quantify the impact of a one-unit change in each predictor on the probability of the outcome. The probability is constrained between values of 0 and 1 using the cumulative distribution function (CDF) of the standard normal distribution. Formally, the probability that the child has a respiratory illness or diarrhoea ($Y=1$), given the treatment X and a vector of covariates Z is estimated using the following equation:

$$P(Y_i = 1 | X_i) = \Phi(\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i}) \quad (2.7)$$

Where $\Phi(.)$ is the standard normal CDF, ensuring that probabilities remain within the $[0,1]$ range.

Appendix Tables 2.6 and 2.7 present the estimates of the average marginal effects of the probit regression to compare with the OLS estimates. The results of this probit model are identical in magnitude, direction, and significance to all coefficients in the OLS estimates in Tables 2.7 and 2.8 for both ARI and diarrhoea outcomes.

We also present the results of a negative binomial regression model in Appendix Table 2.8 since we are interested in modelling both the presence and the severity of symptoms of ARI. For this model, the outcome variable is the number of symptoms of ARI when symptoms are present. This is a count regression model that is truncated at 1 for the magnitude of the outcome. We use negative binomial regression as opposed to Poisson regression, since the distribution of the outcome variable (number of symptoms) shows evidence of overdispersion. This is confirmed by the Poisson goodness of fit test and the likelihood ratio test in the negative binomial model. This is a test of the overdispersion parameter α , which confirms that it is significantly different from zero, and therefore, the Poisson distribution is not appropriate here (Long and Freese, 2006; Cameron and Trivedi, 2013).

The marginal effects in this negative binomial model on caesarean section are positive across all specifications, but it is not statistically significant. This suggests that there is no relationship between caesarean delivery and the expected count of ARI symptoms in children.

2.6.5 Oster Test

Additionally, the Oster test is conducted (Oster, 2019) to explore whether the results would change in the presence of selection on observables. This is a method to assess the robustness to omitted variable bias by testing how much selection on unobserved factors would be needed to explain away the estimated effect of caesarean delivery. The Oster test results (δ and β values) and non-significant t-tests, shown in Appendix Tables 2.9 and 2.10, imply that the effect of caesarean delivery on ARI and diarrhoea is not overly sensitive to omitted variable bias, particularly in Models 4 through 6. In Appendix Table 2.9, the model with the full set of controls (Model 6) shows that the Oster test ($\delta = 1.926$) indicates that selection on unobservables would need to be nearly twice as strong as the observed controls to nullify the effect of caesarean delivery.

2.6.6 Survivorship Bias

The focus of this chapter has been to estimate the effect of caesarean delivery on childhood illness using survey data on children under the age of 5. One important consideration is that health outcomes are not observed for those children who are not alive at the time of the survey (passed away under the age of 5). In our sample, 6.44% of children are not alive at the time of the survey. Survivorship bias can occur when analysing such censored data from children who may have had poor health outcomes, particularly if caesarean section increases early child mortality. Specifically, our estimates may have a downward bias because the children most at risk did not survive. We examine the association between caesarean section and child mortality using the PDHS data on all births in the past 5 years. In the DHS survey, 6.56% of children born by natural delivery

are dead at the time of the survey, while 5.79% of children born by caesarean are dead at the time of the survey.

In our sample from the DHS survey, out of the 1,432 children who were not alive at the time of the survey, 92.67% were under a year old at the time of death. We used a Cox proportional hazards model using the full birth history of all mothers to examine the effect of caesarean delivery on child survival, controlling for socioeconomic and demographic characteristics. In Appendix Table 2.11, we see that children delivered via caesarean section had an 18% higher hazard of death compared to those delivered naturally (HR = 1.19, 95% CI: 0.99–1.43), although this effect was not statistically significant at the 5% level ($p = 0.068$).

To assess potential survivor bias in our main outcomes, we also ran a logistic regression predicting the likelihood of death within the first year of life (infant mortality). The average marginal effect in Appendix Table 2.12 indicates that there is no statistically significant association between caesarean delivery and early child death (average marginal effect 0.008, $p > 0.1$). This is consistent with previous findings on the effects of caesarean delivery on infant death (Costa-Ramón et al., 2018; Amaral-Garcia et al., 2022). Nevertheless, our results on the effect of caesarean should be interpreted as conditional on survival.

2.7 Discussion

In this chapter, we have explored the effects of being born by caesarean section on the likelihood of having ARI symptoms and diarrhoea for children under the age of five using Pakistani survey data. Firstly, we present the results of our OLS estimates, which control for maternal and child characteristics and regional trends. We look at the differences in effects of caesarean by the gender of the child, as male children have a weaker immune response to infection and may suffer more from the effects of caesarean on immune function (Bouman, Heineman and Faas, 2005). Then, we present two methods to control for unobserved heterogeneity. Firstly, we use mother-level fixed effects to look at the effects of caesarean section between siblings, while controlling for the mother’s genetic or

environmental factors. Secondly, we use an instrumental variables approach. We study the sample of children who have an older sibling and use whether the older sibling was born by caesarean section as an instrument for whether the study child was born by a caesarean section. This chapter contributes to the literature by providing evidence on the long-run consequences of caesarean section birth on children's health by using a survey data set that contains information on the characteristics of the mother and child in a low-income country. By using this data, we are also able to include home births (which are around 30% of births in Pakistan) and cases of respiratory illness where they presented symptoms but did not seek any treatment in our sample, as opposed to using hospital data or data from birth certificates.

Initially, we find small, positive but weakly significant OLS estimates of the effect of caesarean on a child having any symptoms of ARI (2.9 percentage points, $p < 0.1$). We find that this effect is slightly larger and statistically significant for male children (3.7 percentage points, $p < 0.05$) but smaller and insignificant for female children. Furthermore, we find some evidence that this effect is concentrated on children under 12 months. However, these results are not robust to the measure of child illness used; we find smaller and insignificant estimated effects of caesarean on the incidence of fever, fever and cough, and having any two symptoms of ARI. After restricting our sample to families with at least two children and using mother fixed effects to control for unobserved maternal characteristics, we also find no significant effect of caesarean on symptoms of ARI in children. By utilising information on the timing of the decision to have a caesarean section (before or after labour begins) from the 2017/18 survey, we find that while the effect of a planned caesarean section on the incidence of ARI is positive and larger than for an unplanned/ emergency caesarean. However, these effects are also statistically insignificant.

Our initial OLS estimates report that children born by caesarean are more likely to have diarrhoea (3.5 percentage points, $p < 0.01$). We also find that the effect is larger and significant for male children (5.3 percentage points, $p < 0.01$) but smaller and insignificant for female children. Using the within-families fixed effects model, we find that children born

via caesarean birth are 9.4 percentage points more likely to have diarrhoea ($p < 0.001$); male children born via caesarean are 11.9 percentage points more likely to have diarrhoea ($p < 0.01$), while the estimated effect of caesarean birth for female children is smaller and not significant. By examining the impact of the timing of the decision to have a caesarean, we find that children who have a planned caesarean are 13.1 percentage points more likely to experience diarrhoea ($p < 0.05$), while we find no significant effect of an unplanned/emergency caesarean birth on diarrhoea. This suggests that there is no increased risk of having diarrhoea when the child is born from a medically necessary caesarean, consistent with the findings in previous literature. Furthermore, we do not find differences in the effect of caesarean between infants and children in our sample; children under 12 months old born by caesarean share the same risk of having diarrhoea as children over 12 months.

We find that our instrument for a child's birth by caesarean in the IV model, the older sibling being born by caesarean, is strong and relevant in the first stage. The estimated effects of caesarean delivery on children's symptoms of ARI and incidence of diarrhoea are smaller in magnitude and statistically insignificant using the Instrumental Variables model. A key consideration is that these estimates represent the Local Average Treatment Effects (LATEs). Specifically, they are the effects of caesarean on the incidence of illness for children who were born by caesarean because their older sibling was born by caesarean. NICE recommendations state is that it is generally safe to have a natural delivery after a caesarean birth, and that there is little to no difference in the risk associated with a planned caesarean birth and a planned natural birth in pregnant women who have had up to four previous caesarean births (National Institute for Health and Care Excellence, 2021). However, in practice one in four women who attempted a natural birth following a previous caesarean require urgent or emergency caesarean section during labour, a higher risk than for women labouring for the first time (10-15%) (Aziz-un-Nisa Abbasi, 2012). This suggests that our sample of younger siblings who were born by caesarean because their mother's previous birth was a caesarean were potentially higher-risk

pregnancies, and caesarean was medically necessary in most of these cases. This could be one possible reason why we find no significant effects for our IV model.

We find that the results of our analysis using a probit specification are similar to those of our OLS results. We also conduct an Oster test, which suggests that our estimates are not sensitive to omitted variables bias.

Lastly, we emphasise that the estimates in this chapter are based on the sample of children who were alive at the time of the survey and therefore are conditional on survival. We conducted a Cox regression hazard model and found no significant increased risk of death following a caesarean birth. We also find no significant effect of a caesarean delivery on early child death (under the age of one) using the full birth history of mothers in the PDHS surveys.

In summary, we estimate that delivery by caesarean section increases the probability of a child having diarrhoea by approximately 9.4 percentage points. Considering that the population of Pakistan is currently 255 million, with approximately 36 million children under the age of five, the incidence of diarrhoea among children under five is 19%, and the caesarean section rate is 20%, we estimate that a caesarean section is associated with roughly 676,800 cases of diarrhoea in Pakistani children under five. We also estimate that planned caesarean increases the likelihood of diarrhoea by 13.1% and given that 70% of caesarean births are planned caesarean in Pakistan, we estimate that approximately 660,240 diarrhoea cases in children under five in Pakistan are associated with planned caesarean. If Pakistan reduced its caesarean rate from 20% to the WHO recommendation of 15%, it would translate to a 2.47% reduction in diarrhoea cases amongst children under five. These are rough, back-of-the-envelope estimates of the potential cases of preventable illness, especially in the absence of markers for clinical need for caesarean sections. However, these findings should encourage action and further research into the prevalence and risks of caesarean sections in developing countries with poor child mortality and morbidity outcomes.

The findings of this chapter are different to the large effects of 11-29% increased risk of caesarean section on respiratory illness found in studies in developed countries (Costa-Ramón et al., 2022) but seems to confirm the findings from the limited evidence from developing countries on the effects of caesarean on childhood health (Iraq and China; (Cardwell et al., 2008; Thavagnanam et al., 2008)) as they also find limited evidence of any effects. Two papers based on Indian data also found no evidence of an increased risk of diarrhoea and ARI in children born by caesarean (Gondwe et al., 2018, 2020), unlike Western findings.

One of the limitations of this study is the unavailability of information on the reason the caesarean section was performed. For the most recent 2017/18 survey, we have information on the timing of the decision which does give some indication of whether the decision was planned or unplanned but it would be beneficial to know if for example, the caesarean was performed due risk of preeclampsia or a breech birth and therefore a potentially lifesaving procedure, or if it was performed out of concern for other health issues such as diabetes or hypertension, or if it was an entirely elective procedure that was not recommended by a health professional. This would be beneficial, as we could then study the effects of elective caesarean sections separately to identify the consequences of an unnecessary medical procedure that should be discouraged. Further information that would be useful to collect at the time of the birth would be birthweight, as over 75% of the children in the sample are not weighed at birth, and the weight of the baby and gestation time can impact whether a child needs to be delivered by caesarean.

Another issue that should be addressed by researchers is the issue of missing data. In the DHS survey, for women interviewed, all births in the past 5 years preceding the survey are recorded, and many of the variables concerning birth history are recorded obligatorily by the interviewer. Therefore, we only have a few missing responses for variables used in our study, specifically (we have information on the mode of delivery for 98.3% of children). However, responding to certain questions in the survey is entirely voluntary, which often results in missing individual-level information on some respondents'

characteristics. This prevents the inclusion of other potential mediating factors or the study of additional outcomes, due to a high proportion of missing responses. For example, we have variables indicating whether the child received certain vaccines, such as those for pneumonia. Additional analysis on the impact of certain vaccines on this relationship would be useful, but there is a high amount of missing information for these variables (69% of responses are missing) that would considerably reduce the sample size and the precision of the estimates. Conducting these survey studies, which involve a fieldworker visiting households and supporting the mother in answering survey questions face-to-face, is very costly. Therefore, researchers may consider strategies to avoid missing answers, particularly when the requested information is not sensitive. Although methods for dealing with missing data (such as multiple imputation and Bayesian simulation methods) could be employed, minimising missing data during data collection would help researchers in studying the impact of numerous factors concerning caesarean section and childhood illness without compromising the statistical power of the results. Furthermore, while birthweight is an important factor to consider in this relationship, approximately 67.41% of children in our survey were reported not to have been weighed at birth. Another 16% did not know the child's weight at birth. The use of complete case analysis and incorporating this variable in such cases would result in a biased sample since this data is not likely missing at random. We note that 69% of children who were born in a hospital and not weighed at birth were born in a public or government hospital. There is a need for improved practices and management of records related to birth history and delivery in order to evaluate risk factors at a national level.

2.8 Conclusion

One important step towards improving practices concerning caesarean section in Pakistan would be to collect more data on birth such as the reason for the method of delivery, complications during pregnancy, issues during delivery, pre-existing conditions of the mother, as well as the infant's birth weight, gestation time, and level of care required after birth. This would be beneficial for researchers who want to study the use of caesarean

section for non-clinical purposes in developing countries where the caesarean rates are a growing concern. It would also be beneficial for healthcare providers to have detailed data on birth history, as it would help them to better coordinate maternal care and enhance patient decision-making, especially in a country like Pakistan, where the fertility rate is high. Awareness of the specific risks faced by any particular mother would also support family planning. The public reporting of such medical decision-making and procedures at a hospital and national level should be encouraged, as child mortality and morbidity are public health concerns. Jordan is an example of a developing country that has successfully reduced its caesarean section rate without adverse effects on birth outcomes. They achieved this by focusing on actively managing labour and encouraging women to undergo a natural birth where it is appropriate based on the available clinical information of the patient (Ziadeh and Sunna, 1995).

Another way to curb the impact of caesarean on child illness is through established education programs that target women. This should involve the use of models of health education to inform mothers who gave birth via caesarean of the health safety measures they should take to protect their children, who are at a higher risk of diarrhoea (Azadi et al., 2021). Childbirth training workshops, nurse-led relaxation training, and psychological support are known to be effective antenatal measures in reducing elective caesarean rates (Hooper et al., 2025). Women's empowerment should be a priority alongside this, as it allows women to have the resources and education to make decisions concerning their own and their child's health (de Loenzien, Mac and Dumont, 2021).

For every 1,000 babies born in Pakistan in 2020, 65 did not reach their fifth birthday (Asian Development Bank, 2021). Governments and international organisations should take immediate action to address the consequences of high caesarean section rates and help Pakistan achieve a lower rate of child mortality and morbidity.

Chapter 3: Child Health and Parental Labour Supply: Evidence from the Growing Up in Ireland (GUI) Cohort Study

3.1 Introduction

Childhood health problems affect development and therefore threaten the child's wellbeing and future economic outcomes. Additionally, health problems in childhood can also adversely affect parental labour supply. Children with poor health require more care at home; support with personal care, visits to the hospital, medical advocacy, help with medications and schoolwork (Morawska, Calam and Fraser, 2015; Spurr *et al.*, 2023). This time-intensive care can make it difficult for parents to maintain employment. This is particularly true for mothers because they are predominantly the primary caregivers. On the other hand, child health problems can put financial pressure on parents to work for extra income and afford private health care, medication, nutrition, or other special needs for their child. Therefore, child health problems could have a positive effect on paternal work outcomes. It is therefore ambiguous which effect dominates, and it may differ between household types. For example, the responses of single-parent and two-parent households might differ. In our study, we examine the effect of poor child health on parental labour market response using the Growing up in Ireland (GUI) survey data. We consider both the extensive (probability of employment) and intensive margin (hours worked). Our study aims to assess whether parents of children with health conditions are worse off than other parents. We are also interested in examining whether the effect differs for single mothers, Cohabiting mothers, and fathers. This would improve our understanding of the challenges faced by parents, especially mothers, in entering the workforce, and the potential economic inequalities caused by the child's health status.

Evidence of a parental labour market response to the presence of a child with a health condition could have important implications for government welfare systems. If poor child health has a negative effect on parental employment and hours worked, it will mean

that more families may require government financial assistance, and fewer contributions are being made to the pension and welfare system. It may also mean that more support from employers, government, and healthcare workers is needed to remove this barrier to employment and success in the workplace, especially for mothers. On the other hand, there is also research that suggests children of parents, especially mothers, who spend more time at home have better outcomes (Chevalier et al., 2013; Mosca, O’Sullivan and Wright, 2021). If mothers of children with health conditions are choosing not to work and are caring for their children instead, this could have a positive effect on their future educational attainment. Government financial assistance could enable more mothers to spend time with their children who have health conditions, if they wish to, and would help reconcile inequalities based on the child’s health.

We present empirical evidence on the effect of long-term health conditions in a child on parental employment and hours worked using data from the Growing Up in Ireland (GUI) infant cohort study. We estimated panel data models using four waves of the GUI data to control for possible unobserved heterogeneity, and we estimated models that account for sample selection bias in the hours worked. Our results show that having a child with a longstanding health condition reduces the probability of a single mother working by almost five percentage points. On the other hand, we find that, conditional on working, mothers of children with health problems do not have significantly different work hours from those of mothers of children without health problems. These findings suggest that health conditions in children may be a significant barrier to the labour force participation of single mothers. Conversely, we find that fathers of children with longstanding health conditions are slightly more likely to work. We also find that fathers work fewer hours if their child has a longstanding condition, conditional on working. This research should motivate policymakers and healthcare providers to implement policies that focus on women in this situation and offer financial support to reduce economic inequalities arising from health differences.

One of the limitations of this chapter is that we cannot differentiate between different conditions or their severity due to data limitations. For instance, our study cannot identify children with conditions like autism spectrum disorder that may be more disruptive than a child with an allergy because we lack information on the specific health condition of the child in all waves. Furthermore, different conditions may require different care and expense needs, and different levels of support available in Ireland. In future research, we aim to categorise different conditions and explore how their effects vary. To do this, access to the Secure Anonymised Files for the Growing Up in Ireland Surveys would be necessary, as they may include information on specific diagnoses through linkage with hospital administrative data. The findings of this paper should be considered with this limitation in mind.

In Section 3.2, we discuss the previous research literature in this area. In Section 3.3, we discuss the context of child health and parental employment in the Republic of Ireland. In Section 3.4, we discuss the Growing Up in Ireland Cohort Study dataset that we used for analysis. In Section 3.5, we outline our methodology. In Section 3.6, we present our results, and in Section 3.7, we present additional analysis to check the robustness of our main results and conduct subsample analysis. Section 3.8 is a discussion and conclusion of our study.

3.2 Literature Review

Our study contributes to the literature on the barriers faced by women in entering the workforce. Becker (1965) introduced a model that describes how couples maximise their joint household utility through collective decision making and the division of labour into household, childcare, and labour market activities. In doing so, women are more likely to choose to substitute work for childcare when childcare needs increase, as they face greater opportunity costs of working. This is because, traditionally, women have a comparative advantage in household and childcare activities due to the cost of childcare, the gender pay gap and societal upbringing (Gronau, 1973; Strauss and Thomas, 1995). The motherhood wage penalty is also well-documented, as mothers tend to select jobs that better balance

family and work, but at the cost of lower pay and fewer career prospects (Goldin, 2014). Significant wage gaps persist between women with children and childless women across many countries, even after controlling for human capital, employment patterns, unobservable individual traits, and social and cultural norms (Kleven, Landais, and Sgaard, 2019; Corts and Pan, 2023). Furthermore, Akerlof and Kranton (2000) proposed an ‘identity model’ where mothers engage in behaviours consistent with their ‘good mother’ identity. Even when the mother has higher earnings outside the household compared to her partner and faces a lower opportunity cost of employment, she may still specialise in childcare due to her identification as the primary caregiver (Bertrand, Kamenica and Pan, 2015). This role is reinforced by societal norms, her traditional upbringing, the expectations of healthcare professionals, and family. Traditionally, women have taken on the primary responsibility of caring for sick family members (Carpenter, 1980; Swinkels *et al.*, 2019), so an increased childcare burden due to child health conditions is also expected to disproportionately fall on the mother.

Table 3. 1: Existing evidence on the effect of child health on parental work				
Paper	Data (cross-section or panel)	Child health measure	Methods	Results
Salkever (1982)	1972 Health Interview Survey, USA (Cross-sectional)	Mobility limitation	OLS regression	Reduces work probability by 10–20% for white two-parent families; no effect for non-white or female-headed families.
Wolfe & Hill (1995)	Survey of Income and Program Participation (SIPP), USA (Panel)	Longstanding physical condition	Tobit two-stage model	Reduces hours worked (coef. -0.43; $p < 0.10$) for female household head
Powers (2001)	1992 Current Population Survey, USA (Cross-sectional)	Parental assessment of the child’s disability status	IV using specific conditions as instruments	Reduces maternal employment by 1.6 to 3 per cent for wives and 3 to 7.6 per cent for female heads of household
Powers (2003)	Pooled SIPP panels 1985-1993, USA	Child disability/condition	Probit, Tobit and OLS estimates	Reduces wives’ LFP by 6 % and hours per week by 3.7 hours. For female heads, reduces LFP by 11% and hours by 7.5

Gould (2004)	1997 Panel Study of Income Dynamics	Child disability; time-intensive illnesses, severe and unpredictable illness, expensive illnesses	Conditional likelihood, Probit and Tobit	Time-intensive illness reduces work by 40% (single mothers); severe/unpredictable illness reduces work by 47% and 0.8 hours (married mothers).
Frijters et al., (2009)	Longitudinal Study of Australian Children (LSAC) 2004 (Panel)	Poor Child development	IV approach: child handedness as an instrument	Reduces maternal LFP by 10%
Wasi et al (2012)	2000 US Census (cross sectional)	Child disability: physical and mental/cognitive impairments	Reduced form probit models	Physical disability reduces mothers' employment 2–8%; mental 0.7–1.1%; reduces hours by 0.2 to 0.9 per week
Kvist et al (2013)	Danish Psychiatric Central Register (cross-sectional)	ADHD	OLS and probit	Reduces maternal LS by 2 per cent
Lafférs & Schmidpeter, (2021)	LSAC children 2004 (Panel)	Poor Child development	IV approach: child handedness instrument	Reduces weekly maternal hours by 9 and income by \$125; no father effect
Eriksen et al., (2021)	Danish administrative registry data; 1990 to 2017 (Panel)	Childhood health shock; onset of type 1 diabetes	Event study and DiD analysis	Mothers' shift to part-time work and a decrease in long-term wages by 4–5%. No long-term father effect
Breivik and Costa-Ramón (2024)	Finish Longitudinal Survey (1988–2018), Statistics Norway (1993–2014) and Norwegian Patient Registry (2008–2014)	Hospitalisations and fatal health shocks of children	DiD analysis	Maternal earnings fall 4.6–4.7% after child hospitalisation (no father effect). Fatal shocks reduce maternal earnings >20% after 3 years; no father effect.
Cheung et al (2025)	Taiwanese administrative Health and Welfare Data Science Center (Panel)	Child disability (congenital conditions)	Event study and DiD analysis	Reduces mothers' employment by 9% and earnings by 12%; persists 10 years; no father effect.

Our study aims to contribute to the literature that aims to estimate the difference in labour market outcomes between mothers of children with a health condition and mothers of children without. We also study fathers and single mothers separately to understand if these barriers differ across parents.

Previous literature in this area studies the effects of the presence of a child with poor health on labour market participation and hours worked for single mothers and mothers with partners. The magnitude and statistical significance of the estimated effects vary depending on the measures of child health used and the sample of mothers studied. Table 3.1 presents a survey of the existing literature. Amongst these studies, studies based on cross-sectional data found a consistently negative effect of child health on maternal employment, as well as reduced hours worked (Salkever, 1982; Wolfe and Hill, 1995; Powers, 2003; Gould, 2004). However, cross-sectional data do not resolve issues with endogeneity in this relationship due to unobserved factors that affect both parental work outcomes and child health. Therefore, these estimates are potentially biased.

Powers (2003) utilised pooled data to estimate changes one and two years later in the work outcomes of mothers whose children have a disability during the first year of analysis. Compared to the previous findings from cross-sectional models (Powers, 2001), the results of the dynamic model were weaker, and for wives, the effects of child health are no longer significant. This paper also found that for female household heads, the effects on the probability of working and on hours worked remain significant in all model specifications and are always larger in magnitude than for wives.

Frijters et al. (2009) and Laff ers and Schmidpeter (2021) contribute to the literature by using child handedness as an instrumental variable to find the causal effect of child development delays on maternal labour force participation, hours worked, and weekly income. However, endogeneity is less of an issue in our study, as our measure of child health is the presence of a longstanding health condition. Such chronic conditions and disabilities are, to some extent, randomly assigned and unpredictable. Yet, there might still be endogeneity if unobserved parental characteristics (for example, health) are correlated with

child health due to genetics or environment, and hence with parental labour market activity.

We contribute to this literature by using a longitudinal dataset on Millennium Irish children. In the context of a Western European country with a relatively high birth rate, we explore whether mothers face a greater burden of caregiving than fathers. We use empirical approaches using panel data to handle unobserved heterogeneity in parents and children, such as differences in family genetics or cultural traits. We also contribute to the literature by studying the effect of longstanding health conditions in children rather than developmental delays or registered disabilities, which are the focus of recent literature in this area. Furthermore, we use the Heckman selection model to correct for sample selection bias when studying the effect on hours worked of parents.

3.3 Irish Context

Over recent decades, there has been a global increase in child health problems. This increase is due to both the improved survival rates of pre-term babies and babies with health conditions, as well as an increased life expectancy for children with health problems or disabilities, because of progress in medicine and pharmaceutical research (Fraser et al., 2012; Chawla and Agarwal, 2022). As a result, rates of chronic illnesses and resulting disability are growing because these babies who survive may have longstanding disabilities or poorer health well into childhood.

Ireland is no exception to this global trend. The 2022 Census of Ireland found that 22 per cent of the population reported experiencing at least one long-lasting condition or difficulty (Central Statistics Office, Ireland, 2023). In the GUI dataset, we observe that the prevalence of long-term conditions is 15-22% for children aged 9 months to 7 years. Therefore, child health is an issue that affects many Irish families.

Until the publication of the Growing Up in Ireland study, there was almost no routine data available on the health and illness of Irish children. Available survey data from the Health Behaviour in School-Aged Children Study is useful, but it covers limited age groups and time periods and is based on relatively small samples. The GUI study is the

first longitudinal study of Irish children with a large sample size, providing valuable information on children and their families to study child health over time. Since most of the existing literature in this research area used datasets from the US and Australia, it is important to study the effect of child health on maternal employment in Ireland, where policies and institutions differ.

Poor child health and development could have an adverse effect on maternal employment if mothers need to spend more time caring for the child at home and therefore choose not to work or work fewer hours. The GUI study finds that in two-parent families where both parents of 9-year-olds were employed, if the child was too sick to attend school, the mother was mainly responsible for caring for the child. The mother was either solely responsible (46%) or shared responsibility with the father (19%) (McNamara et al., 2021). This suggests that child caring responsibilities fall on the mother in most Irish families, and they may face a greater opportunity cost of working because of this. In fact, Article 41.2 of the Irish Constitution references explicitly the role of a mother as a caregiver primarily; “the State shall endeavour to ensure that mothers shall not be obliged by economic necessity to engage in labour to the neglect of their duties in the home” (Houses of the Oireachtas, 2024). A parliamentary bill to remove this from the constitution was defeated in 2024. Although this is not enforced in legislation, it reflects gender stereotypes of the mother’s domestic role in society. Therefore, it is important to look at the effect on mothers and fathers separately.

Additionally, the female-to-male employment ratio has changed very little since 2009. In 2019, the ratio was 0.82 in Ireland, comparable to other similar countries: Australia (0.87), the United Kingdom (0.87), and Denmark (0.87) (World Bank, 2022). While equal opportunity and equal participation in society are considered fundamental values in most Western countries, and despite progress in reducing gender inequalities, there still exist large and persistent gender differences in labour participation and employment. Therefore, it is important to identify the obstacles that continue to hinder Irish women from working, as their employment rates are not only lower than those of men but have also shown little

progress in catching up to male employment rates over the past decade. Women who are parents are also much less likely to work. In 2016, the employment rate for women varied from 85.7% for women with no children to just 60% for women whose youngest child was aged between 4 and 5 years, a difference of 25.7 percentage points (Central Statistics Office, Ireland, 2016). There are several factors that may contribute to this, such as maternity leave regulations, childcare availability, societal norms and inflexible working hours. However, individual factors such as child health can also play a part in these differences. This study will create a better understanding of the obstacles facing mothers around work and what policies or benefits the government or employers can provide to support mothers.

Conversely, poor child health could incentivise parents to work more to afford better care for their child. In the context of Ireland, the Irish healthcare system is based on a mix of private, public, and voluntary services. Around 40% of the Irish population has access to free primary care services through a medical card. To qualify for a medical card, weekly income must be below a certain figure for a given family size (Citizens Information, 2025). These families still have to pay for hospital and emergency care services with a medical card. Other families and individuals can access all healthcare services privately out of pocket or through private health insurance. For mothers with sick children, they may be discouraged from working if they wish to retain the medical card, or they may be encouraged to work more to afford access to primary care privately, as their child would benefit from shorter waiting times and better-quality services. In addition to medical care, other costs of having a child with a health condition may include special equipment, private therapy, and special needs education (Snell et al., 2013)

3.4 Data

The data analysed in our study is drawn from four waves of the Growing Up in Ireland (GUI) Infant Cohort Study. This study is managed and overseen by the Irish Department of Children, Equality, Disability, Integration and Youth (DCEDIY) and the Irish Central Statistics Office (CSO) and is carried out by a group of researchers led by the Economic and Social Research Institute (ESRI) and Trinity College Dublin (TCD). The

GUI Study is the first project that aims to measure and understand the wellbeing of children in the Republic of Ireland. This dataset tracks the development of infants born in the Republic of Ireland between December 2007 and May 2008 through interviews with the parents. Wave 1 is a nationally representative sample of 11,134 infants and their families who were randomly selected from the Child Benefit Register maintained by the Department of Social Protection. By Wave 5, there remained 7,563 9-year-olds whose families participated in the previous waves (68% of the original sample). The data were re-weighted to account for differential response across different groups. This re-weighting is detailed in the summary report for each wave (Quail et al., 2019).

Table 3. 2: Attrition from the GUI by Wave

Wave	Age of Child	Dates	Responses*	Useable Responses**
1	9 months	2008 (Sept.) to 2009 (Apr.)	11,134	10,623
2	3	2010 (Dec.) to 2011 (July)	9,793	9,158
3	5	2013 (Mar.-Sept)	8,712	7,880
4	7/8	2015/16 Postal Wave***	5,086	Excluded
5	9	2017 (June) to 2018 (Feb.)	7,507	5,823
6	11/12	2021 (Sept.) to 2022 (June)	6,655	5,320

*Responses that are also in all previous waves

**We exclude twins (3.58%), households where the main caregiver is the father (0.34% in Wave 1), households where another child has a longstanding health condition in Wave 1 (0.17%) and where there are missing responses to any of the variables used in our analysis (12.3%).

***Wave 4 was a “mini wave” intended to maintain contact between the survey team and the respondents

We analysed Waves 1, 2, 3, and 5, which contain information about the children at 9 months, 3 years old, 5 years old, and 9 years old, respectively. Table 3.2 shows the timing of the waves and attrition from the sample. We did not include Wave 4 in our study as it is a ‘mini wave’ conducted with the intention of maintaining continuity of the survey (Murphy et al., 2018). This wave does not contain information such as the child’s health status and the mother’s working hours. Similarly, in December 2020, an online web survey was conducted to record the experiences of the 12- to 13-year-old cohort since the onset of the COVID-19 pandemic in March 2020. This supplementary survey focused on the impact of COVID-19 and lockdown, specifically on income, schooling, physical activity, stress and emotional wellbeing and was not intended to be a complete survey or wave of the study.

Most importantly, that survey did not include a question on whether the study child had a longstanding condition, which is our main independent variable used in our analysis, and therefore, we do not conduct analysis using data from this wave.

There is also a Wave 6 in which the children were interviewed at 13 years old. This is the latest full wave of the GUI cohort study. However, the collection of this data took place between September 2021 and June 2022, which meant the employment outcomes of parents were affected by the outbreak of COVID-19. Therefore, this survey measures the work outcomes of parents differently from previous waves. Parents are asked whether they were employed immediately before the COVID-19 outbreak and how many hours they were working, rather than measuring their employment status at the time of the interview, as previous waves did. While we have not included this wave in the main analysis of this study due to differences in the measurement of these key variables, and the effect of layoffs and furlough during COVID-19 potentially affecting our results, we did use this wave to conduct additional analysis that is included in the appendix, including studying the impact of a child's health condition on remote working and the additional effects of being vulnerable to COVID-19. This wave contains 5,320 usable responses.

Families were first sent a letter explaining the aims of the study and what would be involved, including the date the fieldworker would visit their home. A trained fieldworker would visit the address to carry out a computer-assisted personal interview (CAPI) with the parent(s), one of whom would be nominated as the Primary Caregiver by the parents (where both were resident). This dataset contains information on diverse topics such as child health, development, parenting, schooling, parental employment and education, and others. For our study, we examined observations where the mother was the Primary Caregiver, 99% of the sample. Furthermore, we excluded children who are twins or triplets, as the effect on parental decision-making is likely to be different when multiple births are involved. We also excluded the small number of families where there was another child with a longstanding health condition in Wave 1 (0.17%). We conducted a complete-case analysis, excluding observations with incomplete or missing information on child health measures,

maternal employment, and covariates. Our final sample comprises 5,823 children. We have data on the fathers of 4,561 of these children who were present as a secondary caregiver in all waves. As mothers are the primary caregivers in 99% of families in our sample, it is not possible to study single fathers due to the very small sample size of households with fathers as primary caregivers.

Table 3. 3. Pattern of longstanding health condition/illness in the cohort children

Pattern of Longstanding Condition	% of Children Among Those Ever Reporting a Longstanding Condition
Present in all waves	7.72%
Present in all but one wave	14.07%
Present in all but two waves	24.37%
Present in only one wave	53.84%
Present in 1 st wave	24.51%
Present in 1 st wave but not in later waves	11.15%

This measure of child health used is mothers' reports of the presence of a longstanding illness, condition, or disability. Among 9-year-olds in Wave 5, about 24% of children were reported to have such a condition, compared to 19% in Wave 3 and 16% in Wave 2. The most common reported conditions were respiratory (e.g., asthma, affecting 13% of all 9-year-olds), behavioural or mental conditions (e.g., ADHD, affecting 6%), and skin conditions (3%). The following are considered longstanding conditions/illnesses: asthma, cystic fibrosis, heart abnormalities, any skin allergy, any kind of respiratory allergy, any kind of digestive allergy or food intolerance, non-food allergies, bone, joint or muscle problems, a problem using his/her arms or legs, a problem using his/her hands or fingers, hyperactivity/problems with attention ADD / ADHD, severe behavioural problems, autism spectrum disorder, other psychological or emotional condition, intellectual disability, diabetes, kidney disease, migraines headaches, epilepsy or seizures, down syndrome, spina bifida/hydrocephalies, cerebral palsy, difficulty hearing, and sight problems. In our sample used for analysis, 44.71 per cent of children are reported to have a longstanding illness, condition or disability in at least one of the waves. Table 3.3 shows the pattern of the presence of a longstanding condition in children in the sample used for analysis.

Table 3. 4. Summary statistics by health status of the child

	(1)	(2)	(3)
	Longstanding Condition	No Longstanding Condition	Difference (2)-(1)
Mother Variables			
Mother Works	0.59 (0.49)	0.64 (0.48)	0.05***
Hours Worked by Mother (Weekly)	28.76 (10.56)	28.93 (10.40)	0.17
Mother's age	34.28 (5.46)	34.68 (5.14)	0.4***
Mother's current health			
Excellent	0.26 (0.44)	0.35 (0.48)	0.09***
Very Good	0.42 (0.49)	0.41 (0.49)	-0.01
Good	0.25 (0.43)	0.19 (0.39)	-0.06***
Fair	0.06 (0.23)	0.04 (0.19)	-0.02***
Poor	0.01 (0.10)	0.00 (0.07)	-0.01***
Mother is single parent	0.12 (0.33)	0.10 (0.29)	-0.02***
Mother born in Ireland	0.82 (0.39)	0.79 (0.41)	-0.03***
Mother has degree	0.39 (0.49)	0.42 (0.49)	0.02**
Father Variables			
Father works	0.77 (0.42)	0.79 (0.41)	0.02**
Hours father works	44.75 (9.79)	45.53 (9.88)	0.78***
Father's age	37.14 (8.75)	37.64 (8.29)	0.50***
Father's Current Health			
Excellent	0.26 (0.44)	0.31 (0.46)	0.05***
Very Good	0.41 (0.49)	0.42 (0.49)	0.01
Good	0.26 (0.44)	0.23 (0.42)	-0.03***
Fair	0.06 (0.23)	0.04 (0.20)	-0.02***
Poor	0.00 (0.07)	0.00 (0.06)	0.00
Father born in Ireland	0.65 (0.48)	0.66 (0.47)	0.01

Father has degree	0.51 (0.50)	0.51 (0.50)	0.00
Child variables			
Low Birthweight	0.04 (0.20)	0.03 (0.18)	-0.01**
Child was in NICU	0.16 (0.36)	0.12 (0.32)	-0.04***
Male Child	0.58 (0.49)	0.48 (0.50)	-0.10***
Number of older siblings	0.78 (0.94)	0.77 (0.96)	-0.01
Number of younger siblings	0.43 (0.67)	0.49 (0.69)	0.07***
Household Variables			
Quintile of Household Income			
1st	0.17 (0.38)	0.16 (0.37)	-0.01
2 nd	0.20 (0.40)	0.17 (0.38)	-0.03***
3 rd	0.19 (0.39)	0.20 (0.40)	0.01
4 th	0.21 (0.41)	0.23 (0.42)	0.01
5 th	0.23 (0.42)	0.24 (0.43)	0.01*
Urban area	0.49 (0.50)	0.51 (0.50)	0.01
Observations	4607	18685	23292

As our outcome variable, we used information on parental labour supply. At each wave, parents were asked if they were employed and how many hours per week they usually worked in their paid jobs (at the time of the survey). Table 3.4 presents summary statistics from our sample by wave for parents whose cohort member has a longstanding condition or illness, and for parents whose cohort member does not have a longstanding health condition. Mothers of children with longstanding health conditions are less likely to report excellent health, less likely to have a degree, and are less likely to work on average. They are more likely to be born in Ireland and more likely to report good, fair or poor health. Fathers of children with longstanding health conditions are less likely to work, work fewer hours on average, and are less likely to report excellent health. Children with longstanding

health conditions are more likely to have been admitted to the neo-natal intensive care unit (NICU) and are more likely to be male.

Figures 3.1, 3.2 and 3.3 illustrate key descriptive statistics from our dataset. Figure 3.1 shows the average work outcomes of Cohabiting mothers in each wave. Figure 3.1A shows that Cohabiting mothers of children with and without longstanding conditions have a similar probability of employment in Wave 1 (around 0.66) when the child is 9 months old. Figure 3.1B shows that, among Cohabiting mothers who are employed, the average weekly hours are also comparable between the two groups in Wave 1. In Wave 2 (child aged 3 years old), the probability of working is lower than in Wave 1 for all Cohabiting mothers, but much more so for mothers of children with longstanding conditions (falls to 0.57 compared to 0.63). In Wave 3 (age 5), the probability of working is slightly higher than in the previous wave for mothers of children without longstanding conditions; however, mothers of children with longstanding conditions are much less likely to work than in the previous wave (0.55). Additionally, employed Cohabiting mothers of children with longstanding conditions work fewer hours than their counterparts when the child is aged 3 and 5. In Wave 5 (age 9), mothers in both groups are more likely to work than in the previous wave. However, while mothers of children without longstanding conditions have a higher probability of working than when the child was an infant, mothers of children with longstanding conditions have a lower probability of working compared to when the child was 9 months old. Indeed, the probability of working does not recover. Figure 3.1B shows that, in Wave 5, although mothers of children with longstanding conditions are less likely to work, they work more hours on average than the other group.

Figure 3.1: Cohabiting Mothers' Work Outcomes by Child Health Status

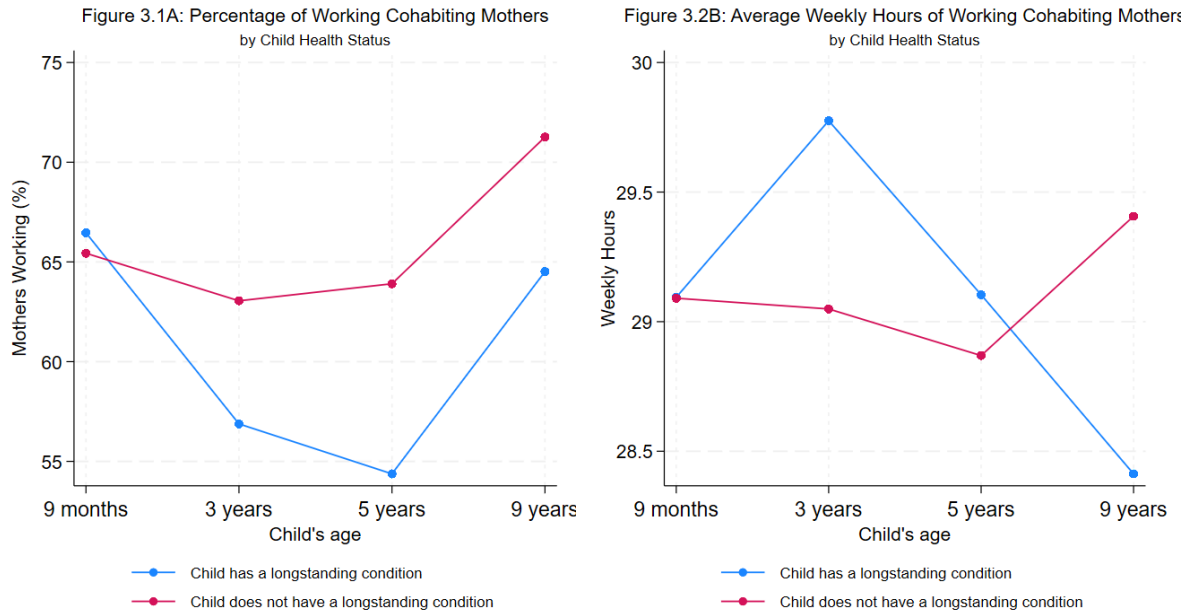
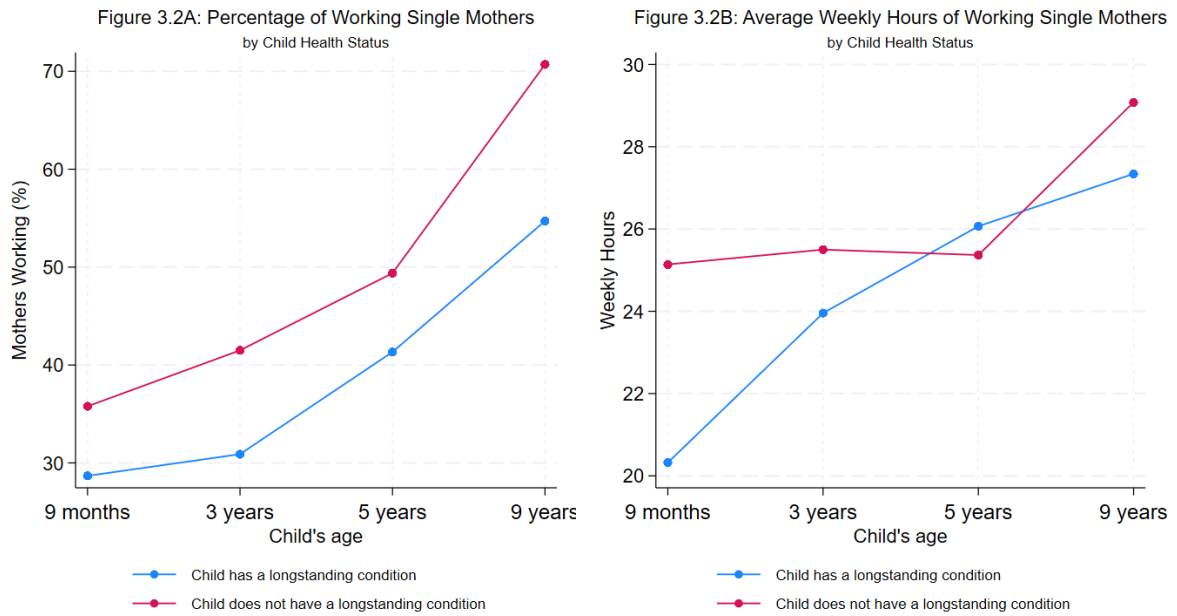


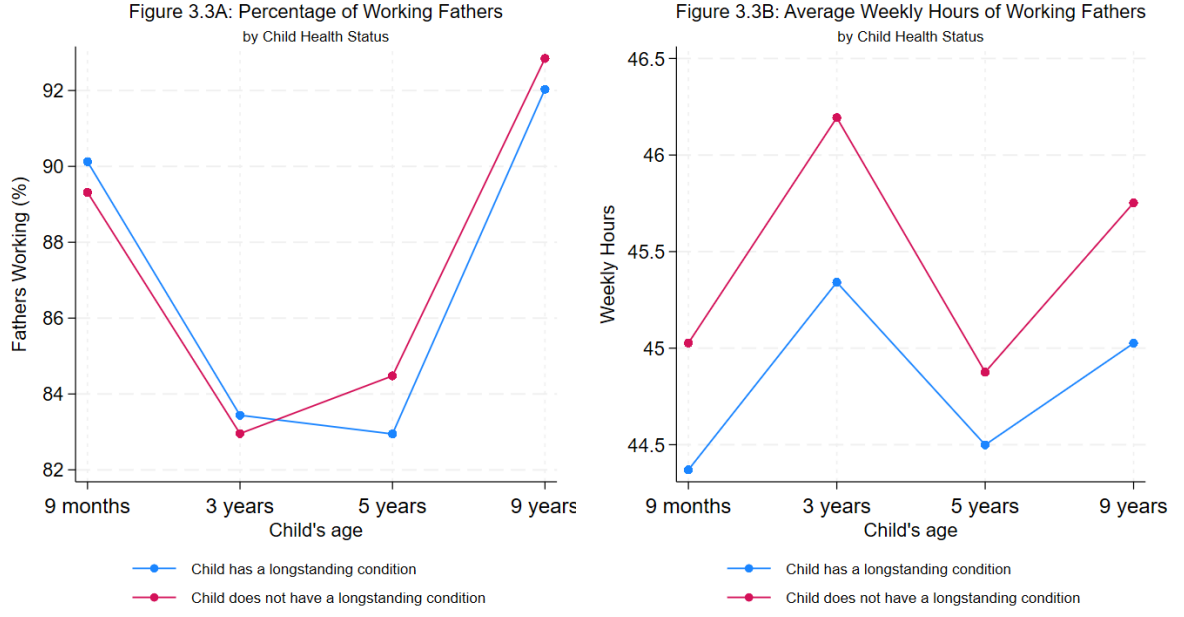
Figure 3.2 shows the same statistics but for single mothers. Compared to Figure 3.1, the single mother's sample has a much lower probability of working in Wave 1 (age 9 months) and 2 (age 3) compared to other mothers. Most likely, this is because the child is not yet of school-going age, and the lack of childcare provided by another parent in the household means most single mothers face greater opportunity costs of returning to work. From Wave 2 onwards, the probability of working increases for all single mothers, although single mothers of children without longstanding conditions increase more steeply, so their probability of working is higher in each wave. Figure 3.2B shows that amongst single mothers who work, those with children who have a longstanding condition work fewer hours on average in each wave, except Wave 3 (age 5) where they are roughly the same. These descriptive statistics are at least suggestive that being a mother to a child with a longstanding condition is a barrier to employment.

Figure 3.2: Single Mothers' Work Outcomes by Child Health Status



Lastly, Figure 3.3 shows the work outcomes of fathers given the health status of their child. Here we can see there is a much smaller gap in employment probabilities of fathers of children with and without a longstanding condition. The probability that a father works is much lower in Waves 2 and 3, but it returns to over 90% in Wave 5. There may be macroeconomic factors that reduced the employment rate of all fathers in our sample for this time period, as unemployment rose sharply in 2009 following the economic crisis that affected Ireland (Central Statistics Office, 2010). As we are using a longitudinal dataset in our study, we can control for the year of the survey that may affect the probability of employment in any particular year due to economic factors or policy changes. The average hours worked per week by fathers of children with and without longstanding health conditions also follow a similar pattern over the waves, however, the average work hours of the former group are lower in every wave. These descriptive statistics show that there are differences in work outcomes for mothers and fathers depending on the age and health status of their child. Further analysis allows us to study how much of this difference is due to the child's health, and how much may be due to other factors.

Figure 3.3: Fathers' Work Outcomes by Child Health Status



3.5 Empirical Approach

For the parent of child i in wave t , we estimated the following model of the probability of employment:

$$(3.1) P(E_{it} = 1|X, Z) = \beta_0 + \beta_1 X_{it} + \beta_2 Z_{it} + e_{it}$$

where $P(E_{it} = 1|X, Z)$ is the probability that the binary variable representing child i 's parent's employment at wave t equals one, X_{it} indicates whether the child i has a longstanding condition in wave t , and e_{it} is a random error term. The coefficient β_1 is our coefficient of primary interest and represents the estimated effect that the child's longstanding condition has on the probability of parental employment. The vector Z_{it} includes child-level characteristics: gender, health at birth (birthweight, NICU admission, premature birth), and the number of older and younger siblings; and parental characteristics: age, indicator variables for highest educational attainment (degree, upper-secondary), income quintile, area of residence (urban) and place of birth (Ireland or elsewhere).

We report OLS estimates of the Linear Probability Model (LPM) of equation (3.1) to allow comparison of our results with other studies. However, given the well-known shortcomings of LPM, such as heteroskedastic errors and predictions beyond the range of zero to one (Chatla and Shmueli, 2017), we also estimate probit models of the probability of employment. Furthermore, panel data allows us to control for time-invariant unobserved characteristics. Thus, we estimate a random-effects model by pooling data from four waves and modelling parental employment (E_{it}) as a function of child health (X_{it}), and child-level and parental-level characteristics.

The Random Effects model allows for time-invariant explanatory variables in Z_{it} . This is important if we are interested in the effects of variables such as gender, ethnicity, parental education, and immigration status, which do not vary over time. Thus, we estimated the model:

$$(3.2) \quad P(E_{it} = 1|X, Z) = G(\beta_0 + \beta_1 X_{it} + \beta_2 Z_{it} + \varepsilon_{it})$$

E_{it} is parental employment status of the parent of child i at time t , X_{it} is the explanatory variable (measure of child health), Z_{it} is a vector of exogenous control variables that affect parental employment. β_1 is the coefficient on our variable of interest; the child having a longstanding health condition, and β_2 is a vector of parameters estimated on the controls used in this study, $\varepsilon_{it} = a_i + u_{it}$ is a random error term composed of a time-invariant and time-variant component respectively that capture unobserved variables affecting parental employment. Time-invariant unobserved characteristics could be preferences for work, genetics, and time-variant unobserved characteristics could be local employment conditions that affect maternal employment. Throughout our study, we report the average marginal effects since the coefficients from a probit specification are not directly interpretable. **In all regressions, weights are included to adjust for unit non-response attrition.**

The estimates of the random effects model present the average of the effect between parents (comparing parents with a child who has a long-standing condition and parents with a child who does not have a longstanding condition) and within parents (the effect of a change in a child's longstanding condition status for a parent between waves). This model allows us to include families where the child has a longstanding condition in all waves used for analysis, and families where the child does not have a longstanding condition in any wave. In contrast, the fixed effects model estimates the effect of a change within waves and excludes observations where there is no variation between waves. Therefore, the random effects model more effectively answers the research question we are interested in: whether parents of children with a longstanding health condition are worse off than parents of children without a longstanding health condition.

When modelling hours worked, we estimated the Heckman Selection model. Hours worked is a truncated dependent variable because almost 36% of mothers in the sample do not report weekly hours worked because they are unemployed or out of the labour force. Therefore, OLS estimates of the effect of a child having a longstanding condition on hours worked could be biased and inconsistent because this specification can only capture the effect on hours worked for parents who are employed, and parents who are employed may be systematically different from mothers who do not work. The Heckman model can account for this type of omitted variable bias, known as sample-selection bias, by modelling employment and hours worked jointly (Heckman, 1979). This allows for correlation in unobservable factors that influence both. While using a standard Tobit model accounts for the probability of selection into employment, it generates one set of marginal effects, which would restrict coefficients on independent variables to be in the same direction for selection into employment and hours worked (Smith, 2011). For example, while the presence of a child with a longstanding condition in the household can negatively affect employment decisions, given that a mother is working, the presence of the longstanding condition can have a positive effect on her hours of work due to a greater need for income to support her child. The Heckman selection model is more appropriate for this estimation because it

allows for the selection into employment and the hours worked to be independent, conditional on observable data. That is, it would allow the coefficient effects to work in different directions.

The Heckman model is:

(3.3) $\Pr(E_{it}) = \varphi(Z_{it}\gamma + a_i + v_{it})$, $E_i = (0,1)$ where $E_{it} = 1$ if the parent is employed and zero otherwise.

(3.4) $H_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Z_{it} + b_i + \varepsilon_{it}$, observed only if $E_{it} = 1$

This model fits a random-effects linear regression model with endogenous sample selection using maximum likelihood estimation (White, 1994).

In the first-stage selection equation (Equation 3.3), we estimated a probit model for the probability that a parent is in employment. $\Pr(E_{it})$ is the probability of employment for parent of child i at time t . Z_{it} is a vector of explanatory variables and γ is the vector of coefficients for these variables. v_{it} is the random error term assumed to have a standard normal distribution, capturing unobserved factors that include the likelihood of employment.

The second stage models the hours of work H_i of parents, conditional on the parent being employed. H_{it} is continuous and only observed for those who are working. The explanatory variables are X_{it} , which is whether child i has a longstanding health condition at time t , and Z_{it} , which is a vector of covariates similar to the selection equation (number of older siblings, number of younger siblings, parents' age, education, health status, income quintile, area of residence, child gender and health at birth). β_1 and β_2 are the coefficients estimating the marginal effects of these covariates on hours worked. The error term ε_{it} captures unobserved factors that affect hours worked. v_{it} and ε_{it} are jointly normally distributed (Wooldridge, 2010) and correlated (so a random shock that makes a mother more likely to work in any particular wave will also increase her hours worked).

a_i and b_i are the individual-level random effects for the selection and outcome equations, respectively. They capture time-invariant unobserved characteristics of the parent and child that influence both employment and hours worked. These random effects are summed to follow a bivariate normal distribution.

An exclusion restriction is desirable in this model to generate plausible estimates so that identification is not solely reliant on functional form. Thus, it is desirable that there is at least one variable which appears with a non-zero coefficient in the selection equation but does not appear in the equation of interest (Puhani, 2000). Based on previous literature (Salkever, 1982; Wasi, Van Den Berg and Buchmueller, 2012), whether the parent is foreign-born enters the first-step probit equation in Z as an exclusion variable, as it affects employment but not hours of work, while maternal education, health, education, and age, and child health variables could enter both equations (Salkever, 1982). Being foreign-born may affect a parent's ability to obtain employment due to bureaucratic constraints on employment or a lack of connections within the local labour force. However, we assume being foreign-born does not affect how many hours they work, given that they are employed.

3.6 Results

LPM estimates are shown for Cohabiting mothers, single mothers, and fathers in columns 1,3, and 5 of Table 3.5. The estimated effect of a child's longstanding health condition on Cohabiting mothers was small and not statistically significant. However, the estimates show that single mothers of children with longstanding conditions are less likely to work relative to single mothers of children without conditions. More specifically, the presence of a child with a longstanding condition reduces the probability of working for single mothers by 4.9 percentage points. The magnitude of this coefficient is similar in size to that of previous studies such as Powers (2001), Wasi et al (2012), and Kvist et al. (2013). The estimates also show that fathers of children with longstanding conditions are more likely to work compared to other fathers.

We present the results of the probit **random effects** estimation in columns 2, 4, and 6 of Table 3.5. For ease of interpretation, the estimates from the probit model have all been converted to average marginal effects. These are calculated by predicting maternal employment twice for each observation, once with the child's longstanding condition variable set to zero and once with it set to one, then the difference between the two predictions is taken for each observation. The average marginal effect is the average of these differences across the sample. For binary independent variables, such as whether the mother has a degree, the average marginal effects present the estimated effect of a change in the variable's value from 0 to 1 on the dependent variable. For continuous independent variables, such as mother's age, the average marginal effects present the estimated effect of a one-unit increase in the variable's value on the dependent variable. When maternal employment is the dependent variable, the estimated average marginal effects are on the probability of being employed. These average marginal effects are similar in magnitude and statistical significance to the LPM estimates.

Table 3. 5. LPM and RE probit estimates (average marginal effects) on parental employment

	(1) Cohabiting Mother LPM	(2) Cohabiting Mother RE	(3) Single Mother LPM	(4) Single Mother RE	(5) Father LPM	(6) Father RE
Child has longstanding condition	-0.010	-0.011	-0.053**	-0.049**	0.016***	0.017***
	(0.007)	(0.007)	(0.022)	(0.021)	(0.005)	(0.006)
Log-Likelihood		-9465.38		-1168.98		-
						4184.49
Wald Chi ²		1822.16		356.50		1281.51
Panel ICC		0.69		0.49		0.49
Observations	20916	20916	2376	2376	18245	18245

Standard errors in parentheses. See Appendix Table 3.1 for the average marginal effects of other covariates: child gender, low birthweight, premature status, NICU admission, number of older and younger siblings, parental age, education, health, income quintile, area of residence, and whether they were born in Ireland.

* p < 0.10, ** p < 0.05, *** p < 0.01

We estimate the effect of the presence of a child with a longstanding condition on the likelihood that the mother works and find negative and insignificant effects for Cohabiting mothers. For single mothers, the negative effect is larger and statistically

significant, suggesting that single mothers of children with longstanding health conditions are 5.3pp less likely to work than single mothers of children without longstanding conditions. negative relationship between having a child with a longstanding condition and single mothers' employment. The effect on fathers' likelihood of working is positive and highly significant, suggesting that fathers are more likely to be employed if their child has a longstanding condition, although the effect is much smaller in magnitude than that of the mothers.

In Appendix Table 3.1, we present the estimated average marginal effects for the full set of covariates included in these regressions in order to put the magnitudes of the effects of the child's longstanding condition into perspective. The marginal effects for mothers' characteristics are generally significant and consistent with the literature. We find large, significant negative effects of poor self-reported parental health on the probability of being employed, particularly for Cohabiting mothers and fathers. For mothers, having both more children older than the study child and younger than the study child is negatively associated with maternal employment. However, for fathers, having more children, particularly younger ones, is slightly positively associated with employment. A higher education level and being born in Ireland have a strong positive effect on the probability of employment across all groups. In fact, the positive effects of having a degree or being born in Ireland cancel out the adverse effects of a child having a longstanding condition for single mothers. The size and direction of these significant effects of maternal characteristics are very similar to those of Frijters et al. (2009). Other characteristics of the child, such as low birth weight, NICU admission at birth, and pre-term birth, have no significant effect on employment across all groups.

Furthermore, Wald χ^2 statistics presented in Table 3.5 are highly significant, suggesting that this model jointly explains a significant amount of variation in employment probability for all three samples. The Panel ICC (intraclass correlation coefficients) show that a high amount of variation in the probability of employment is due to differences between children or parents (across panels).

Lastly, in Table 3.6, we present the estimates of Heckman selection models of the effect of a child with a longstanding condition on hours worked by the parent. In the upper panel of Table 3.6, we present the estimated effect on the hours worked per week. We do not find any evidence of a significant effect on mothers' hours worked. For Cohabiting mothers, the coefficient on hours worked, 0.154, is small and insignificant. This suggests that having a child with a longstanding condition does not significantly affect the working hours of Cohabiting mothers. For single mothers, the coefficient on hours worked is negative (-1.121 hours a week) but not statistically significant, meaning there is no evidence that single mothers reduce their working hours when a child has a longstanding condition. For fathers, we found a small, negative, albeit statistically significant effect on hours worked if the child has a longstanding condition. Fathers with children who have a longstanding condition work approximately half an hour less a week than fathers without. This finding may reflect increased caregiving responsibilities that reduce participation in work. In previous studies, Laff ers and Schmidpeter (2021) found that the effect of poor child development was a reduction in mothers' hours worked by 4-9 hours a week.

In the lower panel of Table 3.6, we present the selection equation for factors affecting the probability of employment. The coefficient for the variable "Parent born in Ireland" is positive and highly significant across all three groups, supporting its validity as an exclusion restriction since it affects employment probability. Appendix Table 3.2 presents the results of the Heckman selection model with the full set of controls for both equations.

Concerning selection bias and model fit, the results from our Heckman selection model in Table 3.6 show that the correlation between unobserved factors affecting employment and unobserved factors affecting hours worked is negative and statistically significant for the fathers and Cohabiting mothers sample, suggesting that selection bias is present. This means that unobservable factors affecting the employment of Cohabiting mothers and fathers are negatively correlated with factors influencing their hours worked, so parents who are more likely to be employed due to unobservable factors tend to work

fewer hours than expected based on observed characteristics alone. This reinforces the importance of using the Heckman correction model to adjust for selection bias.

Table 3. 6. Heckman model of hours worked with Random Effects

Hours worked conditional on being employed			
	(1) Cohabiting Mother Hours Worked	(2) Single Mothers Hours Worked	(3) Father Hours Worked
Child has a longstanding condition	0.154 (0.208)	-1.121 (0.726)	-0.495*** (0.179)
Probit model of selection into employment			
	Cohabiting Mother Employed	Single Mother Employed	Father Employed
Parent born in Ireland	0.679*** (0.064)	0.581*** (0.133)	0.619*** (0.137)
Child has longstanding condition	-0.045 (0.041)	-0.245** (0.102)	0.165*** (0.055)
var(ϵ_i) in hours worked equation	45.994*** (1.075)	63.867*** (5.828)	45.570*** (1.599)
correlation between error terms in selection equation and outcome equation: $\text{corr}(u_i, \epsilon_i)$	-0.056*** (0.021)	0.146 (0.127)	-0.161*** (0.018)
variance of hours worked: $\text{var}(H[i])$	62.055*** (1.877)	56.274*** (7.731)	49.926*** (1.616)
variance of probability of working: $\text{var}(E[i])$	2.706*** (0.130)	1.508*** (0.221)	1.367*** (0.128)
$\text{corr}(E[i], H[i])$	0.440*** (0.023)	0.503*** (0.114)	0.344*** (0.073)
Observations	20916	2376	18245
p value	0.000	0.000	0.000
Wald test	331.289	72.973	83.361

Standard errors in parentheses. Other covariates included in selection equation as in Table 3.5 All covariates in selection equation are included in outcome equation except for parent born in Ireland * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For single mothers, since this correlation is not significant, it appears that selection bias is not a major concern in the equation for hours worked. Furthermore, the p-value for the Wald test is <0.01 for all three groups, meaning that the null hypothesis that all the estimated selection parameters are jointly equal to zero is rejected. This shows that the covariates in this model have a statistically significant effect on both employment and

hours, confirming the overall significance and validity of the model. We also find that the correlation between the employment probability and hours worked of individuals is strong and positive for all groups, suggesting that individuals who are more likely to be employed also tend to work more hours. Since employment status and hours worked are linked in this way, there is a need to correct for employment bias using the Heckman model.

Lastly, we present the variances of hours worked and the probability of employment across individuals in each group. Strong positive variance suggests that there are differences in working hours and employment probability across individuals in each group, even after controlling for observable factors. A high variance suggests that individual differences (random effects) are important in explaining the outcome variable beyond the observed characteristics in our model, like education or age. This supports the use of a Random effects Heckman model because it captures this heterogeneity across individuals in each group.

3.7 Additional Analysis

In this section, we present additional analysis to check the robustness of our main results, including testing the marginal effects for specific subsamples, and utilising data from Wave 6 collected during the COVID pandemic, which was not included in our main sample. We also examine the use of other measures of child health as explanatory variables, such as the utilisation of medical services and the child having emotional or behavioural problems. This section also presents the results of a fixed-effects model. Finally, we conduct a robustness check to determine whether the child's health status affects the family structure of Cohabiting mothers.

3.7.1 Heterogeneity

To explore heterogeneity in the relationship between the presence of a longstanding health condition in the child and parental employment, we extend our probit random effects models to include interaction terms that capture the differential effects across certain subsamples. Table 3.7 presents these additional effects.

Table 3. 7. Marginal effects of interaction terms (probit random effects): parental employment

	(1) Cohabiting Mother Working	(2) Single Mother Working	(3) Father Working
Panel A:			
Child has longstanding condition (Full Medical Card==0)	0.000 (0.008)	0.030 (0.052)	0.023*** (0.007)
Child has full medical card	-0.098*** (0.008)	-0.176*** (0.023)	-0.075*** (0.005)
Longstanding Condition*Full Medical Card	-0.030** (0.015)	-0.080 (0.054)	-0.009 (0.011)
Main + additional effect	-0.030**	-0.050**	0.052
Panel B:			
Child has a longstanding condition (Female child)	-0.004 (0.011)	-0.072** (0.030)	0.015* (0.008)
Male Child	0.004 (0.009)	0.030 (0.023)	-0.001 (0.005)
Longstanding Condition*Male Child	-0.013 (0.015)	0.040 (0.043)	0.003 (0.011)
Main + additional effect	-0.017*	-0.032	0.017**
Panel C:			
Child has a longstanding illness	0.010 (0.013)	-0.033 (0.042)	0.006 (0.008)
Wave 2	0.004 (0.008)	-0.040* (0.024)	-0.064*** (0.006)
Wave 3	-0.000 (0.010)	-0.018 (0.029)	-0.055*** (0.007)
Wave 5	0.116*** (0.012)	0.203*** (0.031)	0.027*** (0.009)
Longstanding Condition*Wave2	-0.035*** (0.014)	-0.003 (0.041)	-0.005 (0.012)
Longstanding Condition*Wave3	-0.041*** (0.014)	-0.012 (0.037)	-0.000 (0.012)
Longstanding Condition*Wave5	-0.025** (0.012)	-0.095* (0.038)	-0.006 (0.008)
Panel D:			
Child has a longstanding condition (Present Grandparents)	-0.010 (0.007)	-0.043* (0.023)	0.016*** (0.006)
Absent Grandparents	-0.015 (0.014)	-0.089*** (0.034)	-0.021** (0.009)
Longstanding Condition*Absent Grandparents	-0.011 (0.028)	-0.066 (0.063)	0.008 (0.019)
Main + additional effect	-0.021	-0.109	0.019

Panel E:			
Child has a longstanding condition (Above Median Income)	-0.006 (0.009)	-0.062* (0.035)	0.026*** (0.008)
Household below Median Income	-0.160*** (0.008)	-0.270*** (0.021)	-0.139*** (0.005)
Longstanding Condition*Below Median	-0.001 (0.015)	0.034 (0.040)	-0.016 (0.011)
Main + additional effect	-0.007	-0.031	0.012
Observations	20916	2376	18245

Standard errors in parentheses. All regressions contain full set of controls, as in Table 3.5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Firstly, in Panel A of Table 3.7, we examine whether the effect of the child's longstanding condition differs by the child's full medical card status. In Ireland, the medical card scheme entitles certain people to free public health services such as GP services, public hospital services, and short-term counselling. If someone has a medical card, their child is added as a dependent on that card and can receive the same medical services. It sometimes also includes some non-medical benefits such as free school transport, a waiver of state exam fees in publicly funded second-level schools, and financial help with buying schoolbooks in certain schools. To qualify for a medical card, a person's weekly income must be below a certain amount for their family size. The qualifying limit was €266.50 for couples and single individuals with dependent children, with additional allowances based on the number of children under 16. (Citizens Information, 2025).

Panel A shows that among Cohabiting mothers, there is no significant effect of a child having a longstanding condition on employment for those that do not have a full medical card. However, among those with a medical card, Cohabiting mothers are 3pp less likely to work ($p < 0.05$). Similarly, for single mothers, there is no significant effect among those without a full medical card but those with a medical card are 5 pp less likely to work if their child has a longstanding health condition ($p < 0.05$). This suggests that for those with a full medical card, there may be a reduced financial incentive to work due to the child's health status, and we are observing the effect of additional childcare responsibilities on the likelihood of working. Fathers, on the other hand, are 2.3pp more likely to be

employed if the child does not have a medical card and has a longstanding health condition, while the effect is statistically insignificant for those with a full medical card.

Panel B explores the role of the child's gender. For single mothers, having a daughter with a longstanding health condition reduces their employment by 7.2pp ($p < 0.05$), but there is no significant effect if the child is a son. Cohabiting mothers are 1.7pp less likely to work when the child with a longstanding condition is a boy ($p < 0.10$) but we find no significant effect if the child is a girl. For fathers, the differences in effects due to child gender are small and statistically insignificant.

In Panel C, we interact child longstanding condition with survey wave indicators to test temporal variation in the effects. The coefficient on the interaction term suggests that for Cohabiting mothers, the negative impact of a child having a longstanding condition on employment probability becomes stronger over time. This could be due to increased caregiving responsibilities as the child is older, and complications from their health condition can develop. For fathers, the effects of child longstanding condition is not significantly different across waves.

In Panel D, we investigate the effect of having contact with grandparents. Grandparents can be an invaluable resource to parents in providing childcare. Therefore, we examine whether the relationship between child health status and parental employment differs depending on whether the family has contact with grandparents. For many families, having grandparents available for childcare can reduce the opportunity costs associated with employment. This may be especially important in families with a child who has a longstanding condition because childcare needs are high, but there is also a greater need for income. In the GUI dataset, only Waves 1 and 2 measure whether the grandparent babysits at all, and we find that approximately 82% of households have a grandparent who provides childcare. In all waves, it is reported whether the family is in contact with their grandparents, if they live abroad, or if they have passed away. Therefore, 'No contact' here means that the child's grandparents are living abroad, are deceased or are not in contact. Overall, approximately 10% of children have no contact with their grandparents. This

additional analysis helps us understand how mothers and fathers adjust their employment based on potential childcare availability.

In Table 3.7, Panel D, we find that single mothers with absent grandparents are 8.9pp less likely to work ($p < 0.01$), and fathers are 2.1pp less likely to work ($p < 0.05$). Fathers with present grandparents are 1.6pp more likely to work if their child has a longstanding health condition, while there is no effect if they have absent grandparents.

Lastly, the subsample analysis presented in Table 3.7, Panel E, investigates whether the effects vary by household income, using a binary indicator for below median income. In our sample, 34% of households are below the median income. For mothers, the child's health condition has no significant differential effect by income status. Fathers are more likely to work if they are above the median income and have a child with a longstanding health condition, but there is no significant effect on their employment if they are below the median income.

Table 3. 8. Marginal Effects (Probit RE): Employment Probability in Cohabiting Households (Other Parent Working)

	(1) Cohabiting Mother Working	(2) Father Working
Child has longstanding condition (Other parent is unemployed)	-0.019 (0.019)	0.004 (0.008)
Father working	-0.017* (0.010)	
Longstanding Condition*Father Working	0.010 (0.020)	
Mother working		-0.020*** (0.005)
Longstanding Condition*Mother Working		0.023** (0.011)
Main + additional effect	-0.009	0.025***
Observations	18245	18245

Standard errors in parentheses. All controls included in (as per Table 3.5).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table 3.8, we study how the employment decision of the other parent in the household can affect the probability of employment in two-parent households. We added

an additional covariate for the other parents' employment status, and its interaction with the child's longstanding health condition, in our random effects probit model. For Cohabiting mothers, having a working partner reduces their probability of employment by 1.7 pp ($p < 0.10$), although the interaction with child condition is insignificant. This suggests some substitution between partners' labour supply but not necessarily driven by the child's health condition.

For fathers, the presence of a working mother reduces their employment probability by 2 pp ($p < 0.01$). When the mother is employed and the child has a longstanding condition, fathers are 2.3 percentage points more likely to work ($p < 0.05$).

3.7.2 Ordered Probit

We estimated ordered probit models to analyse separately the probability of a parent being unemployed, in full-time work, or part-time work. This model can be used when the outcomes can be ordered in a qualitative sense (Chiburis and Lokshin, 2007). In Table 3.9, we present the average marginal effects from this model.

Table 3. 9. Average marginal effects (ordered probit model): Not working; Part-time; Full-time Work

	(1) Cohabiting Mother Not Working	(2) Cohabiting Mother PT	(3) Cohabiting Moth FT	(4) Single Mother Not Working	(5) Single Mother PT	(6) Single Mother FT	(7) Father Not Working	(8) Father PT	(9) Father FT
Child has a longstanding condition	0.009 (0.006)	0.001 (0.000)	-0.009 (0.006)	0.061*** (0.019)	- 0.017*** (0.006)	-0.043*** (0.014)	-0.011** (0.004)	-0.002** (0.001)	0.013** (0.005)
Observations	20916	20916	20916	2376	2376	2376	18245	18245	18245

Standard errors in parentheses

In all regressions we include controls for parents, child and household characteristics as per Table 3.5.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The estimates of these models show that having a child with a health condition does not significantly impact a Cohabiting mothers' employment decisions. For single mothers, having a child with a longstanding condition significantly increases their probability of unemployment by just over 6%. It also significantly decreases their probability of part-time and full-time work, particularly the latter. For fathers, having a child with a longstanding condition decreases their probability of being unemployed, decreases their probability of being in part-time work and increases their probability of being in full-time work.

3.7.3 Measures of Child Health

In Table 3.10, we estimate the probit random effects model with two alternative measures of child wellbeing instead of the presence of a longstanding condition in a child: the number of medical visits they have had in the last year, and their score from the Strengths and Difficulties Questionnaire (SDQ).

Table 3. 10. Alternate child wellbeing measures (Random effects): Parental employment

	(1) Cohabiti ng Mother Working	(2) Single Mothers Working	(3) Father Working
Panel A:			
Total number of medical visits in the last year	-0.003 (0.002)	-0.003*** (0.001)	0.001** (0.000)
Observations	20916	2376	18245
Panel B:			
Child has a high SDQ score (>16)	0.013** (0.007)	0.005 (0.021)	0.001 (0.005)
Observations	15687	1786	13683

Standard errors in parentheses. Panel B shows the average marginal effects.

* p < 0.10, ** p < 0.05, *** p < 0.01

In all regressions we include controls for parents, child and household characteristics as per Table 3.5.

The total number of medical visits the child has had in the last year includes GP visits, paediatrician visits, nurse visits, and emergency visits. In our sample, 92% of children have had at least one medical visit in the first wave, 87% in the second wave, 78% in the

third wave, 64% in the fourth wave. The average number of visits is 3 for children without longstanding conditions, and 6.5 for those with longstanding conditions.

In Table 3.10, Panel A, we find that the effect of an additional medical visit in the last year is insignificant for Cohabiting mothers but significant for both single mothers and fathers, albeit with a small effect. However, for each additional medical visit, the probability of employment is reduced by 0.3 per cent for Cohabiting mothers. This helps us understand how the use of medical care is a mechanism by which having a child with a longstanding condition can affect parental work outcomes. Parents of children who have frequent medical visits might need to take more time off work, and this can affect their ability to stay in employment if it is disruptive.

We are also interested in the effect of emotional and behavioural issues on their parents' work outcomes. In the GUI study, emotional and behavioural problems are measured by the Strengths and Difficulties Questionnaire, which is filled in by the mother. SDQ is reported in Waves 2, 3 and 5 only at ages 3, 5 and 9, respectively. Therefore, we only include Waves 2, 3 and 5 in this additional analysis. The SDQ contains 25 items concerning the child's behavioural and emotional symptoms (e.g. 'often has temper tantrums', 'often unhappy, depressed or tearful'). Each item is rated as either not true (0), somewhat true (1), or certainly true (2). These ratings can be used to form a total difficulties score. A total difficulties score of 17-40 is high and "there is a substantial risk of clinically significant problems" (Goodman and Goodman, 2009). We use a binary variable indicating whether the child has a "high SDQ score" (i.e., a score greater than 16) as our explanatory variable (child EBPs) in all our regressions. Findings from the final sample that we used show that 35.13%, 34.48%, and 38.2% of children have a high SDQ score at ages 3, 5, and 9, respectively.

If a child has emotional or behavioural problems (EBPs), childcare needs are greater as there is increased dependence for medical advocacy, medication, therapy sessions, and/or additional help with schoolwork (Beagan et al., 2008). There is also very limited substitution available for childcare that can manage children with EBPs, which further

increases the opportunity cost of working. The World Health Organization (2003) reports that the burden of providing care for a child with mental health issues is almost entirely on parents, as opposed to healthcare services and respite care. Therefore, it is important to look at EBPs in conjunction with other health issues.

In Table 3.10, Panel B, we present the average marginal effects of the estimated effect of a high SDQ score on the probability of employment, finding a small but statistically significant positive effect for Cohabiting mothers (1.3 percentage points, $p < 0.01$). There is no effect on the probability of working for single mothers and fathers if the child has a high SDQ score.

3.7.4 Wave 6 Analysis

As we previously elaborated on in Section 3.4, we did not include the data from Wave 6 in our main analysis since the main variables used in our study are reported differently from other waves. Particularly, parents are asked whether they worked before the COVID pandemic started and how many hours they worked prior to the outbreak, rather than their current employment outcomes, while all other independent variables needed are reported at the time of the survey. However, this wave has information on remote working and vulnerability to COVID-19 that we use to conduct additional analysis. This wave contains 5,320 usable responses. Amongst these, 3,400 observations are present in all six waves.

In Table 3.11, we first present the results from replicating our main analysis (see Table 3.5) when including Wave 6 in our sample. Our results show that having a child with a longstanding condition significantly increases the probability of a father working by 2.1 percentage points. We also find that it reduces the probability of single mothers' employment, but this result is not significant in this sample. The negative effect on Cohabiting mothers is small and significant at the 10% level.

Table 3. 11. LPM and RE probit estimates (average marginal effects) on parental employment (inclusion of Wave 6)

	(1)	(2)	(3)	(4)	(5)	(6)
	Cohabiting	Cohabiting	Single	Single	Father	Father
	Mother	Mother	Mother	Mother	Working	Working
	Working	Working	Working	Working	LPM	RE
	LPM	RE	LPM	RE		
Child has a longstanding condition	-0.013*	-0.014*	-0.026	-0.021	0.018***	0.021***
	(0.008)	(0.008)	(0.027)	(0.027)	(0.006)	(0.006)
Observations	17042	17042	1543	1543	14775	14775

Standard errors in parentheses

In all models, we included controls for parent, child, and household characteristics as per Table 3.5.

* p < 0.10, ** p < 0.05, *** p < 0.01

In Table 3.12, we show the results of the Heckman selection model using this sample of all six waves. We find that the effect on hours worked is negative and significant, as it was in the main results, for the fathers sample. We find no significant effect on the hours worked by Cohabiting mothers. For single mothers, the estimated effect is negative and similar in magnitude to our main results found in Table 3.6, and it is also not statistically significant. For the sake of brevity, we omitted the control variables from the table; however, these variables were included in the model.

By analysing the Wave 6 sample on its own, we can study the additional effects of the study child being at an increased risk of COVID-19 infection and remote working on the effect of the child's longstanding condition on employment probability. Table 3.13 shows the effect of a child having a longstanding condition on the parents' probability of entering remote work or increasing remote work hours in the Wave 6 sample. We find that having a child with a longstanding condition significantly increased the probability of fathers either entering remote work or increasing remote work hours by 4 percentage points. However, we find that the effect of a child's longstanding health condition on the probability that Cohabiting or single mothers work remotely is statistically insignificant. This means that fathers of children with longstanding conditions were more likely to engage in remote work during the COVID pandemic than fathers of children without longstanding conditions. This could be because the opportunity to work from home would allow for flexibility and support with their child's care.

Table 3. 12. Heckman selection model estimates (inclusion of Wave 6)

	(1) Cohabiting Mother Hours Worked	(2) Single Mothers Hours Worked	(3) Father Hours Worked
Child has a longstanding condition	-0.036 (0.221)	-1.343 (0.879)	-0.382** (0.195)
var(ϵ_i) in hours worked equation	45.383*** (1.147)	62.835*** (6.236)	42.651*** (1.089)
correlation between error terms in selection equation and outcome equation: $\text{corr}(u_i, \epsilon_i)$	-0.062*** (0.020)	0.008 (0.087)	-0.159*** (0.021)
variance of hours worked: $\text{var}(H[i])$	61.218*** (2.002)	56.929*** (8.242)	49.869*** (1.561)
variance of probability of working: $\text{var}(E[i])$	2.752*** (0.149)	1.576*** (0.297)	1.364*** (0.124)
$\text{corr}(E[i], H[i])$	0.423*** (0.026)	0.474*** (0.114)	0.359*** (0.034)
Observations	17042	1543	14775
Wald test	241.250	69.091	94.653

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In all models, we included controls for parent, child, and household characteristics as per Table 3.5.

Table 3. 13. Average marginal effects on Remote Working during Wave 6 (probit RE)

	(1) Cohabiting Mother Working	(2) Single Mother Working	(3) Father Working
Child has longstanding condition	-0.035 (0.036)	0.014 (0.016)	0.040** (0.017)
Observations	484	3984	3440

Standard errors in parentheses

In all regressions the dependent variable is switch to remote work or increase in remote work hours.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Wave 6 Only. Models include controls as per Table 3.5 (measured at Wave 6).

In Table 3.14, we present the results on the effect of a child having a longstanding condition on the probability of parental employment, including controls for and interactions with whether the child is also at risk of COVID-19 infection. The results show that having a child with a longstanding illness who is not at risk of COVID-19 does not have a

statistically significant effect on parental employment. The standalone effect of a child being at increased risk of COVID-19 is negligible for Cohabiting mothers and fathers, but positive (8.7 percentage points) for single mothers, although not statistically significant. The interaction between longstanding illness and COVID-19 risk is significant and negative (-21 percentage points, $p < 0.10$) for single mothers, however, the joint effect is not significant. Therefore, we do not have sufficient evidence to conclude that single mothers are particularly vulnerable to employment disruptions when their child has both a longstanding condition and is vulnerable to COVID-19. Similarly, the interaction terms for Cohabiting mothers and fathers are small and negative (-1.9 and -1.8 percentage points, respectively) but not statistically significant, suggesting that there is no difference in employment effects based on COVID-19 risk.

Table 3. 14. Average marginal effect of parental employment (probit RE): the role of COVID-19 vulnerability

	(1) Cohabiting Mother Working	(2) Single Mother Working	(3) Father Working
Child has longstanding condition	-0.019 (0.013)	0.045 (0.037)	-0.007 (0.008)
Increased Risk of Covid	-0.005 (0.039)	0.087 (0.107)	-0.005 (0.023)
Longstanding Condition* Increased Risk of Covid	-0.019 (0.048)	-0.210* (0.124)	-0.018 (0.027)
Main + additional effect	-0.038	-0.165	-0.025
Observations	3984	484	3440

Wave 6 Only.

Standard errors in parentheses

Controls as per Table 3.5 (measured at Wave 6)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.7.5 Fixed Effects Model

In this section, we present the results of including child-fixed effects in a linear probability model of parental employment, as well as the Heckman Fixed Effects model, to estimate the effect on hours worked. Using OLS, we estimated the following LPM model:

$$(3.5) \quad P(E_{it} = 1|X, Z) = \beta_0 + \beta_1 X_{it} + \beta_2 Z_{it} + \alpha_i + e_{it}$$

Where $P(E_{it} = 1|X, Z)$ is the probability that the binary variable representing parent of child i 's employment at wave t equals one, X_{it} indicates whether the child i has a longstanding condition in wave t , e_{it} is a random error term, and α_i is the individual fixed effect (the time invariant characteristics of the child and their parent, such as unobserved ability, talent, or labour market preferences). The coefficient β_{it} is our parameter of primary interest and represents the effect of child health on the probability of parental employment. The vector Z_{it} includes time-variant child-level characteristics, such as the number of older and younger siblings, and parental characteristics, such as age, age squared, and indicator variables for the highest educational attainment (degree, upper-secondary) and parental health.

While the estimates of the random effects model present the average of the effect between mothers and within mothers (the effect of a change in a child's longstanding condition status for a mother between waves), the fixed effects model presents the within regression. That is, we are looking at the time-variant variation in the same parents across different waves. A fixed effects model removes time-invariant unobserved effects by differencing them out or using a within transformation. A fixed effects model can help address concerns of omitted variables bias due to these unobserved individual differences, if these factors correlate with the independent variables (e.g. education, health condition status).

Table 3. 15. Probability of employment (with child fixed effects):

	(1)	(2)	(3)
	Cohabiting	Single	Father
	Mother	Mother	Working
	Working	Working	
Child has longstanding condition	0.002	-0.026	0.019***
	(0.008)	(0.029)	(0.007)
R squared	0.065	0.142	0.057
Observations	20916	2376	18245

Standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

The results from this model, in Table 3.15, show that the coefficient on a child having a longstanding illness is close to zero and statistically insignificant for Cohabiting mothers. The coefficient on a child having a longstanding illness is negative but not statistically significant for single mothers. For fathers, the coefficient is positive and significant, suggesting that fathers with a child who has a longstanding condition are more likely to be employed. This is similar to the results we found in our Linear Probability Model and RE in Table 4.6. However, it is important to note that these estimates represent the effects of a change in child health status across time for the same mother. The effects on work outcomes for parents are likely to persist over time, even if the child's health improves, depending on the elasticity of labour supply, which may explain why we find no significant effect for single mothers in Table 3.15.

Next, we will present the results of a fixed effects model to study the relationship between children's longstanding conditions and their parents' hours worked per week. The Heckman fixed effects model, using Stata, utilises panel data with selection and endogenous variables as proposed by Wooldridge (1995) and Semykina and Wooldridge (2010). This is a correlation random effects model that retains time-invariant variables by including their individual-level means (across all waves) in the model. The Mundlak transformation (Mundlak, 1978) adds group-level means of the time-varying variables as additional regressors in the model to control for correlation between individual-specific effects and the explanatory variables. This model also consists of two equations: the selection equation

(probit model for panel data) and the outcome equation (a fixed effects model with a correction term).

(3.6) $\Pr(E_{it}) = \varphi(Z_{it}\gamma + v_{it} + u_i)$, $E_i = (0,1)$ where $E_{it} = 1$ if the parent is employed and zero otherwise.

(3.7) $H_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Z_{it} + \mu_i + \varepsilon_{it}$, observed only if $E_{it} = 1$

where u_i and μ_i are the individual fixed effects and are assumed to be correlated with the regressors.

The results are presented in Table 3.16. We find that there is a small, negative, and insignificant effect on the father's hours worked per week. The effect on hours worked by Cohabiting mothers and single mothers is also negative and insignificant when using a fixed-effect Heckman Selection model.

Table 3. 16. Heckman Model on hours worked (with fixed effects)

	(1) Cohabiting Mother Hours Worked	(2) Single Mother Hours Worked	(3) Father Hours Worked
Child has longstanding condition	-0.010 (0.316)	-1.218 (0.875)	-0.075 (0.283)
Number of older siblings	0.081 (0.260)	-0.406 (1.111)	0.213 (0.161)
Number of younger siblings	-0.664** (0.277)	-2.290** (1.149)	0.008 (0.169)
Parent's age	0.556 (0.386)	2.162** (0.968)	1.003*** (0.280)
Parent's Age Squared	-0.003 (0.005)	-0.039*** (0.014)	-0.008*** (0.003)
Parent has degree	1.202*** (0.457)	2.413 (2.427)	0.066 (0.419)
Parent completed upper secondary school	-1.138 (1.334)	-0.796 (3.057)	-0.800 (0.655)
Parent's current health (Omitted: Excellent)			
Very Good	0.226 (0.247)	-0.402 (1.164)	0.498*** (0.182)
Good	0.487* (0.252)	-0.150 (1.236)	0.720*** (0.261)
Fair	0.400 (0.589)	2.848 (2.105)	1.838*** (0.457)

Poor	-0.096 (1.501)	3.489 (4.126)	-1.453 (2.060)
Urban Region	-0.106 (0.129)	0.209 (0.725)	-0.395*** (0.123)
Income Quintile (Omitted: Lowest)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
2nd	0.719 (0.551)	1.291 (1.228)	-0.701 (0.557)
3rd	0.969* (0.568)	3.327** (1.455)	-2.123** (0.640)
4th	1.036 (0.722)	8.084*** (1.805)	-2.281*** (0.660)
Highest	1.857** (0.815)	10.005*** (1.874)	-2.262*** (0.713)
Wave 2	0.498 (0.633)	2.776 (2.808)	1.159** (0.572)
Wave 3	0.376 (0.901)	3.486 (3.668)	-0.281 (0.923)
Wave 4	-0.364 (1.352)	8.443* (4.338)	-1.023 (1.333)
Observations	20916	2376	18245

Bootstrap standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Selection equation estimates and estimates for group-level means omitted for brevity

3.7.6 Family Structure

In Table 3.17, we present a robustness check to estimate whether the child's health has an effect on the father's departure from the household. This is because our main analysis is estimating the effect of a child's longstanding health condition on parental employment for subsamples of mothers who are single and Cohabiting. This helps us compare our estimates to those observed in previous literature on the effects of child health on maternal employment (Wolfe and Hill, 1995; Powers, 2003; Gould, 2004). However, there is literature on the negative effects of child illness/health on the parents' relationship (Mauldon, 1992; Reichman, Corman and Noonan, 2004; Wei and Yu, 2012), finding that separation may be more likely in families of children with an illness/disability. We conduct this robustness check to test if this is the case for our sample. As previously mentioned, our sample includes households where the primary caregiver is the mother (99.8% of cases). We further restrict the sample to mothers who were partnered with the child's father and

living together at Wave 1. A small number of families where the partner departed multiple times are excluded. To measure paternal departure, we use information on the mother's partnership status and the father's presence in the household at wave t and wave $t-1$. Therefore, if the mother is partnered with the father at wave $t-1$ but not partnered at time t , and the father has departed the household at time t , this is observed as a permanent departure of the father from the household. In the first column, we use child fixed effects to control for time-invariant unobserved differences in families. In the second column, we present the average marginal effects from a probit random effects model. In the sample used for analysis, 10% of families experienced parental departure between Wave 1 and Wave 5. We find no significant effect of a child's longstanding condition on the father's departure from the household.

Table 3. 17. Child longstanding condition: Father departure

	(1)	(2)
	LPM FE	Probit RE
Child has a longstanding illness	0.003 (0.004)	0.003 (0.003)
Observations	21123	21123

Standard errors in parentheses

In all regressions, the dependent variable is Father departure from household. Full set of controls include maternal education, age, health, area of residence, nationality and household income

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.8 Discussion

In our study, we estimated the effect that children's longstanding conditions have on parental employment. For instance, parents of children with health conditions might face greater childcare demands and may stay at home to meet them. Conversely, they might enter the workforce or increase their working hours to afford expensive care. We examined which of these two responses dominates empirically. We were also interested in studying whether mothers respond differently to fathers and whether single mothers are affected differently as the household head/ breadwinner. We also study the effect on parental hours of work, conditional on employment.

To examine this, we analysed data from four waves of the Growing up in Ireland (GUI) study, which includes information on child and parental characteristics. Similar to other studies in this area (Powers, 2001, 2003), we found that having a child with longstanding conditions has significant negative effects on the probability of single mothers working. We found no effect for mothers with partners. This might be because Cohabiting mothers have more support with childcare from their partner and do not need to adjust their work behaviour.

We found significant positive effects of 1.75 percentage points on the probability of fathers being employed if they have a child with a longstanding condition. This result contrasts with other recent studies, which have shown no effect on fathers (Eriksen et al., 2021; Laff rs and Schmidpeter, 2021). This may be because of the high cost of health and childcare for Irish parents compared to parents in Australia and Denmark. Expensive care for children with long-term conditions may incentivise fathers to enter the workforce if they are unemployed. Unlike previous studies, we also found small but significant negative effects on the hours worked by fathers who remain in employment. This suggests that even if fathers stay employed, they reduce their working hours if they have a child with a longstanding condition.

Additional analysis in this chapter explores the role of various factors in the relationship between child health and parental employment. We find that Cohabiting mothers and single mothers with a full medical card have a lower likelihood of employment if their child has a longstanding health condition (3 and 5 percentage points, $p < 0.01$), while the effects for those without a medical card are not significant. Fathers of children with a longstanding health condition, on the other hand, are more likely to work (2.3 percentage points, $p < 0.01$) if they do not have a full medical card. We also find some differences by the gender of the child; if the child has a longstanding health condition, single mothers are less likely to work if the child is female (7.2 percentage points, $p < 0.01$), but we find no significant effect if the child is male. While we found no overall effect for Cohabiting mothers, we find significant adverse effects on their probability of working in

Waves 2,3, and 4 (1.5 to 3.1 percentage points). Lastly, we find that fathers also have a significant positive effect if they are above median income (2.6 percentage points, $p<0.01$) but no significant effect if they are below median income, a significant positive effect if their partner is also working (2.5 percentage points, $p<0.001$), but no significant effect if their parent is not working.

We employ an ordered probit model to estimate the effect of a child having a longstanding health condition on the probability of unemployment, part-time work, and full-time work; single mothers are more likely to be unemployed (6.1 percentage points, $p<0.01$) but less likely to be in part time work or full time work (1.7 and 4.3 percentage points, $p<0.01$). Fathers are less likely to be unemployed and less likely to be in part-time work (1.1 and 0.2 percentage points, $p<0.05$), but more likely to be in full-time work (1.3 percentage points, $p<0.05$).

While Gould (2004) also found similar negative and insignificant effects on married mothers, once they categorise illnesses by time-intensity, expense and severity/unpredictability, they found that the coefficient for severe/unpredictable conditions has a large, negative and significant effect on work hours and employment. In future research, we would like to categorise different conditions and tease out the differences in their effects. For example, our study cannot distinguish between conditions like ADHD and Down Syndrome because we do not have information on which specific health condition the child has. We would need information on specific conditions, as they may each have different care and expense needs, and different levels of support available in Ireland. For this purpose, it would be necessary to access the Secure Anonymised Files for the Growing Up in Ireland Surveys, which may have information on specific diagnoses through linkage with hospital administrative data.

We do attempt to make a distinction between the type and level of care that a child may need by using alternate measures of poor health; the number of medical visits, and the SDQ score (a measure of emotional and behavioural problems in children). More medical visits significantly reduce employment probabilities for Cohabiting mothers but have no

effect on fathers. Emotional and behavioural problems, measured through the Strengths and Difficulties Questionnaire (SDQ), have a significant but small positive effect on the probability of employment of Cohabiting mothers only. These findings encourage further research into how different aspects of child health can influence parental work outcomes.

While the Republic of Ireland has a relatively strong social welfare system, the findings of our study suggest that targeted policies could, nonetheless, help parents who have children with longstanding conditions, particularly single mothers. Currently, Ireland has the Working Family Payment (WFP) for low-income working families, and the Carer's Allowance, mainly for parents who do not work to care for a disabled child. Working parents of children with longstanding conditions could benefit from an additional allowance that is based on an assessment of the child's care needs, additional medical care and takes into account the loss of income parents who care for children with health conditions face compared to parents of healthy children.

Another policy recommendation would be to prioritise access to childcare for single mothers who have children with longstanding illnesses as part of the National Childcare Scheme (NCS), and also to provide more suitable childcare options for children with additional needs. Improvements in income supports, childcare access and affordability, and work flexibility can help address the complicated challenges parents face when supporting a child with additional needs and health concerns.

Chapter 4: Parental Health and Child Educational Outcomes: Evidence from the Millennium Cohort Study (MCS)

4.1 Introduction

Parental health can influence children's educational achievements. Parents who have poor health may deprive their children of valuable non-monetary parental investments, such as help with homework or reading and involvement in school events, teacher meetings or other educationally beneficial activities (Platt, Williams and Ginsburg, 2016; Aaskoven, Kjær and Gyrd-Hansen, 2022). Parents who suffer from poor health may also struggle to provide emotional support and advice for their children, which can affect their motivation and concentration and lead to poor academic achievement. Additionally, children of parents with health issues may experience anxiety, stress, and caregiving burden (Umberson and Thomeer, 2020) which may affect their academic performance.

Educational attainment and enrolment are important indicators of child development and influence outcomes later in life, including employment, income, housing, offending, as well as physical health and ongoing mental health disorders (Hale and Viner, 2018). Therefore, the educational outcomes of children and the factors that influence them are of interest to policymakers. The link between parents' health and children's education has been a subject of increasing interest in recent years; the transfer of human capital from one generation to the next has significant implications for long-term social and economic disparities. While previous research has identified a range of socioeconomic and demographic factors that influence educational outcomes, including family income, parental education, gender, ethnicity and school quality, the impact of parents' health on children's education has received less attention. It is also unclear to what extent the association between parental health and child educational outcomes is indirect and a result of the

influence of these confounding factors. Therefore, it is important to account for these factors when studying this relationship.

In this chapter, we will explore the effect of having a parent with poor parental health on children’s GCSE outcomes using data from the Millennium Cohort Study (MCS) and National Pupil Database (NPD). We contribute to the literature by studying the effects of poor parental health in early childhood and poor parental health in mid-childhood separately. We also consider the effects of poor parental health on the child’s school absences as well as emotional and behavioural problems (EBPs) in adolescence. We include school-level fixed effects to control for unobserved factors, such as school quality and environment.

One of the limitations of this paper is that it does not sufficiently address the issue of endogeneity. While the Millennium Cohort Study (MCS) dataset is longitudinal in nature, the main outcome of interest, GCSE exam results, is only observed in Wave 7. Our empirical strategy, therefore, does not allow us to adjust for unobserved time-varying factors affecting educational outcomes and parental ill-health, such as the onset of domestic violence or parental substance abuse. Consequently, our models cannot establish causality, but the use of this rich dataset provides important insights into the relationship between parental health and child educational outcomes.

Overall, this research falls within the “linked lives” aspect of a life course approach, where parental health problems can reflect throughout the family, potentially affecting various child outcomes, including their education and emotional and behavioural well-being (Elder Jr., 1998; Carr, 2018). Childhood and adolescence, in particular, stand out as sensitive periods where poor parental health can have a significant or long-lasting impact during this time (Shonkoff et al., 2012; Umberson and Thomeer, 2020). Therefore, this research contributes to the understanding of the role of health in the intergenerational transmission of inequalities (Ahlburg, 1998; Houweling and Grünberger, 2024).

4.2 Literature Review

Most studies examining non-fatal parental health issues have focused on developing countries and on outcomes related to school enrolment and attendance (Sun and Yao, 2010; Bratti and Mendola, 2014; Alam, 2015; Dhanaraj, 2016; Woode, 2017; Dinku, Fielding and Genç, 2018; Mendolia, Nguyen and Yerokhin, 2019). This is because, depending on the setting, parental ill health can impact children’s ability to afford education and may even require them to contribute economically. The results from these studies find a negative association of poor parental health with child schooling, but cannot be generalised to developed countries with well-established public education systems and mandatory schooling laws.

Table 4.1 presents the existing evidence in this research area. One of the few studies focusing on developed countries, Aaskoven, Kjær, and Gyrd-Hansen (2022) examine how severe parental health shocks affect children’s school achievement using a longitudinal administrative dataset of Danish children born between 1987 and 2000. This study uses coarsened exact matching (CEM) to control for potential endogeneity between parental health and children’s school outcomes. Cancer-specific survival rates are used to measure the size of the parental health shock. Children affected by parental cancer are matched with non-affected children one year before the cancer diagnosis to ensure that outcomes are associated with the health shock and not by other characteristics of the child. The findings indicate that experiencing parental cancer lowers the child’s GPA in ninth grade by 0.6% of the average GPA and reduces the probability of finishing secondary school by 1.3%, but having a poor cancer prognosis on average reduces the child’s GPA by 1.6% and lowers the probability of secondary school completion by 3.7%. Therefore, these results suggest that the severity of the illness and the risk of death have a larger impact on educational outcomes. While statistically significant, these results are of smaller magnitude than those of developing countries. The study also finds that girls are more affected by these health shocks than boys. This is in line with the findings of most literature in this

area that shows that girls are more severely affected (Sun and Yao, 2010; Mendolia, Nguyen and Yerokhin, 2019) or that there is no gender difference (Alam, 2015).

Table 4. 1. Existing evidence on the effect of parental health on children's educational outcomes				
Paper	Data	Parental Health measure	Methods	Results
(Sun and Yao, 2010)	Chinese Longitudinal National Fixed-Point Survey	Self-reported illness in any adult household member	Fixed effects (village-level)	Primary students 9.9 p.p. less likely to enter middle school; no effect on graduating middle school
(Bratti and Mendola, 2014)	Longitudinal Living Standards Measurement Survey (Bosnia & Herzegovina)	Parental self-reported poor health	Fixed effects (child-level)	Maternal poor health reduces school enrolment by 7 p.p.; paternal health has no significant effect
(Alam, 2015)	Longitudinal Kagera Health and Development Survey (Tanzania)	Self-reported parental illness	Fixed effects (child-level)	Father's illness reduces attendance by 4.3 p.p. and schooling by 1.5 years; mother's illness has small positive effect (ages 7-15)
(Dhanaraj, 2016)	Longitudinal Young Lives Survey (India)	Self-reported serious parental illness	Fixed effects (community-level)	Parental health shock delays primary enrolment and reduces schooling by 0.26 years
(Dinku, Fielding and Genç, 2018)	Longitudinal Ethiopian Young Lives surveys	Self-reported serious parental illness	Fixed effects (child-level)	Reduces time in school by 9%; maternal illness has no effect.
(Joergensen, Kjaer Urhoj and Nybo Andersen, 2018)	Danish National Patient Registry	Parental cancer experience (before age 15)	General Linear Model & Multinomial logistic regression	Lower GPA in ninth grade and a higher risk of low attainment (RRR: 1.20; 95% CI 1.14 to 1.25)
(Mendolia, Nguyen and Yerokhin, 2019)	Longitudinal Vietnam Household Living Standards Survey	Self-reported parental illness	Fixed effects (child level)	Reduces enrolment by 2.5 p.p.; stronger maternal effect; girls face 5 p.p. decline. (between 11 and 23 years old)
(Kristiansen, 2021)	Danish administrative data	Parental health event; admission with acute cardiovascular disease or cancer	Quasi-experimental: compare children exposed just before vs. just after key outcomes.	Reduce test scores/enrolment; no effect if shock is more than 1 year apart from exams

(Aaskoven, Kjær and Gyrd-Hansen, 2022)	Longitudinal Danish administrative data	Parental cancer diagnosis and survival rates to measure the severity	Coarsened exact matching	Lowers child's GPA by 0.6% of average GPA, reduces the probability of starting and finishing secondary education by 0.6% and 1.3%, respectively.
(Ferrara et al., 2025)	German Socio-Economic Panel	Parental health shocks (hospitalisation, cancer, stroke, cardiac disease, depression)	Fixed effects (family and individual level)	No significant effect on being in employment, education, or training at ages 17-25, or socio-emotional skills

Results from Kristiansen (2021), on the other hand, indicate that the math scores of Danish boys are more sensitive. Aaskoven, Kjær and Gyrd-Hansen (2022) also find that children ages 13-15 at the time of diagnosis experience greater detriments in their GPA, suggesting that the timing of the shock relative to the outcomes appears to matter. Other studies have not been able to show a clear age gradient (Joergensen, Kjaer Urhoj and Nybo Andersen, 2018; Mendolia, Nguyen and Yerokhin, 2019). Possibly due to the strong Danish welfare system, this paper does not find any difference in effects due to parental education or family income. It is important to note that Denmark has high social and gender equality, a generous welfare system and a large public sector so the effects on educational outcomes found here represent the ‘best-case’ scenario. Furthermore, the results for cancer might not accurately represent all health shocks, as there could be a high level of awareness and resources for cancer, allowing children to benefit from a support system.

Kristiansen (2021) uses Danish administrative data for all children born between 1972 and 1998 and shows that parental hospitalisation with cancer and acute cardiovascular disease in childhood has immediate and long-term effects on the educational outcomes of children. By exploiting the randomness in the exact timing of a parental health event within a short period in a quasi-experimental design, this paper finds that experiencing a parent's hospitalisation with cancer or acute cardiovascular disease shortly before an exam decreases the child's test score significantly by 9.8% of a standard deviation. In addition, children who experience a parent's hospitalisation before the application deadline to

secondary schooling have reduced school enrolment rates one to five years after completing ninth grade. The reduced school enrolment rates result in an increased probability of having compulsory education as the highest level of completed education five years after ninth grade (the last year of compulsory education in Denmark). The results, however, also suggest that children are resilient, as experiencing a parental health event more than one year prior to the exam has no significant impact on their school grades. No clear evidence is found to suggest that the negative impact on test scores or school enrolment varies between families with different incomes or nuclear and divorced families.

Using data from Finland, Australia and Germany, previous findings on the effects of parental health on children's emotional and behavioural problems also appear to be small or non-existent, despite considering serious parental health shocks and various socio-emotional skills (Le and Nguyen, 2017; García-Miralles and Gensowski, 2023; Ferrara et al., 2025). There is also a body of literature that focuses on the effects of parental death on child education. This literature usually finds a negative effect (e.g. Case, Paxson and Ableidinger, 2004; Case and Ardington, 2006; Chen, Chen and Liu, 2009).

Most of the evidence suggests that a mother's death has a more severe impact on children than a father's death. For instance, Himaz (2013) uses the Young Lives Study data for Ethiopia and finds that the death of a mother during the child's middle childhood (8-12 years of age) was associated with reduced school enrolment, and with children doing more paid work by the age of 15 years. The death of a mother during the child's adolescence produced fewer observable impacts on education. In contrast, the death of a father was associated with reductions in enrolment, test scores, and sense of agency. Gimenez et al. (2013) use data from Taiwan and find that children's educational attainment is, on average, more affected by the death of a mother than the death of a father. Similarly, Evans and Miguel (2007), Case and Ardington (2006) and Chen, Chen and Liu (2009) find that maternal death has a much larger impact on child education than paternal death. Chen, Chen and Liu (2009) find that losing a parent (either a mother or a father, to all death types) induces a 1 percentage point decrease in college enrolment rates. When

distinguishing maternal from paternal death, this paper finds that losing a father has a very small and insignificant effect on children's college attainment, irrespective of the cause of death. In contrast, losing a mother has a drastic impact on college enrolment: the average enrolment rate decreases by 4.4 percentage points if the death is unforeseeable and by 2.1 percentage points for all deaths.

Case and Ardington (2009) use South African longitudinal data to examine the impact of paternal death on children's outcomes. After controlling for total expenditure per member and household assets, fathers' deaths have no significant association with children's schooling outcomes. In contrast, these results show a large and significant association between schooling outcomes and mothers' deaths. Maternal-only and double orphans are at a significant disadvantage concerning their schooling, with or without controls for household characteristics. Children who have lost their mothers complete a quarter of a year less schooling than other children their age, on average. They are two percentage points less likely to be enrolled in school and have fifteen to twenty per cent less education-related spending, relative to other children.

By focusing on parental poor health rather than death, we can see the effect caused by the stress and need for care from the child, rather than the effect of the absence of the parent. Non-fatal health concerns are also more common as medical advances have improved survival rates of illnesses (OECD Publishing, 2018) and as the average age of parents is older than it used to be (OECD Family Database, 2018). Therefore, this chapter focuses on parental poor health using subjective measures of health. We will look at how poor parental health affects child educational attainment using a nationally representative dataset that is able to account for a range of potentially explanatory factors. We will pay particular attention to the educational outcomes from the standardised GCSE level examinations at age 16. If poor parental health has a negative long-term impact on children, it is relevant for policymakers to know whether these effects differ across child, parent, and family-related characteristics. This helps identify children who are in high-risk groups and may benefit from additional support. We will consider factors such as family

income, the cohabiting status of the parents, the gender of the child, and the gender of the ill parent. We will also examine the extent to which poor parental health influences other factors such as child emotional and behavioural problems (EBPs), and school absences.

4.3 Institutional Context

4.3.1 Healthcare

Healthcare in England is provided through the National Health Service (NHS). This is funded primarily through taxation and provides universal coverage. Therefore, most medical treatment related to illness is free at the point of use, and access to healthcare does not depend on the ability to pay for it. The role of private insurance is limited in the UK. If a working individual is too ill to work, statutory sick pay (SSP) is provided by employers for up to 28 weeks. Employers can also offer enhanced sick pay if they have a sick pay scheme or an occupational scheme. SSP is paid at a fixed weekly rate of up to £118.75 per week. To be eligible, the employee must earn at least £125 per week and have been off work for more than three consecutive days. After SSP ends, they can apply for Employment and Support Allowance (ESA), which provides financial support based on health assessments and ability to work or keep a job. If an individual has a longstanding illness, condition, or disability, they may be eligible to apply for Personal Independence Payment (PIP) or Universal Credit.

Despite the availability of support, studies find that individuals with poor health exhibit significantly lower earnings (The Health Foundation, 2024) and that following a health shock, household income declines significantly and persistently in the UK (García-Gómez et al., 2013; Lenhart, 2019). Using data from the British Household Panel Survey (BHPS) and self-reported health measures, Lenhart (2019) finds that a health shock reduces annual labour income by an estimated £1181.40 for the year after the shock and total household income by £2,834. Additionally, they find that these effects are not only for those who become unemployed due to their health, but also for those individuals who remain employed. García-Gómez et al. (2013) suggest that the negative effects of health

shocks on labour market outcomes may exist because disability benefits create incentives not to work or work less. However, given that disability benefits in the UK are provided at a flat rate, there are few incentives for individuals to reduce their employment voluntarily compared to, for example, other countries where disability benefits are tied closely to previous income (van Doorslaer and Koolman, 2004).

4.3.2 School System

Compulsory education in England spans from Year 1 to Year 11, with a duty to remain in education or training until the age of 18, effective since 2015. Children usually start Year 1 in September following their fifth birthday and typically complete Year 11 in the academic year that they turn 16. During this time, students work towards their General Certificate of Secondary Education (GCSE) qualifications, for which examinations take place at the end of Year 11. After Year 11, young people must either stay in full-time education (sixth form or college), begin an apprenticeship or traineeship, or work or volunteer for at least 20 hours a week while continuing part-time education or training until the age of 18.

Depending on the type of course, sixth forms and colleges do have a minimum GCSE qualification requirement. To pursue an academic route for A-levels, students typically require a minimum of 5 GCSEs at grades 4-9, including Mathematics and English Language at grade 4 or above. Most universities also require GCSEs in these two subjects at a grade 4 or 5 minimum for entry, and more competitive courses and universities have higher requirements. Therefore, the results of the GCSE examinations are an indicator of the route that a young person takes to post-secondary education, and their eligibility to apply for higher education at universities (Babbini, 2024).

In England, children can attend publicly funded state schools free of charge during compulsory education from Year 1 to Year 11. While most families must pay for uniforms, school meals (means-tested) and extracurricular activities, there is no cost to core education at the primary and secondary levels at public schools.

4.3.3 Support Available to Children of Parents with Health Problems

In England, children under the age of 18 who help to look after a relative with an illness, disability, mental health condition, drug or alcohol problem are identified as young carers. This includes providing physical assistance or emotional support to a parent. If requested by the parent or child, or identified by the local authority, the Children and Families Act 2014 requires a local authority in England to organise a young carer's assessment to determine what support the family and child in its area may need (UK Public General Acts, 2014). This assessment may result in support with respite care, emotional support, or links to youth groups. Schools can also offer pastoral care, homework flexibility, counselling, or referrals to external support if they identify a student as a young carer. The level of support offered is dependent on the resources provided by schools and local authorities, as well as the proactive involvement of families and schools. Children under 16, however, are not eligible for Carer's Allowance or the carer element of Universal Credit, which provides financial support.

4.4 Data

This study examines the effect of parental health on the educational outcomes of English children using data from the UK Millennium Cohort Study (MCS). This is an ongoing longitudinal study that follows a cohort of children who were born in the UK between 2000 and 2002 (see Joshi and Fitzsimons, 2016). For this study, 19,244 children were recruited with an overall response rate of 71 per cent. The sample was obtained through a stratified cluster design, and is nationally representative of UK children, with survey weights provided to adjust for non-response and inter-wave attrition, and to enhance representativeness (Fitzsimons et al 2020). Families were first interviewed when the children were 9 months old and were followed up at ages 3, 5, 7, 11, 14, and 17. Families can be identified using the MCSID identifier, and a person number can also identify parents. At age 17, the sample size had declined to 10,625 children, mainly due to attrition. However, attrition in this study is not absorbing, and re-entry of participants is possible. In each

wave, the data is gathered in face-to-face interviews with the main parent (normally the mother), the resident partners of mothers, and, as the child grows older, with the cohort member and, where applicable, teachers. Responses from these surveys contain detailed information on the family, including parental education, employment and income, housing, family structure, ethnicity, parenting activities (such as reading to a child), developmental indicators (such as bedwetting), and parental relationship status. The initial survey contains information on items specific to infant development and birth such as birthweight, gestational age, and smoking during pregnancy.

4.4.1 Sample Selection

The sample used in this chapter is selected to meet the focus and methodological approach of our current study. The sampling process is fully detailed in Table 4.2. Firstly, families with twins and triplets are excluded, which is standard procedure, as different child developmental models are likely to apply (Babatunde et al., 2018). Secondly, we select families who are present in Waves 1-7. This is because we use valid responses on the parents' subjective health in Waves 1-6, and Wave 6 (age 14) is the age at which family and individual characteristics used as controls are measured. As we study the effect of parental health on child education outcomes, a primary consideration is the availability of GCSE results, which are collected at Wave 7 (at the age of 17). Therefore, we then select families who agreed to have their data linked to the National Pupil Database (NPD). Finally, we use the sample that has no missing responses on the control variables or other outcomes. The final study sample includes 3,694 children across all seven sweeps.

Table 4. 2. Sample selection from the MCS	
Families entered in MCS	19,243
Families with twins and triplets excluded	18,980
Families participating in Wave 6	10,483
Families participating Waves 1-6	11,293
Families participating at all sweeps from 1 to 6 and NPD linkage (for GCSE results) in Wave 7	4,845
Families with complete parental health data (wave 1 to 6)	4,801
Complete Cases (No missing responses on control variables and other outcomes)	3,694

4.4.2 Measures

4.4.2.1 GCSE Attainment

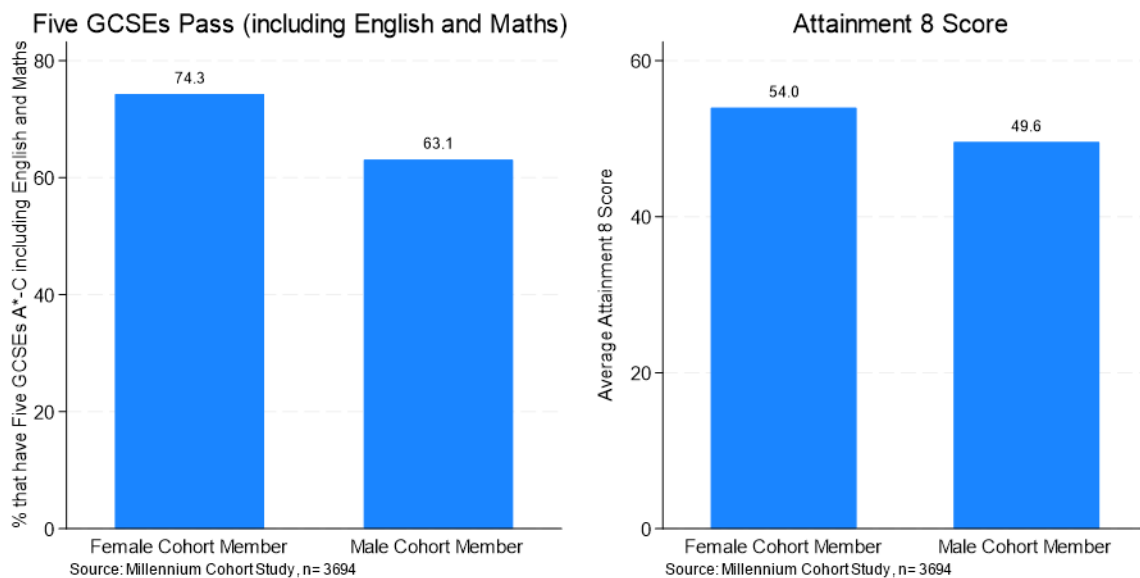
In Wave 7, at age 17, the MCS survey is linked with administrative data from the National Pupil Database, where respondents were asked to report the results of their GCSEs. The English national curriculum has a framework for five key stages of learning (Key Stages 1-5) that all state-funded schools must follow. The GCSE (General Certificate of Secondary Education) is a set of academic qualifications based on state examinations in a variety of subjects, typically taken at the age of 16 at the end of secondary school education (Key Stage 4). The GCSE is taken in state schools in England, Wales, and Northern Ireland. In Scotland, the Scottish Qualifications Certificate is used, with a different grading system. While the GCSE qualifications are taken in Wales, there are differences in the grading system and structure of some subjects (Meadows et al., 2023). Therefore, we focus our analysis on the GCSE results of children in England, and this does not include the Scottish cohort in the MCS, nor those who took alternative qualifications to the GCSE.

GCSE data were available for 8,200 respondents, or 77% of the Wave 7 cohort. In our final sample used for analysis ($N = 3694$), 50.97% of cohort members are female, and the other 49.03% are male. Typically, a student takes GCSEs in nine subjects, and there are nine possible grades from 1 to 9. While all children in the MCS study are the same cohort, they are born between September 2000 and January 2002; therefore, due to differences in when they started school, children in our study either took their GCSE examinations in 2017 or 2018. During these years, the GCSE grading system was transitioning from a letter grading system to a numeric one, and any letter grades (marked in subjects other than English and Mathematics) were therefore converted to numerical grades within the National Pupil Database. Due to the change in the grading system to the 9-1 grading system, overall GCSE results in 2018 were lower compared to 2017 for the subjects of English, English Literature, and Mathematics. This is because the new grading system made it more difficult to achieve top grades (9, 8 and 7) compared to the old system

(Ofqual, 2019). Therefore, we include fixed effects for the academic year in which GCSE examinations were taken in all models.

Overall achievement can be measured using the ‘Attainment 8’ score by adding up all the marks of eight GCSEs. This score is commonly used in research related to GCSEs and school performance, as it is a standardised measure of overall academic achievement across eight subjects (Wilkinson, Bryson, and Stokes, 2018; Department of Education, 2019; Hayes, 2019; Alterman et al., 2022; Easterbrook et al., 2022). The eight subjects that make up the Attainment 8 are English, Maths, three subjects that count towards English Baccalaureate (like sciences, language and history), and three more GCSE qualifications. Each subject grade is assigned a point score from 9 to 1, and these points are added up to calculate the Attainment 8 score, with English and Mathematics counted twice. The maximum attainable score is 90. The mean attainment 8 score in our sample is 49.37.

**Figure 1: Average GCSE Outcomes
by Gender of the Cohort Member**



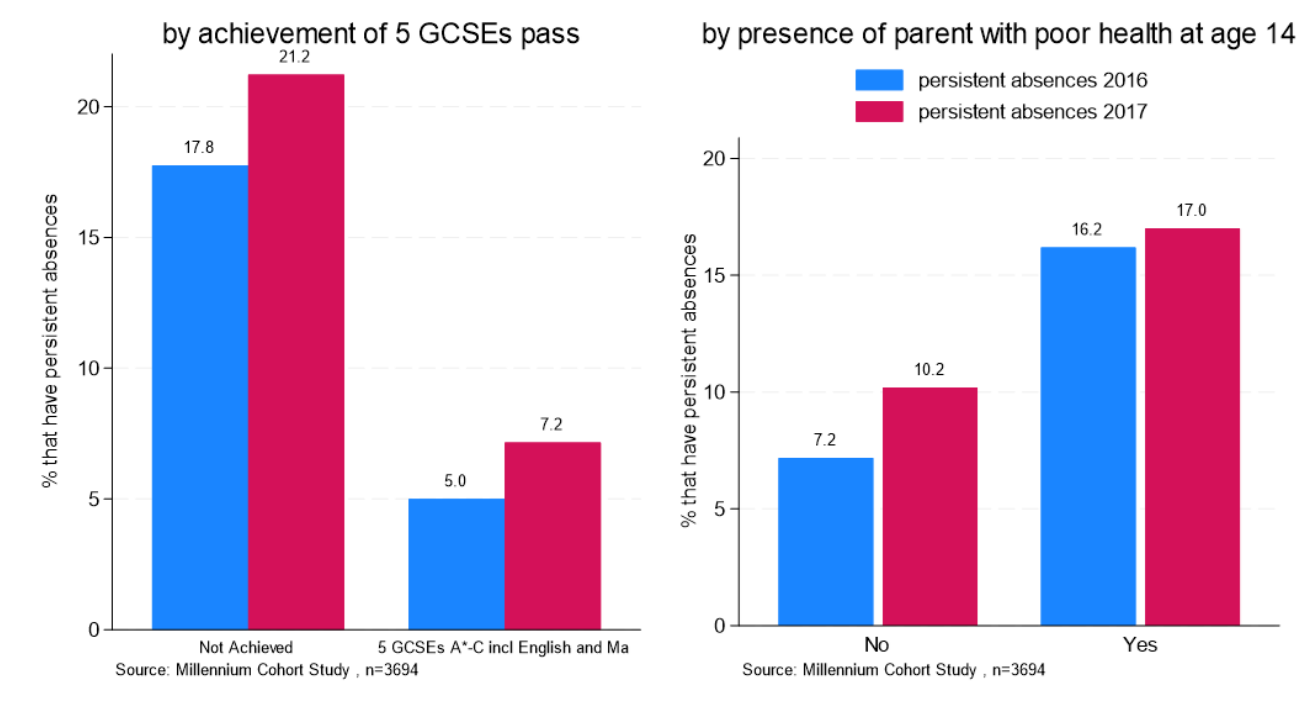
We can also evaluate achievement based on a binary measure for whether the child passed at least five GCSEs with marks greater than 5 (A*-C), including English and Mathematics. In our sample used for analysis, 68.7% of students achieved this outcome. In this chapter, we will refer to this outcome as “5 GCSEs A*-C” for brevity.

Figure 1 shows the average academic achievement by gender of the cohort members for our sample for analysis. This figure shows that female students, on average, perform better than male students.

4.4.2.2 Other Outcomes

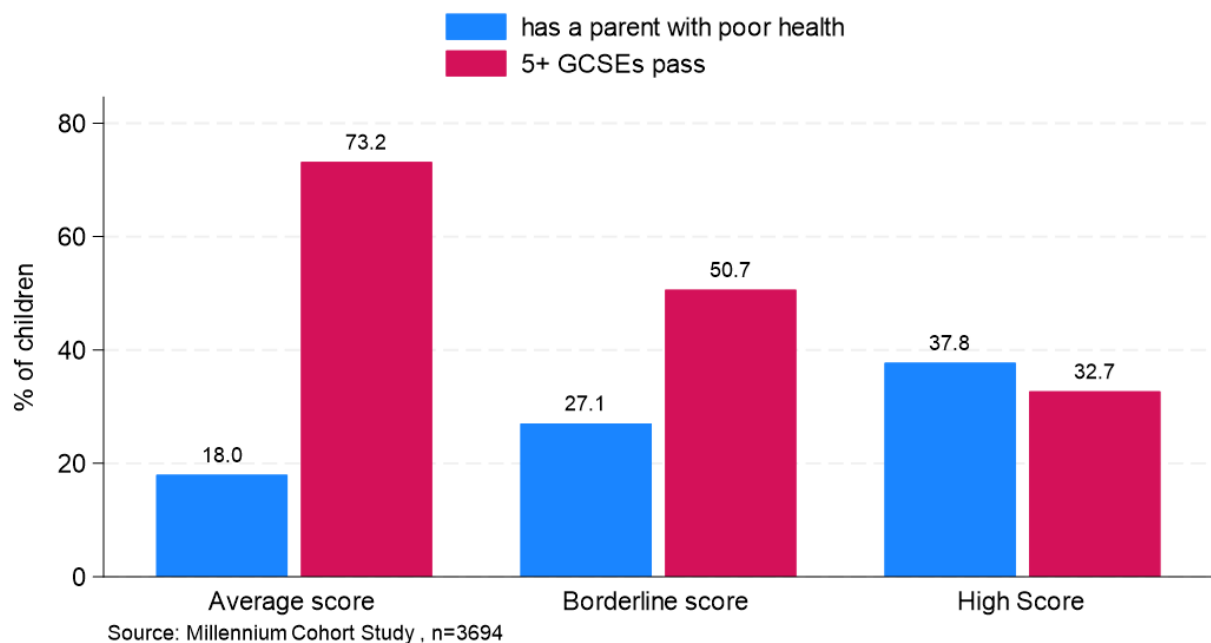
We have information on the school absences of cohort members in the 2015/2016 academic year and 2016/2017 academic year (children aged 14-16) from the National Pupil Database. We use this to create a binary variable that indicates that the child has persistent absences. The Department of Education defines persistent absences as missing 10% or more of school sessions over an academic year. As shown in Figure 2 on the right-hand side, cohort members who performed poorly in their GCSEs (did not achieve 5 GCSEs at A*-C, including English and Mathematics) are more likely to have had persistent absences in school between the ages of 14 and 16. The left-hand side of Figure 2 shows that cohort members who have at least one parent with poor health at age 14 are more likely to experience persistent absences in school between ages 14 and 16. We study the effect of having a parent with poor health on persistent school absences in children, as this may be a mechanism through which parental health affects academic achievement in children.

Figure 2: Persistent Absences



Lastly, we will study the effect of parental health on the child's emotional and behavioural problems (EBPs). We measure child EBPs at age 14 using the parental responses to the Strengths and Difficulties Questionnaire (SDQ) at Wave 6. This is a widely used screening tool for emotional and behavioural problems in children aged 3-16 (Hobbs, Little and Kaoukji, 2007; Goodman and Goodman, 2009; Armitage et al., 2023). It assesses children using a score that focuses on emotional symptoms, conduct problems, hyperactivity/inattention, peer relationships, and prosocial behaviour. In Britain, the total SDQ scores are generally found to provide an accurate and unbiased method of assessing mental health in children as well (Goodman and Goodman, 2011). We create a binary variable indicating that the child has a high SDQ score (an abnormal score that warrants concern) (Black, Panayiotou and Humphrey, 2025). In our sample used for analysis, 7.53% of children have a high SDQ score. Figure 3 shows that children with higher SDQ scores at age 14 are less likely to achieve 5 GCSEs at A*-C grades and are more likely to have a parent with poor health at the same age. We are interested in studying the effect of parental health on child emotional and behavioural problems, as this is a potential mechanism through which parental health affects child academic achievement.

Figure 3: Child SDQ score categories

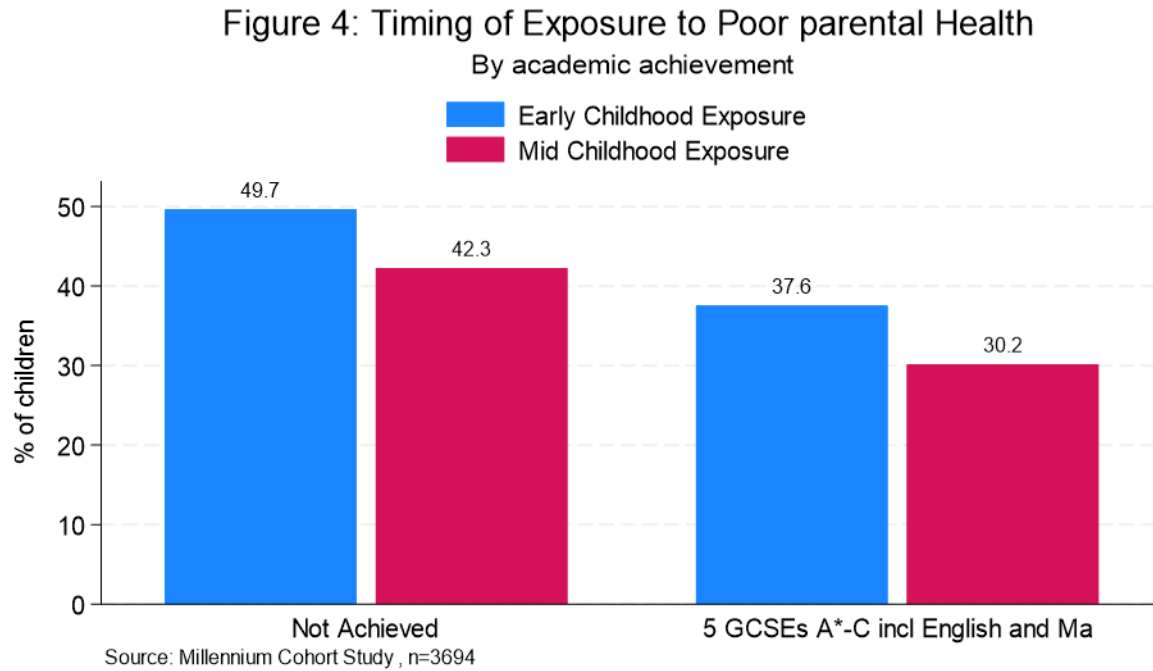


4.4.2.3 Parental Health

In the same questionnaires, the parent(s) reported on their own physical health. In MCS, in each wave, the main carer and partner (if applicable) each reported their general health using a scale of 1 (Excellent) to 5 (Poor). We use this data to create a binary variable for whether the parent has poor self-reported health. We have coded a zero if the respondent answered “Good”, “Very Good” or “Excellent” and 1 for those who answered “Fair” or “Poor”. The construction of this variable is supported by Havari and Peracchi (2017) and Côté-Sergent, Fonseca and Strumpf (2020), who follow the same levels for re-coding self-perceived health. In our sample ($N = 3615$), 13.47% of mothers and 12.17% of fathers report poor self-reported health when the child is age 14 (Wave 6). In this chapter, we look at the effects of having at least one parent with poor self-reported health on educational outcomes. In our sample used for analysis, 20.05% of children have at least one parent with poor health at age 14. The second column in Table 4.5 shows that 25, 24, 19, 18, and 18% of children have a parent with poor health at ages 9 months, 3, 5, 7, and 11 years, respectively, in our sample ($N = 3694$).

Table 4. 3: Distribution of children by poor parental health patterns across survey waves		
Pattern of at least one parent with poor health	% of children who have at least one parent with poor health	Number of Observations
In all waves	2.44	90
In 5 Waves only	4.06	150
In 4 Waves only	5.14	190
In 3 Waves only	7.61	281
In 2 Waves only	11.72	433
In one Wave only	20.98	775
In no waves	48.05	1,775
Only in Wave 6 but no earlier Wave	3.44	127

Table 4.3 summarises the distribution of the number of survey waves in which the child has at least one parent with poor health. This table shows the percentage of children who were exposed to poor parental health in all waves. This provides insights into the persistence and duration of poor parental health exposure across the child’s development.



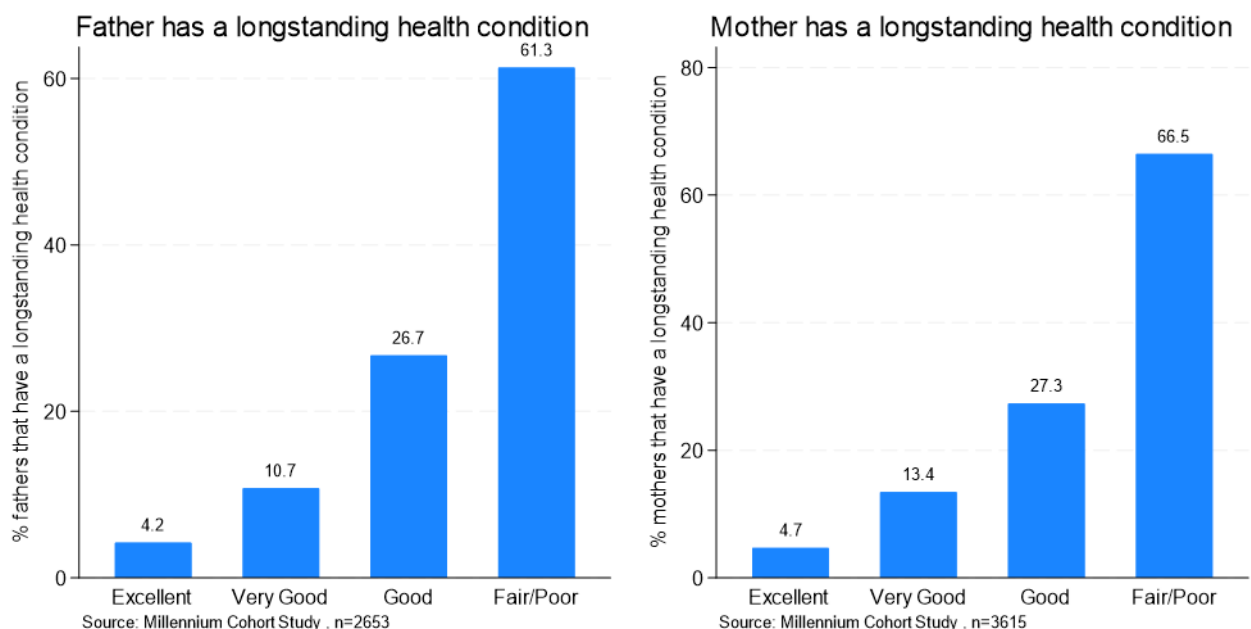
To further study the effects of timing and duration of poor parental health exposure on children’s academic achievement, we will categorise the presence of a parent with poor health across waves into (1) early childhood exposure (ages 8 months to 5 years) if at least one parent reported poor health between waves 1 and 3, and (2) mid childhood exposure (ages 7 to 14 years) if at least one parent reported poor parental health between waves 4 and 6. Figure 4 shows the percentage of children who are exposed to poor parental health in early childhood and mid-childhood, categorised by their academic achievement of 5 GCSEs A* to C, including English and Mathematics. This figure shows that, among those children who did not achieve this milestone (N=1154), approximately 50% were exposed to poor parental health in early childhood, and 42.3% were exposed in mid-childhood, compared to only 37.6% and 30%, respectively, for the group that did achieve this milestone (N=2540).

In each wave, the main parent and partner also reported whether they had a longstanding illness. We constructed binary variables with a value of 1 indicating that one or both parents (if applicable) had a longstanding health condition for each wave. In our sample, 43% of children have a parent with a longstanding health condition at age 14. The main analysis in this chapter is using a binary variable constructed for whether the parent

has poor self-reported health because this captures dimensions of well-being that may not be reflected in the presence or absence of a diagnosed long-term condition.

However, as a robustness check, we also use whether the parent has a longstanding health condition as a measure of poor parent health. Figure 5 shows how fathers and mothers who reported a longstanding health condition at their child's age 14 rated their health. This figure shows us that parents who rate their health as “poor” or “fair” are more likely to have a longstanding health condition, but 15% of fathers and 18% of mothers with longstanding health conditions rate their health as good or very good.

Figure 5: Parents with a longstanding health condition at child Age 14 by self-reported health rating



4.4.2.4 Mental Wellbeing

In the MCS, the six-item Kessler Psychological Distress (K6) scale was used for parents to report their mental health. This is an abbreviated version of the K10 (Kessler et al., 2003). The K10 is an established scale to measure psychological distress or depression in teenagers and adults (Rutter, Tizard and Whitmore, 1970). It consists of a set of 24 ‘yes/no’ self-completion questions which cover emotional disturbance and associated physical symptoms. Individuals responding ‘yes’ to eight or more of the 24 items are considered to be at risk of depression (Rodgers et al., 1999). In the K6, each question

pertains to an emotional state and response choices are based on a five-point Likert-type scale ranging from 0 (none of the time) to 4 (all the time). A cut-off of 6+ indicates psychological distress, and 13+ indicates severe psychological distress. MCS parents have completed the scale in surveys when the child was aged 3, 5, 7, 11, 14 and 17 (Wave 2 onwards). As shown in Table 4.5, three per cent of children have at least one parent with severe psychological distress at age 14. In this chapter, we also study the effects of parental mental health on child academic achievement using this measure in our additional analyses.

4.4.2.5 Control Variables

In this study, we control for a range of individual, child-level, and family-level background characteristics that the literature has shown to be associated with both parental health and child educational outcomes. Table 4.4 shows a detailed list of the variables used in our analysis.

In linear models, we control for time varying parental measures (measured at Wave 6 when the child begins secondary school at age 14); parental education (highest educational attainment by either parent based on a scale of 1 lowest to 5 highest), income (OECD income quantiles), MCS adjusted for family size using the OECD equivalence scale of a value of 1 for the first adult, 0.7 for each adult after that and 0.5 for each child in the household, and single parent status.

We can also control for time-invariant parental factors: the age of the mother at the birth of the child, and whether the mother smoked during pregnancy. The child variables we can control for are child subjective health, gestation time, birth weight, gender, and ethnicity. To deal with missing data on any of these variables, we include unit-nonresponse attrition weights (Mostafa 2015).

Figure 6 shows the variation in educational attainment among the cohort children across various background characteristics of the child and family. This figure shows that children with poorer health are less likely to achieve 5 GCSEs at A*-C. It also shows that children with more educated parents are more likely to perform well at GCSE, with children who have degree-educated parents (NVQ level 4 and 5) most likely to perform well.

Moreover, a higher income quantile corresponds to a higher probability of performing well. Lastly, Indian students are most likely to perform well, while Pakistani or Bangladeshi students are least likely to perform well.

Table 4. 4: Variables used for analysis	
Child Educational Outcomes	GCSE exams results/ KS4: Binary, 5 subjects including English and Mathematics with a grade ≥ 5 (A*-C)
	Attainment 8 score
	School absences: Binary, persistent absences ($>10\%$ of sessions)
	Prior Attainment Key Stage 2 (English and Maths at age 11/ Wave 5)
Other outcomes	Child mental health: Binary, high SDQ score
Parental Health	Binary, at least one parent has a longstanding illness
	Binary, at least one parent has self-reported poor health
	Mental Health: Binary, at least one parent with Severe Psychological Distress Kessler 6
Child factors	Binary, Low birthweight (<2500 grams)
	Binary, Premature Birth (<37 weeks gestation time)
	Child Gender
	Ethnicity: 6 Categories 2021/22 Census (White, Black, Asian, Mixed/Multiple, Other)
	School identification number
	Child Health: Binary, parent reported poor health
	Family Size
	Age at birth of child, categorical
Parent Invariant Factors	Smoked during the pregnancy of cohort member
	Cohabiting status: single or cohabiting
Parental variant/ Socio-economic factors	Education: Highest education level of either parent (None, completed compulsory schooling, completed upper secondary schooling, completed a higher education degree, overseas qualification)
	Family income: Binary $<60\%$ median OECD income
	Employment status: Binary, at least one parent is employed at age 14

We also have information on prior educational attainment at KS2 level (age 11). These are exams that children take prior to entering secondary school. Our measure of prior attainment at KS2 level is classified in bands: high, average and low achievement. We use prior academic achievement as a control in some models. As shown in Figure 7, children with better prior attainment at Key Stage 2 are more likely to achieve at least five GCSEs (A*-C), including English and Mathematics, at the end of secondary school.

Figure 6: Educational outcome by background characteristics

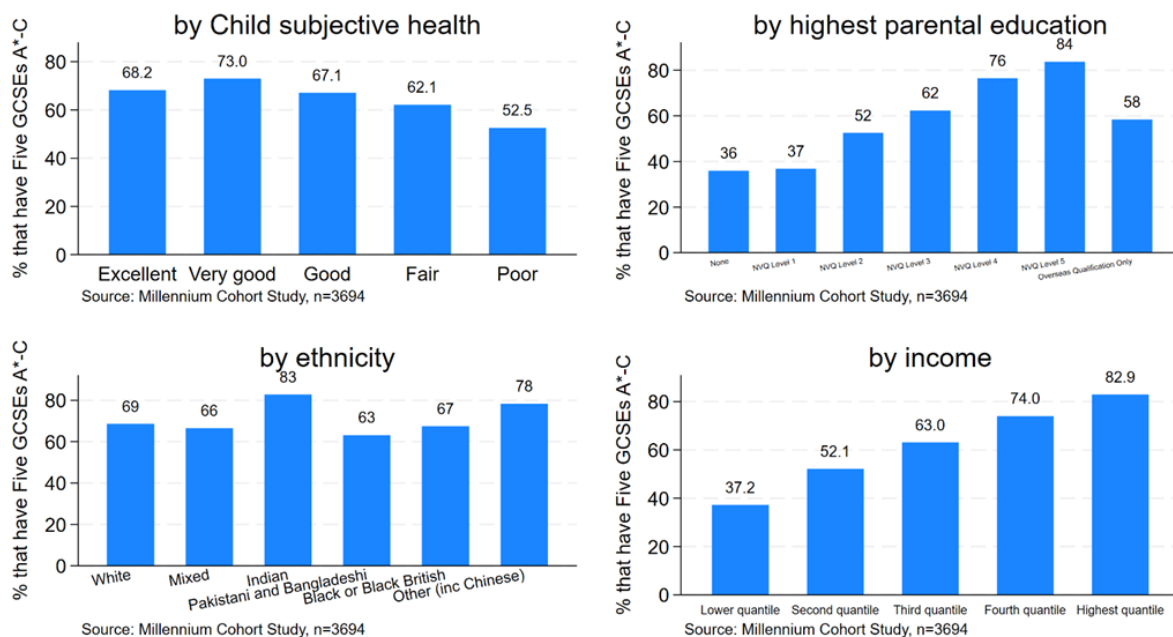
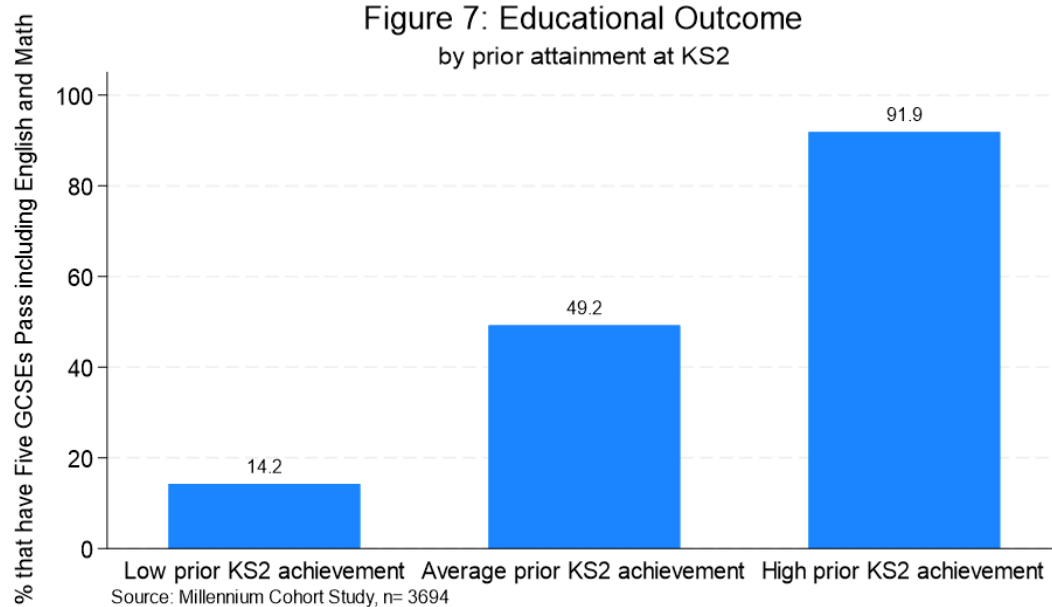


Figure 7: Educational Outcome
by prior attainment at KS2



4.5 Estimation Methods

We study the relationship between parental health and children’s educational attainment by estimating the following equation:

$$Y_i = \beta_0 + \beta_1 H_i + \varepsilon_i \quad (4.1)$$

where i denotes the cohort child. The dependent variable Y_i is the educational outcome of the child, measured by the outcome of the GCSE examinations. H_i is a binary indicator that is equal to one if the child i has at least one parent in the household that reports having a poor health at Wave 6 (the start of secondary school), and zero otherwise. X_i is a vector of baseline control variables including the child’s prior attainment at KS2 level, parental education, parental employment, maternal age at birth, family income, single parent status, and child characteristics such as gender, ethnicity, birthweight, gestational age, family size, health and month and year of birth measured at Wave 6. The coefficient β_1 captures the effect of parental health on educational attainment. Standard errors are clustered at the school level to adjust for within-school correlation in the error term ε_i . All models are weighted using survey weights provided by MCS to adjust for sampling design, non-random attrition from the survey, and differential non-response (Ploubidis and Mostafa, 2017).

$$Y_i = \beta_0 + \sum_{t=1}^2 \beta_t H_{it} + \beta_3 X_i + \varepsilon_i \quad (4.2)$$

The second model shown in equation 4.2 disaggregates the health status of the parent by wave to see if poor parental health closer to GCSE examination age has a greater impact on child GCSE outcomes, and whether poor parental health in early childhood can have a lasting impact. H_{it} is a binary indicator that is equal to one if either of child i ’s parents report having poor health at time period t (early or mid-childhood), and zero otherwise. We did not include parental health at Wave 7 since GCSEs are taken at age 16,

and Wave 7 reports parental health when the child is 17. In this equation, i denotes the cohort child, and t refers to the time-period in which parental health is reported. X_i is a vector of the same baseline control variables measured at Wave 6 that are included in the previous model. The coefficients β_1 and β_2 capture the effect of exposure to poor parental health in early childhood (ages 9 months to 5 years old) and the effect of exposure to poor parental health in mid-childhood (ages 7 years to 14 years old) on educational attainment.

We include controls for the academic year the child took their GCSE examinations in all models. We additionally estimate a model with school fixed effects. We include these fixed effects to address potential endogeneity in educational attainment or attendance outcomes. Adding school fixed effects allows us to control for unobserved, time-invariant differences between schools that could potentially influence student educational outcomes. This includes school-level characteristics such as teaching quality, OFSTED rating, location and resources in the local education authority (LEA), and school environment. This is particularly important as the support available to students who are young carers or struggling at home can vary between schools and LEAs. By using school and academic year fixed effects, we are essentially comparing students within the same school who took their GCSE exams in the same year, and not across different schools. This allows us to study our research question more precisely, as we are comparing children within the same school and academic year who have a parent with poor health with those who do not. We will compare estimates with and without school fixed effects.

4.6 Results

4.6.1 Descriptive Statistics

Table 4. 5. Mean characteristics for analysis sample and sample of all families present in waves 1-6.

	(1) Sample Present in Waves 1-6	(2) Sample used for analysis
Wave 6 At least one parent has poor health	0.21 (0.40)	0.20 (0.40)
Wave 1 At least one parent has poor health	0.24 (0.43)	0.25 (0.43)
Wave 2 At least one parent has poor health	0.24 (0.42)	0.24 (0.43)
Wave 3 At least one parent has poor health	0.19 (0.39)	0.19 (0.40)
Wave 4 At least one parent has poor health	0.18 (0.38)	0.18 (0.39)
Wave 5 At least one parent has poor health	0.18 (0.38)	0.18 (0.39)
Wave 6 At least one parent has Psychological Distress (Kessler 6)	0.06 (0.25)	0.06 (0.24)
Child is male	0.49 (0.50)	0.49 (0.50)
At least one parent is employed	0.90 (0.30)	0.93 (0.26)
Single Parent Household	0.16 (0.37)	0.22 (0.41)
Premature Birth (<37 weeks gestation)	0.05 (0.21)	0.06 (0.24)
Low Birthweight (<2.5kg)	0.04 (0.20)	0.06 (0.24)
Mother smoked during pregnancy	0.28 (0.45)	0.28 (0.45)
OECD Below 60% Median Income	0.23 (0.42)	0.27 (0.38)
MCS adjusted family size	2.32 (0.65)	2.27 (0.61)
Mother's age at child's birth	29.79 (5.53)	29.83 (5.33)
Poor Child Health	0.12 (0.32)	0.12 (0.33)
High Total Difficulties Score (≥ 17) Age 14	0.08 (0.28)	0.08 (0.26)
Highest Educational Qualification of either parent:	0.05	0.02

None	(0.21)	(0.14)
NVQ Level 1	0.04	0.04
	(0.19)	(0.29)
NVQ Level 2	0.18	0.20
	(0.38)	(0.40)
NVQ Level 3	0.13	0.13
	(0.34)	(0.34)
NVQ Level 4	0.40	0.43
	(0.49)	(0.49)
NVQ Level 5	0.19	0.18
	(0.39)	(0.39)
Overseas Qualification Only	0.01	0.01
	(0.11)	(0.08)
Child's ethnicity: White	0.85	0.85
	(0.36)	(0.35)
Mixed	0.02	0.03
	(0.16)	(0.18)
Indian	0.03	0.03
	(0.16)	(0.17)
Pakistani and Bangladeshi	0.06	0.05
	(0.24)	(0.21)
Black or Black British	0.02	0.02
	(0.15)	(0.15)
Other Ethnic group (including Chinese, Other)	0.01	0.01
	(0.12)	(0.11)
Observations	11293	3694

Notes: Values are for baseline at age 14 if not otherwise indicated. Standard deviations are shown in parentheses.

Table 4.5 presents the descriptive characteristics of the sample participating in all waves (1-6) ($N = 11,293$) and the sample used for analysis, which includes only those children with educational outcomes available from the National Pupil Database and excludes missing values ($N = 3,694$). This table shows that the study sample has more families from lower income, and more families with at least one working parent than the full sample. Moreover, more children are from single-parent households, have low birthweight, and more families have at least one university-educated parent.

Table 4. 6: Balance table of characteristics by parental health status at child age 14

	(1) No Parent with Poor Health	(2) At least one Parent with Poor Health	(3) Diff (1)- (2)
Whether achieved 5 GCSE A*-C	0.72 (0.45)	0.58 (0.49)	0.14***
Attainment 8 score	53.00 (17.87)	46.98 (18.31)	6.01***
Child is male	0.50 (0.50)	0.48 (0.50)	0.01
At least one parent is employed	0.96 (0.21)	0.82 (0.39)	0.14***
Single Parent Household	0.22 (0.41)	0.22 (0.42)	-0.01
Premature Birth (<37 weeks gestation)	0.06 (0.24)	0.07 (0.26)	-0.01
Low Birthweight (<2.5kg)	0.06 (0.24)	0.07 (0.25)	-0.01
Mother smoked during pregnancy	0.26 (0.44)	0.35 (0.48)	-0.09***
OECD Below 60% Median Income	0.14 (0.34)	0.32 (0.47)	-0.18***
MCS adjusted family size	2.26 (0.60)	2.31 (0.66)	-0.05*
Mother's age at child's birth	29.88 (5.23)	29.65 (5.71)	0.23
Poor Child Health	0.11 (0.31)	0.18 (0.38)	-0.07***
Highest Educational Qualification of either parent: None	0.01 (0.12)	0.05 (0.21)	-0.03***
NVQ Level 1	0.03 (0.18)	0.05 (0.22)	-0.02*
NVQ Level 2	0.18 (0.39)	0.25 (0.44)	-0.07***
NVQ Level 3	0.13 (0.34)	0.13 (0.34)	-0.00
NVQ Level 4	0.44 (0.50)	0.37 (0.48)	0.08***
NVQ Level 5	0.19 (0.40)	0.13 (0.34)	0.07***
Child's ethnicity: White	0.87 (0.34)	0.81 (0.40)	0.06***
Mixed	0.03 (0.17)	0.04 (0.21)	-0.01
Indian	0.03 (0.17)	0.03 (0.18)	-0.00
Pakistani and Bangladeshi	0.04 (0.20)	0.07 (0.25)	-0.03**

Black or Black British	0.02 (0.15)	0.03 (0.17)	-0.01
Other (including Chinese, other)	0.01 (0.10)	0.02 (0.14)	-0.01*
Prior Achievement KS2: Low	0.08 (0.27)	0.13 (0.33)	-0.05***
Average	0.37 (0.48)	0.43 (0.50)	-0.06**
High	0.55 (0.50)	0.44 (0.50)	0.11***
Observations	2953	741	3694

Notes: Values are for baseline at age 14 if not otherwise indicated. Standard deviations are shown in parentheses.

Table 4.6 presents the balance table of educational outcomes and characteristics for children who do not have a parent with poor health at age 14, compared to those who do. Families with at least one parent with poor health are more likely to have no working parent in the household, more likely to be low income (below 60% median income), and less likely to have a higher-educated parent. Children who have at least one parent with poor health have poorer GCSE outcomes on average; are less likely to achieve 5 GCSEs A*-C and have lower attainment 8 scores on average. They are also more likely to have poor health themselves, and less likely to have high prior KS2 attainment. Additionally, they are less likely to be white, more likely to be Pakistani or Bangladeshi, and more likely that their mother smoked during their pregnancy. This table highlights that parental health is not random, and it is important to account for these observed variables.

Balance Table 4.7 shows the health of parents in previous waves for families who do not have a parent with poor health at age 14, and those who do. This table shows that households that have a parent with poor health at child age 14 are also more likely to have a parent with poor health in all previous waves.

Table 4. 7: Balance Table of prior health by parental health status at child age 14

	(1) No Parent with Poor Health	(2) At least one Parent with Poor Health	(3) Diff (1)-(2)
Wave 1 At least one parent has poor health	0.19 (0.39)	0.48 (0.50)	-0.29***
Wave 2 At least one parent has poor health	0.18 (0.38)	0.49 (0.50)	-0.31***
Wave 3 At least one parent has poor health	0.13 (0.33)	0.44 (0.50)	-0.31***
Wave 4 At least one parent has poor health	0.12 (0.32)	0.42 (0.49)	-0.30***
Wave 5 At least one parent has poor health	0.09 (0.29)	0.51 (0.50)	-0.42***
Observations	2953	741	3694

4.6.2 Main Results

Estimates from equation (4.1) using OLS are shown in Tables 4.8 and 4.9. Table 4.8 estimates the model when the educational outcome is having achieved five GCSEs A*-C, including Mathematics and English. In Tables 4.8-4.11, column (1) includes the full set of controls and column (2) includes the full set of controls as well as the school fixed effects. The full set of controls for highest parental education, child health, gender, ethnicity, birthweight, premature birth, whether the mother smoked during pregnancy, mother's age at birth, single parent status, MCS adjusted family size, parental employment, household income (as reported at child age 14 (Wave 6)) and prior academic achieved of the child at Key Stage 2.

In Table 4.8, column (1) shows a weakly significant and negative effect of poor parental health on a child having 5 GCSEs A*-C. Children with at least one parent with poor health are 3.2 percentage points less likely to perform well at the GCSE level. However, this effect is only statistically significant at the 10% level. In these results, we

find that prior attainment at KS2 level (age 11) is a strong predictor of the grades attained at GCSE level.

The effect of poor parental health is higher in these OLS estimates without fixed effects and is diminished in the model with school fixed effects (column (2)) which accounts for unobserved time-invariant differences between schools that could influence GCSE outcomes. In the fixed effects model, there is a small and statistically insignificant negative effect of poor parental health on child performance at GCSE level, with and without controlling for prior attainment. This illustrates the upward bias in OLS estimates of the effect of parental health on child educational outcomes, which reduces when the effects of unobserved school-level time-invariant heterogeneity correlated with GCSE outcomes or poor parental health are removed from the estimates.

Table 4. 8. Main Analysis: GCSE results; Achieved 5 GCSEs A*-C

	(1)	(2)
	All controls	All controls + FE
Wave 6 At least one parent has poor health	-0.032*	-0.015
	(0.018)	(0.030)
Observations	3694	3694
R-Squared	0.374	0.627
Mean of Dep. Variable	0.707	0.707
Academic Year FE	No	Yes
School FE	Yes	Yes

Standard errors in parentheses. All controls include parental education & employment, maternal smoking during pregnancy, age at birth, single parent, child health, birthweight, prematurity, ethnicity, gender, family income, adj. family size (at child age 14/ Wave 6 unless otherwise indicated) and prior academic attainment at KS2 level.

Standard errors are cluster robust at school level. Degrees of Freedom= 1317

* p < 0.10, ** p < 0.05, *** p < 0.01

Appendix Table 4.1 shows the estimated effects of all covariates (that have been excluded from Table 4.8 for brevity). Using the full set of controls in column (2), we find that male children and children of low-income families are less likely to achieve 5 GCSEs at A*-C. In contrast, children who have a mother who was older than 30 at their birth, or average to high prior attainment at KS2 level, are more likely to perform well in their GCSEs.

Table 4. 9. Main Analysis: GCSE results Attainment 8

	(1)	(2)
	All controls	All controls + FE
Wave 6 At least one parent has poor health	-1.330** (0.621)	-1.037 (0.920)
Observations	3694	3694
R-Squared	0.511	0.748
Mean of Dep. Variable	52.511	52.511
Academic Year FE	No	Yes
School FE	Yes	Yes

Standard errors in parentheses All controls include parental education & employment, maternal smoking during pregnancy, age at birth, single parent, child health, birthweight, prematurity, ethnicity, gender, family income, adj. family size (at child age 14/Wave 6 unless otherwise indicated) and prior attainment at KS2 level.

Standard errors are cluster robust at school level. Degrees of Freedom= 1317

* p < 0.10, ** p < 0.05, *** p < 0.01

Table 4.9 estimates the model using the Attainment 8 score as the measure of educational outcome. In Table 4.8, column (1) shows a statistically significant but small negative effect of poor parental health on a child's Attainment 8 score. Having a parent with poor health at age 14 reduces the total Attainment 8 score by 1.3. To put this in context, a 1-point increase in Attainment 8 score is equivalent to moving up one grade (e.g., from a B to C in the old grading system) in one of the eight best subjects for the student. Appendix Table 4.2 shows the estimated effects on the covariates. This table shows that prior attainment at KS2 level (age 11) is a strong predictor of the Attainment 8 score. A high score at KS2 level increases the Attainment 8 score at GCSE level by 30 points (equivalent to achieving A* in both English and Mathematics, which are double-weighted).

The estimated effect of poor parental health on the Attainment 8 score is slightly reduced in the school fixed effects model shown in column (2), and statistical significance is also diminished.

4.6.2.1 Timing of Exposure

Estimates from equation (4.2) using OLS are shown in Table 4.10 (5 GCSEs A*-C) and Table 4.11 (Attainment 8). These tables show the effects of exposure to poor health in early childhood (ages 9 months to 5 years old) in the first panel, and the effects of exposure

to poor health in mid-childhood (ages 7 to 14 years old) in the second panel on educational outcomes. This allows us to analyse the effects of the timing of exposure to poor parental health.

In panel 1 of Table 4.10, the estimates of the OLS and FE regressions show that there is no significant effect of early childhood exposure to poor parental health on achieving 5 GCSEs at A*-C. This suggests that exposure to poor parental health does not have a long-term effect on children's educational outcomes, as the presence of a parent with poor health between 8 months and 5 years does not affect educational outcomes at age 16.

In panel 2 of Table 4.10, the estimate in column (1) shows that exposure to poor parental health in mid-childhood (and closer to entering secondary school) reduces the likelihood of the child performing well at GCSE level by 2.7 percentage points ($p < 0.10$). Adding school fixed effects in column (4) diminishes the statistical significance of this estimate.

Table 4. 10. Timing of exposure to poor parental health: GCSE results- 5 GCSEs A*-C

	(1)	(2)
	All Controls	All controls + FE
Early Childhood exposure to poor parental health (ages 8 months to 5 years)	-0.003 (0.015)	0.012 (0.022)
Mid Childhood exposure to poor parental health (ages 7 to 14 years)	-0.027* (0.016)	-0.033 (0.024)
$\beta_1 + \beta_2$	-0.030*	-0.021
Observations	3694	3694
R-Squared	0.375	0.627
Mean of Dep. Variable	0.707	0.707
Academic Year FE	No	Yes
School FE	Yes	Yes

Standard errors in parentheses. All controls include parental education & employment, maternal smoking during pregnancy, age at birth, single parent, child health, birthweight, prematurity, ethnicity, gender, family income, adj. family size (at child age 14/ Wave 6 unless otherwise indicated) and prior attainment at KS2 level.

Standard errors are cluster robust at school level. Degrees of Freedom= 1317

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In panel 1 of Table 4.11, the estimates of the OLS and school FE regressions show that there is a very small but significant effect of early childhood exposure to poor parental health on the Attainment 8 score. Since the Attainment 8 score double weighs the English and Mathematics scores, one possible reason for seeing this small effect on Attainment 8 score but not the achievement of our other outcome is that the parents' poor health in early childhood may be impacting the development of fundamental language and mathematics skills.

In panel 2 of Table 4.11, the estimates in column (1) and (2) show that exposure to poor parental health in mid-childhood (and closer to entering secondary school) do not significantly effect the Attainment 8 score.

Table 4. 11. Timing of exposure to poor parental health: GCSE results Attainment 8

	(1) All Controls	(2) All controls + FE
Early Childhood exposure to poor parental health (ages 8 months to 5 years)	-1.080** (0.461)	-1.263* (0.648)
Mid Childhood exposure to poor parental health (ages 7 to 14 years)	-0.737 (0.527)	-0.439 (0.758)
$\beta_1 + \beta_2$	-1.817***	-1.702**
Observations	3694	3694
R-Squared	0.512	0.749
Mean of Dep. Variable	52.511	52.511
Academic Year FE	No	Yes
School FE	Yes	Yes

Standard errors in parentheses. All controls include parental education & employment, maternal smoking during pregnancy, age at birth, single parent, child health, birthweight, prematurity, ethnicity, gender, family income, adj. family size (at child age 14/ Wave 6 unless otherwise indicated) and prior attainment at KS2 level.

Standard errors are cluster-robust at the school level. Degrees of Freedom= 1317

* p < 0.10, ** p < 0.05, *** p < 0.01

4.6.2.2 Heterogeneity

Tables 4.12 shows the effects of poor parental health on child educational outcomes by different subgroups of our sample. We include interactions to statistically test whether there is a difference in effects by the child's gender, the child's family income, and single-

parent status. Column (1) shows the estimates on attainment of 5 GCSEs at A*-C grade, and column (2) shows the estimates on the Attainment 8 score. Both columns include school-level fixed effects and the complete set of controls.

Table 4. 12. Heterogeneity: the role of gender, income and single parenthood

Panel A: Interaction with Child's Gender		
	Five GCSEs A*-C	Attainment 8 score
Wave 6 At least one parent has poor health	-0.008 (0.036)	-1.835* (1.113)
Child is male	-0.096*** (0.021)	-4.009*** (0.764)
Parent Poor Health * Male Child	-0.014 (0.049)	1.630 (1.580)
Panel B: Interaction with Low Income Household		
Wave 6 At least one parent has poor health	-0.015 (0.033)	-1.144 (1.010)
OECD Below 60% Median Income	-0.110** (0.047)	-2.352* (1.245)
Parent Poor Health * Below 60% income	0.002 (0.067)	0.634 (2.088)
Panel C: Interaction with Single Parent Status		
Wave 6 At least one parent has poor health	-0.011 (0.032)	-1.478 (1.021)
Single Parent Household	-0.045 (0.035)	-1.894* (1.093)
Parent Poor Health * Single Parent	-0.018 (0.066)	2.416 (1.999)
Observations	3694	3694
R-Squared	0.626	0.748
Mean of Dep. Variable	0.707	52.511
Academic Year FE	Yes	Yes
School FE	Yes	Yes

Standard errors in parentheses. Full set of controls included: parental education & employment, maternal smoking during pregnancy, age at birth, single parent, child health, birthweight, prematurity, ethnicity, gender, family income, adj. family size (at child age 14/ Wave 6 unless otherwise indicated), prior KS2 attainment.

Standard errors are cluster robust at school level. Degrees of Freedom= 1317

* p < 0.10, ** p < 0.05, *** p < 0.01

Panel A shows the effects by gender of the child. The first estimate in each column shows the effect of poor parental health on female children, while the third estimate shows the additional effect of poor parental health if the child is male. This shows that there is no statistically significant difference in the effect of poor parental health on child educational outcomes by the child's gender. By jointly testing the parameters, we find that the effect of poor parental health is not statistically significant for the sample of male children.

Panel B shows the effects of poor parental health on educational outcomes by relative poverty status (below 60% of median income) of the child's family at age 14. This table shows that we do not find a statistically significant difference in the effect of poor parental health on educational outcomes between children who are not living in relative poverty and those who are. By jointly testing the parameters, we find that the effect of poor parental health is not statistically significant for the sample of children in relative poverty.

Lastly, Panel C estimates whether there is an additional effect of poor parental health on educational outcomes if the parent with poor health is a single parent. We find that there is no statistically significant difference in the effect of poor parental health on the educational outcomes of children from two-parent families and children from single-parent families. By jointly testing the parameters, we find that the effect of poor parental health on educational attainment is not statistically significant for single-parent families, as well as two-parent families.

4.6.3 Other Outcomes

We explore two potential channels through which parental health could potentially affect children's educational outcomes: child emotional and behavioural problems (EBPs), and school absence at ages 14 to 16. In Tables 4.13, 4.14, and 4.15, we examine the direct impact of poor parental health on child EBPs and school absences at ages 14-15 and 15-16. In Table 4.13, column (1) includes the full set of controls. Column (2) includes the full

set of controls and school fixed effects. The full set of controls includes highest parental education, child health, gender, ethnicity, birthweight, premature birth, whether the mother smoked during pregnancy, mother's age at birth, single parent status, MCS adjusted family size, parental employment, household income (as reported at child age 14 (Wave 6)) and prior academic attainment at KS2 level.

Table 4.13 shows the effect of poor parental health on the likelihood of the child having a high SDQ score at age 14, a marker of emotional and behavioural problems in children. This table shows that children who have at least one parent with poor health at age 14 are approximately 5 percentage points more likely to have emotional and behavioural problems at age 14. These findings suggest that while present parental health does impact child EBPs at the beginning of secondary school at age 14, this does not then affect their educational attainment at the end of secondary school.

Table 4. 13. Other outcomes: High SDQ score at age 14.

	(1)	(2)
	All Controls	All controls + FE
Wave 6 At least one parent has poor health	0.052*** (0.014)	0.051** (0.020)
Observations	3694	3694
R-Squared	0.076	0.450
Mean of Dep. Variable	0.070	0.070
Academic Year FE	No	Yes
School FE	Yes	Yes

Standard errors in parentheses. All controls include parental education & employment, maternal smoking during pregnancy, age at birth, single parent, child health, birthweight, prematurity, ethnicity, gender, family income, adj. family size (at child age 14/ Wave 6 unless otherwise indicated) and prior attainment at KS2 level.

Standard errors are cluster-robust at the school level. Degrees of Freedom= 1317

* p < 0.10, ** p < 0.05, *** p < 0.01

Table 4.14 shows the estimated effects of poor parental health on the likelihood of the child having persistent absences (>10% of all school sessions) in the 2015/2016 academic year (age 14-15) in Columns (1) and (2). These results show that children who have at least one parent with poor parental health at age 14 are 6.4 percentage points more likely to be persistently absent from school between ages 14-15. As children of this age are ordinarily able to transport themselves to school, complete schoolwork, and attend classes

without parental assistance, this result is potentially due to caregiving responsibilities that children with a parent in poor health may have.

Table 4. 14. Other outcomes: Persistent absences

	2015/16 school year		2016/17 school year	
	(1)	(2)	(3)	(4)
	All Controls	All controls + FE	All Controls	All controls + FE
Wave 6 At least one parent has poor health	0.063*** (0.015)	0.064*** (0.022)	0.032** (0.016)	0.044* (0.024)
Observations	3694	3694	3694	3694
R-Squared	0.076	0.429	0.050	0.480
Mean of Dep. Variable	0.085	0.085	0.111	0.111
Academic Year FE	No	Yes	No	Yes
School FE	Yes	Yes	Yes	Yes

Standard errors in parentheses. All controls include parental education & employment, maternal smoking during pregnancy, age at birth, single parent, child health, birthweight, prematurity, ethnicity, gender, family income, adj. family size (at child age 14/ Wave 6 unless otherwise indicated) and prior attainment at KS2 level.

Standard errors are cluster robust at school level. Degrees of Freedom= 1317

* p < 0.10, ** p < 0.05, *** p < 0.01

Columns (3) and (4) of Table 4.14 show the estimated effects of poor parental health on the likelihood of the child having persistent absences (absent in more than 10% of all school sessions) in the 2016/2017 academic year (age 15-16). These results show that children who have at least one parent with poor parental health at age 14 are 4.4 percentage points more likely to be persistently absent from school at age 15-16. This suggests that the impact of poor parental health on school absences persists, and children with a parent with poor parental health are more likely to have poor attendance throughout their GCSE education.

4.6.3.1 Timing and Other Outcomes

Following the results in the previous section, we are interested in further examining the impact of poor parental health on child EBPs and school absences. Therefore, in Tables 4.15 and 4.16, we examine the impact of poor parental health in early childhood and poor parental health in mid-childhood separately on these outcomes.

Table 4. 15 Other outcomes (Timing of exposure): High SDQ score

	(1) All Controls	(2) All controls + FE
Early Childhood exposure to poor parental health (ages 8 months to 5 years)	0.029*** (0.010)	0.045*** (0.015)
Mid Childhood exposure to poor parental health (ages 7 to 14 years)	0.024** (0.011)	0.020 (0.015)
$\beta_1 + \beta_2$	0.053***	0.065***
Observations	3694	3694
R-Squared	0.077	0.453
Mean of Dep. Variable	0.070	0.070
Academic Year FE	No	Yes
School FE	Yes	Yes

Standard errors in parentheses. All controls include parental education & employment, maternal smoking during pregnancy, age at birth, single parent, child health, birthweight, prematurity, ethnicity, gender, family income, adj. family size (at child age 14/ Wave 6 unless otherwise indicated) and prior attainment at KS2 level.

Standard errors are cluster robust at school level. Degrees of Freedom= 1317

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.15 shows that, after including school fixed effects in column (2), the effect of poor parental health on the probability of a child having a high SDQ score is due to exposure to poor parental health in early childhood. That is, we find that children with exposure to poor parental health in early childhood are 4.5 percentage points more likely to have a high SDQ score at age 14, whereas exposure to poor parental health in mid-childhood has no significant effect on the child's likelihood of having a high SDQ score.

Table 4.16 (columns 1 and 2) shows that, after including school fixed effects, the effect of poor parental health on the probability of a child having persistent absences in the 2015/2016 school year is due to exposure to poor parental health in both early childhood and mid-childhood.

Table 4.16 also shows that, after including school fixed effects in column (4), the effect of poor parental health on the probability of a child having persistent absences in the 2016/2017 school year is due to exposure to poor parental health in early childhood. That is, we find that children with exposure to poor parental health in early childhood are 3.8 percentage points more likely to have persistent absences in the school year they took

their GCSE examinations, while exposure to poor parental health in mid-childhood has no significant effect on the child's likelihood of having persistent absences.

Table 4. 16 Other outcomes (Timing of exposure): Persistent absences

	2015/16 school year		2016/17 school year	
	(1)	(2)	(3)	(4)
	All Controls	All controls + FE	All Controls	All controls + FE
Early Childhood exposure to poor parental health (ages 8 months to 5 years)	0.020*	0.032*	0.025**	0.038**
	(0.011)	(0.017)	(0.012)	(0.017)
Mid Childhood exposure to poor parental health (ages 7 to 14 years)	0.035***	0.031*	0.010	0.026
	(0.012)	(0.018)	(0.012)	(0.019)
$\beta_1 + \beta_2$	0.055***	0.063***	0.035**	0.064***
Observations	3694	3694	3694	3694
R-Squared	0.075	0.429	0.050	0.482
Mean of Dep. Variable	0.085	0.085	0.111	0.111
Academic Year FE	No	Yes	No	Yes
School FE	Yes	Yes	Yes	Yes

Standard errors in parentheses. All controls include parental education & employment, maternal smoking during pregnancy, age at birth, single parent, child health, birthweight, prematurity, ethnicity, gender, family income, adj. family size (at child age 14/ Wave 6 unless otherwise indicated) and prior attainment at KS2 level.

Standard errors are cluster robust at school level. Degrees of Freedom= 1317

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.7 Additional Analysis

In this section, we present the results from estimating equation (4.1) using two different measures of poor parental health: whether at least one parent has a longstanding health condition, and whether at least one parent has severe psychological distress as a measure of poor mental health. This is a robustness check to see if the measure of parental health we use has an effect on our estimates. We also present the estimates of equations (4.1) and (4.2) using a probit model specification and multiple imputation to deal with the missing values for the control variables.

4.7.1 Measures of Parental Health

Table 4. 17 Robustness check: Longstanding health condition and parent mental health status

	(1)	(2)	(3)	(4)
	5 GCSE A*-C	5 GCSE A*-C	Attainment 8	Attainment 8
Wave 6 At least one parent has a longstanding health condition	-0.013		-0.453	
	(0.019)		(0.699)	
Wave 6 At least one parent has Severe Psychological Distress (Kessler 6)		-0.012		-0.963
		(0.045)		(1.368)
Observations	3694	3694	3694	3694
R-Squared	0.627	0.626	0.748	0.748
Mean of Dep. Variable	0.707	0.707	52.517	52.511
Academic Year FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes

Standard errors in parentheses. Full set of controls included: parental education & employment, maternal smoking during pregnancy, age at birth, single parent, child health, birthweight, prematurity, ethnicity, gender, family income, adj. family size (at child age 14/ Wave 6 unless otherwise indicated), prior KS2 attainment.

Standard errors are cluster robust at school level. Degrees of Freedom 1317

* p < 0.10, ** p < 0.05, *** p < 0.01

Table 4.17 shows the effect of at least one parent having a longstanding health condition (columns 1 and 3) and at least one parent having poor mental health (columns 2 and 4) on child educational outcomes. All columns contain the full set of controls and school-level fixed effects. We find that the estimates in this table of the impact of poor parental mental health, and the presence of a parent with a longstanding health condition on the probability of achieving 5 GCSEs at A*-C and the attainment 8 score is nearly identical to the estimate we found in columns 4 of Table 4.8 and Table 4.9 of the effect of poor parental health on educational outcomes.

4.7.2 Probit Specification

Table 4. 18 Probit (average marginal effects): 5 GCSEs A*-C

	(1) All controls
Panel A: Poor Parental Health at age 14	
Wave 6 At least one parent has poor health	-0.030* (0.017)
Panel B: Timing of exposure to poor parental health	
Early Childhood exposure to poor parental health (ages 8 months to 5 years)	-0.004 (0.014)
Mid Childhood exposure to poor parental health (ages 7 to 14 years)	-0.026* (0.015)
Observations	3694

Standard errors in parentheses. All controls include parental education & employment, maternal smoking during pregnancy, age at birth, single parent, child health, birthweight, prematurity, ethnicity, gender, family income, adj. family size (at child age 14/ Wave 6 unless otherwise indicated) and prior attainment at KS2 level.

Standard errors are cluster robust at school level. Degrees of Freedom= 1317

* p < 0.10, ** p < 0.05, *** p < 0.01

In Table 4.18, we present the estimates of the average marginal effects from a probit specification of poor parental health on the probability of achieving 5 GCSEs with A*-C. This is because the outcome measure is a binary variable, and the probit specification provides the probability that the outcome is equal to 1. This is because OLS can give predicted probabilities outside 0 and 1, and heteroskedastic residuals when the dependent variable is binary (Greene, 2012). A probit model uses a cumulative normal distribution to ensure predicted probabilities are always between 0 and 1. This probit model does not include fixed effects for school, as including many fixed effects like school in nonlinear probit models causes them to suffer from “the incidental parameters problem”, and estimates become inconsistent and biased (Lancaster, 2000). Therefore, we are comparing the estimates of Panel A with column (1) of Table 4.8 using OLS without school fixed effects and comparing Panel B with column (1) of Table 4.10. We find that these probit estimates are nearly identical to the OLS estimates in size, direction, and statistical significance.

4.7.3 Multiple Imputation

As shown in Table 4.4, the default estimate used in all our regressions is based on complete case analysis. As a robustness check, we performed multiple imputation using all available information. For this, we use all observations that contain complete responses on parental health and GCSE outcomes (N=4,815) but may have missing responses on the control variables (Li, Stuart and Allison, 2015). Here, despite the percentage of missing data, the remaining sample of respondents with complete information is still large enough to conduct a complete case analysis without risking a loss of statistical power. However, Multiple Imputation is also performed as a sensitivity analysis in Tables 4.19 and 4.20, to compare with the results previously presented in Tables 4.8 and 4.9. In Table 4.19, the estimates without fixed effects in column (1) are nearly identical to those in column (1) of Table 4.8 using complete case analysis. In column (2) of Table 4.19, although larger in magnitude, the estimate is also no longer significant when controlling for prior attainment. In Table 4.20, we find that the multiple imputation estimates are nearly identical in magnitude and direction to those in Table 4.9, which uses complete case analysis; however, they lose statistical power in the model with school fixed effects.

Table 4. 19 Multiple imputation: GCSE results- 5 GCSEs A*-C

	(1) All Controls	(2) All controls + FE
Wave 6 At least one parent has poor health	-0.038** (0.016)	-0.034 (0.023)
Observations	4812	4812
Mean of Dep. Variable	62.364	62.364
Academic Year FE	No	Yes
School FE	Yes	No

Standard errors in parentheses. All controls include parental education & employment, maternal smoking during pregnancy, age at birth, single parent, child health, birthweight, prematurity, ethnicity, gender, family income, adj. family size (at child age 14/ Wave 6 unless otherwise indicated) and prior attainment at KS2 level.

Standard errors are cluster robust at school level. Degrees of Freedom= 1720

* p < 0.10, ** p < 0.05, *** p < 0.01

Table 4. 20 Multiple imputation: GCSE results Attainment 8

	(1)	(2)
	All Controls	All controls + FE
Wave 6 At least one parent has poor health	-1.751*** (0.557)	-1.595** (0.733)
Observations	4812	4812
Mean of Dep. Variable	40.880	40.880
Academic Year FE	No	Yes
School FE	Yes	Yes

Standard errors in parentheses. All controls include parental education & employment, maternal smoking during pregnancy, age at birth, single parent, child health, birthweight, prematurity, ethnicity, gender, family income, adj. family size (at child age 14/ Wave 6 unless otherwise indicated) and prior attainment at KS2 level.

Standard errors are cluster robust at school level. Degrees of Freedom= 1720

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.7.4 Two-Parent Analysis

In this additional analysis, we look at the sample of two parent families where there are complete responses on the health of both parents. This allows us to estimate the effect of the gender of the parent that has poor health, while controlling for the health of the other parent. Our sample size for this analysis is 2085 children. We estimate the effects of poor maternal health and poor paternal health separately for all the outcomes studies in this chapter.

Table 4.21 presents the summary statistics of this sample. In this sample, 10% of children (N=209) have a father with poor health, while 11% of children (N=229) have a mother with poor health. Additionally, 23% of children (N=480) had exposure to poor maternal health in early childhood, while 18% (N=375) had exposure to poor maternal health in mid-childhood. In comparison, 27% of children (N=563) had exposure to poor paternal health in early childhood, while 19% (N=396) had exposure to poor parental health in mid-childhood. On average, children in this sample have slightly higher educational attainment, are slightly less likely to have high SDQ scores, and are slightly less likely to have persistent absences.

Table 4. 21 Sample statistics: Children from two-parent families

	(1) Mean (SD)
Wave 6 Mother Poor Health	0.10 (0.30)
Wave 6 Father Poor Health	0.11 (0.31)
Early Childhood: Mother Poor Health	0.23 (0.42)
Early Childhood: Father Poor Health	0.27 (0.44)
Mid Childhood: Mother Poor Health	0.18 (0.38)
Mid Childhood: Father Poor Health	0.19 (0.39)
Whether achieved 5 GCSE A*-C (including English and Maths)	0.75 (0.43)
Attainment 8 score	54.56 (17.74)
High Total Difficulties Score (≥ 17) Age 14	0.06 (0.23)
Persistent Absence 2016 academic year	0.06 (0.23)
Persistent Absence 2017 academic year	0.08 (0.27)
Child is male	0.51 (0.50)
At least one parent is employed	0.98 (0.15)
Single Parent Household	0.00 (0.00)
Premature Birth (< 37 weeks gestation)	0.06 (0.23)
Low Birthweight (< 2.5 kg)	0.05 (0.22)
Mother smoked during pregnancy	0.21 (0.41)
OECD Below 60% Median Income	0.06 (0.24)
MCS adjusted family size	2.41 (0.46)
Mother's age at child's birth	30.61 (4.77)
Poor Child Health	0.09 (0.29)
Highest Educational Qualification of either parent: None	0.01 (0.08)
NVQ Level 1	0.01

	(0.12)
NVQ Level 2	0.15
	(0.36)
NVQ Level 3	0.13
	(0.33)
NVQ Level 4	0.48
	(0.50)
NVQ Level 5	0.21
	(0.41)
Overseas Qualification Only	0.01
	(0.08)
Child's ethnicity: White	0.89
	(0.31)
Mixed	0.02
	(0.15)
Indian	0.03
	(0.17)
Pakistani and Bangladeshi	0.03
	(0.17)
Black or Black British	0.01
	(0.11)
Other (incl Chinese, other)	0.01
	(0.11)
Prior Achievement KS2: Low	0.08
	(0.27)
Average	0.34
	(0.47)
High	0.58
	(0.49)
Observations	2085

Table 4.22 presents the results of the estimated effects of poor maternal health at age 14 and poor paternal health at 14 for all outcomes.

Table 4. 22 Two-parent analysis: Poor maternal health and poor paternal health

	(1)	(2)
	All Controls	All Controls + FE
Panel 1: 5 GCSEs A*-C		
Wave 6 Mother Poor Health	-0.038	-0.017
	(0.028)	(0.051)
Wave 6 Father Poor Health	-0.005	0.008
	(0.029)	(0.047)

$\beta_1 + \beta_2$	-0.043	-0.009
R-Squared	0.372	0.681
Mean of Dep. Variable	0.760	0.760
Panel 2: Attainment 8 Score		
Wave 6 Mother Poor Health	-2.317**	-1.110
	(0.980)	(1.674)
Wave 6 Father Poor Health	-1.524	-1.042
	(1.040)	(1.768)
$\beta_1 + \beta_2$	-3.841***	-2.152
R-Squared	0.512	0.776
Mean of Dep. Variable	55.086	55.086
Panel 3: High SDQ Score		
Wave 6 Mother Poor Health	0.069***	0.058*
	(0.023)	(0.034)
Wave 6 Father Poor Health	0.013	0.016
	(0.021)	(0.028)
$\beta_1 + \beta_2$	0.082***	0.074*
R-Squared	0.059	0.505
Mean of Dep. Variable	0.054	0.054
Panel 4: Persistent Absences 2015/16		
Wave 6 Mother Poor Health	0.068***	0.042
	(0.024)	(0.038)
Wave 6 Father Poor Health	0.067***	0.037
	(0.024)	(0.034)
$\beta_1 + \beta_2$	0.135***	0.079**
R-Squared	0.053	0.485
Mean of Dep. Variable	0.055	0.055
Panel 5: Persistent Absences 2016/17		
Wave 6 Mother Poor Health	0.030	0.032
	(0.024)	(0.038)
Wave 6 Father Poor	0.026	0.042

Health	(0.024)	(0.041)
$\beta_1 + \beta_2$	0.056*	0.074
R-Squared	0.019	0.543
Mean of Dep.	0.082	0.082
Variable		
Observations	2085	2085
Academic Year FE	No	Yes
School FE	No	Yes

Standard errors in parentheses

Controls are at child age 14 (wave 6) unless otherwise indicated. Standard errors are cluster-robust at the school level. Degrees of Freedom 916

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.22 shows that poor maternal health at age 14 has significant negative estimated effects on the Attainment 8 score, and positive effects on the likelihood of a high SDQ score and persistent school absences in 2015/16 in column (1). However, after controlling for school-level characteristics in column (2), there is no significant effect of poor maternal health on either of the educational outcomes or absences in 2015/16 and 2016/17. Poor maternal health at age 14 has a positive but weakly significant effect on the likelihood of a high SDQ score (5.6pp, $p < 0.1$) in column (2).

Poor paternal health at age 14 has a positive effect on persistent school absences 2015/16 (column 1). However, in column (2) with school fixed effects, poor paternal health has no significant effects on any of the outcomes. Poor paternal health also has no significant effect on child EBPs or the Attainment 8 score across all models.

The effects of poor maternal health and poor paternal health on achieving 5 GCSE A*-C is negative but statistically insignificant across all models. Additionally, the joint effect of poor health in both parents at age 14 on educational outcomes is small and insignificant (column 2).

By testing the joint estimated effect of poor health in both parents at age 14 in column (2), we find that this has a large positive and statistically significant effects on the likelihood of having a high SDQ score (7.4 p.p., $p < 0.1$) and absences in the 2015/16 school year (7.9 p.p., $p < 0.05$).

Table 4. 23 Two-parent analysis: Interaction with the Gender of the child

	(1) 5 GCSEs A* to C	(2) Attainment 8	(3) High SDQ Score	(4) Persistent Absences 2016	(5) Persistent Absences 2017
Mother Poor Health (Fair/Poor): Female Child	-0.013 (0.060)	-1.933 (2.317)	0.021 (0.033)	0.065 (0.059)	0.014 (0.055)
Mother Poor Health (Fair/Poor) # Child is male=1	-0.007 (0.098)	1.774 (3.448)	0.071 (0.077)	-0.050 (0.080)	0.037 (0.088)
Father Poor Health (Fair/Poor): Female Child	-0.018 (0.056)	-2.532 (2.134)	0.051 (0.038)	0.072 (0.057)	0.030 (0.052)
Father Poor Health (Fair/Poor) # Child is male=1	0.049 (0.081)	2.816 (3.287)	-0.062 (0.056)	-0.065 (0.069)	0.022 (0.069)
Child is male	-0.088*** (0.030)	-4.397*** (1.001)	0.001 (0.021)	0.000 (0.019)	-0.012 (0.024)
Observations	2085	2085	2085	2085	2085
R-Squared	0.681	0.777	0.506	0.487	0.543
Mean of Dep. Variable	0.760	55.086	0.054	0.055	0.082
Academic Year FE	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. All regressions include full set of controls and school level fixed effects

Controls are at child age 14 (wave 6) unless otherwise indicated. Standard errors are cluster robust at school level.

* p < 0.10, ** p < 0.05, *** p < 0.01

Table 4.23 presents the estimated effects of poor maternal health and poor paternal health on all outcomes, while including an interaction term for the child's gender. We did

not find any significant differences in the estimated effects by the gender of the child across all outcomes. Joint tests of significance show that the estimated effects of poor paternal health and poor maternal health are not significant for male children, as well as female children, for all outcomes.

Table 4.24 further examines the difference in outcomes by the gender of the parent who has poor health by looking at the estimated effects of poor maternal health in early and mid-childhood, and the estimated effects of poor paternal health in early and mid-childhood. We also test the joint effects of poor parental health in both parents in early childhood and mid-childhood.

In Panel 1 Column (1), we find that poor maternal health in mid-childhood significantly reduces the likelihood of attaining 5 GCSEs at A*-C (5.5 p.p., $p < 0.05$). However, this effect is not significant once school fixed effects are added. Paternal health has no significant effect across all models. Panel 2 shows that poor maternal health in early childhood is associated with a small but significant decrease in Attainment 8 scores (-2.48 , $p < 0.05$) even after adding school fixed effects. In contrast, no other significant parental health effect is found.

Table 4. 24 Two parent analysis: Timing of exposure

	(1) All Controls	(2) All controls + FE
Panel 1: 5 GCSEs A*-C		
Early Childhood: Mother Poor Health	-0.002 (0.023)	-0.022 (0.038)
Early Childhood: Father Poor Health	-0.009 (0.020)	0.012 (0.035)
Mid Childhood: Mother Poor Health	-0.055** (0.024)	-0.044 (0.039)
Mid Childhood: Father Poor Health	0.021 (0.023)	0.026 (0.040)
R-Squared	0.373	0.682
Panel 2: Attainment 8 Score		
Early Childhood: Mother Poor Health	-1.069 (0.737)	-2.476** (1.184)

Early Childhood: Father Poor Health	-0.748 (0.727)	-0.576 (1.301)
Mid Childhood: Mother Poor Health	-1.547* (0.815)	-0.753 (1.298)
Mid Childhood: Father Poor Health	-0.450 (0.888)	0.380 (1.539)
R-Squared	0.513	0.778
Panel 3: High SDQ Score		
Early Childhood: Mother Poor Health	0.024 (0.016)	0.047** (0.023)
Early Childhood: Father Poor Health	0.010 (0.014)	0.015 (0.025)
Mid Childhood: Mother Poor Health	0.042** (0.018)	0.017 (0.024)
Mid Childhood: Father Poor Health	0.001 (0.015)	0.017 (0.027)
R-Squared	0.060	0.508
Panel 4: Persistent Absences 2015/16		
Early Childhood: Mother Poor Health	0.019 (0.016)	0.041 (0.029)
Early Childhood: Father Poor Health	0.012 (0.014)	0.027 (0.025)
Mid Childhood: Mother Poor Health	0.054*** (0.020)	0.035 (0.035)
Mid Childhood: Father Poor Health	0.019 (0.018)	0.001 (0.028)
R-Squared	0.050	0.491
Panel 5: Persistent Absences 2016/17		
Early Childhood: Mother Poor Health	0.047** (0.021)	0.067* (0.034)
Early Childhood: Father Poor Health	-0.002 (0.017)	-0.013 (0.027)
Mid Childhood: Mother Poor Health	-0.002 (0.019)	-0.000 (0.033)
Mid Childhood: Father Poor Health	0.019	0.057*

	(0.020)	(0.034)
R-Squared	0.022	0.549
Academic Year FE	No	Yes
School FE	No	Yes
Observations	2085	2085

Standard errors in parentheses

Controls are at child age 14 (wave 6) unless otherwise indicated. Standard errors are cluster robust at school level.

Degrees of Freedom= 916

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Panel 3, poor maternal health in early childhood increases the likelihood of a high SDQ score by 4.7 percentage points ($p < 0.05$), whereas the effects for mid-childhood maternal health and paternal health at either time are not significant after adjusting for controls. Panel 4 shows that poor maternal health in mid-childhood significantly increases the likelihood of persistent absences in 2015/16 in column (1) (5.4 p.p., $p < 0.05$). However, these effects are not significant once school-level fixed effects are added to the model. Finally, Panel 5 finds that poor maternal health in early childhood increases the likelihood of persistent absences in 2016/17 by 6.7 percentage points ($p < 0.1$). Additionally, mid-childhood paternal health also has a positive effect on this outcome (5.7 percentage points, $p < 0.1$). By jointly testing the parameters, we find that poor parental health in both parents during early childhood has significant effects on the Attainment 8 score (-3.05, $p < 0.10$), the likelihood of having a high SDQ score (6.2 pp, $p < 0.10$) and persistent absences in 2015/2016 (6.8 p.p., $p < 0.10$).

Overall, poor maternal health, particularly in early childhood, shows more consistent associations with adverse outcomes in children than paternal health.

4.8 Discussion

Poor parental health has the potential to affect children's educational outcomes, especially if it means that the child has caregiving responsibilities for the parent. While many previous studies exist, only a few address this relationship in the context of a developed country with enforced compulsory schooling laws and using an important measure of academic achievement, such as GCSE results. Using the UK Millennium Cohort

Study, which has collected data on individual and household characteristics at various stages of childhood, we examine the effects of poor parental health at age 14 on GCSE examination outcomes at the end of secondary school for children in England. We use fixed effects to control for unobserved school-level factors. A key contribution is to investigate the important aspect of the timing of exposure to poor parental health, whether this was in early childhood (ages 0-5) or mid-childhood (ages 7-14). We also consider heterogeneity in effects along several dimensions.

In summary, we do not find a significant effect of poor parental health in early or mid-childhood on child educational outcomes at GCSE level when we control for unobserved heterogeneity using school fixed effects. This suggests that the educational outcomes of children in England are surprisingly resilient against poor parental health. It is possible that the institutional framework in England sufficiently protects children from the negative consequences of poor parental health. Further research can explore how specific policies in England, such as the Personal Independence Payments or other income support for health conditions and Young Carer assessments, help mitigate the impact of parental health on children's educational outcomes. Additionally, the psychological theory of "posttraumatic growth" highlights how challenges in life can potentially lead to positive changes in the long run (Tedeschi, 2004). Parents with poor health may have a greater appreciation for life or especially prioritise the well-being of their child and family. Children of parents with poor health may also adjust their behaviour or attitude to avoid burdening their parents, such as becoming more diligent in their schoolwork (Meyerson et al., 2011; Ferris and O'Brien, 2022).

We also do not find any significant differences in our estimates relating to gender differences of the child, low income, or single parent status.

However, we also examined some of the mechanisms that may contribute to poor academic performance in secondary school and estimated the effect of poor parental health on these outcomes. Specifically, we found that children who have parents with poor health at age 14 are more likely to have emotional and behavioural issues at age 14. We also found

that children who have a parent with poor health at age 14 are more likely to be persistently absent at school in both the 2015/2016 and 2016/2017 academic years (ages 14-16), just before taking the GCSE examinations. Further analysis shows that the effects on school absences, and emotional and behavioural problems are rooted in early childhood exposure to poor parental health.

Our results highlight the importance of accounting for unobserved confounding; in models estimated without school fixed effects, the effect sizes are consistently higher than those with fixed effects and therefore overstate the negative impact on child educational outcomes.

Another consideration is that our study is more recent, based on a contemporaneous sample of adolescents. Our sample of families experiencing parental health shock is arguably quite different to those in earlier studies, due to the increase in chronic illness and health conditions over time, and this may affect findings. Notwithstanding these differences, there are several reasons that may underlie discrepancies in the findings. The first relates to the fact that our outcomes span ages 14-16, whilst most previous work considers younger children. This is not a mild distinction as the outcomes at GCSE level are an important indicator for outcomes later in life, such as earnings, socio-emotional outcomes, and career trajectories (Department of Education, 2021; Starr, Haider and von Stumm, 2024).

4.8.1 Limitations

Despite the number of strengths of this study, there are some limitations. Firstly, the data from the MCS survey is observational. While the empirical strategy allows us to adjust for unobserved variables at the school level that are correlated with the outcome variables, there may still be residual confounding due to unobserved time-varying factors affecting educational outcomes. For example, the onset of domestic violence or parental substance abuse could be significant factors causing both poor parental health and poor educational attainment. Therefore, our models cannot establish causality, but the use of

this rich dataset offers important insights into the relationship between parental health and child educational outcomes.

Secondly, since the MCS Waves 6 and 7 took place when the cohort child was aged 14 and 17, respectively, no survey was conducted around the time the cohort members took their GCSE examinations. Therefore, we do not observe time-varying control factors near the time of the exam. Instead, we only observe them at the beginning of secondary school, and we compare the outcomes of children who have poor health at age 14 or earlier with those of children who do not.

We also cannot fully exploit the longitudinal nature of this dataset due to our outcome of interest, GCSE grades, which are only observed at one point in time. Our study considers the effects of parental health on educational attainment at GCSE level, but we cannot observe any relationship between parental health and intermittent educational outcomes or performance at age 14. Due to the educational system in the UK, formal educational qualifications from school years 9-11 are measured by the results of examinations at the end of year 11 (age 16) only. Any other test scores or academic achievements do not count towards this grade. Therefore, if poor parental health affected short-term academic performance at age 14, but if it did not affect the GCSE grades, we would not observe this in our study. We acknowledge that we cannot observe the parental health just before the child takes the GCSE exams, and this could affect our results. This is an important consideration for further research in this area, and when collecting data.

In conclusion, our study emphasises the importance of accounting for unmeasured confounding in estimating the effects of poor parental health on child educational attainment, as OLS estimates tend to overstate the negative effects compared to school-level fixed effects methods. From a policy perspective, this study highlights that there are negative consequences to poor parental health on child EBPs and school absences. Children who have parents with poor health may need additional support to deal with emotional and behavioural issues. If children of parents with poor health are persistently absent from school due to caregiving burden, more support should be provided to young carers to help

them manage family life and schooling. Our study also suggests that some of the effects of poor parental health on GCSE outcomes can be mitigated if the child has a strong academic background (high prior academic achievement). Further research can continue to examine the effects of poor parental health on emotional and behavioural outcomes by analysing the impacts on internalising and externalising skills separately, and by investigating the longer-run effects on the mental health outcomes of teenagers in the MCS at age 17 using the Kessler 6 in Wave 7.

Chapter 5: Conclusion

This thesis examines the role of health within a family unit, specifically investigating the importance of health in three key stages of childhood (at birth, early childhood, and adolescence).

In summary, Chapter 2 studies the impact of a caesarean delivery on the child's incidence of illness in early childhood. This chapter focuses on respiratory health and diarrhoea as measures of childhood illness. It considers the effects of planned and unplanned caesarean sections separately. Using the Pakistan Demographic Health Survey (PDHS) data, mother-level fixed effects are utilised to control for unobserved time-invariant factors. Additionally, information on the birth delivery of older siblings is used to find the causal effect of a caesarean delivery with an IV model. In Chapter 3, the effects of longstanding health conditions in children on the likelihood of employment for Cohabiting mothers, single mothers, and fathers are examined using the Growing up in Ireland (GUI) cohort study. The Heckman selection model is used to correct for sample selection bias in studying the effect on parents' hours worked. Finally, Chapter 4 examines the impact of having a parent with poor health on the GCSE attainment of English children in the Millennium Cohort Study (MCS). The effects on children's emotional and behavioural problems and school attendance in adolescence are also considered. Finally, the differences in the effects of poor parental health in early childhood and mid-childhood are estimated for this chapter.

The findings suggest that poor parental health has an intergenerational effect on adolescents, increasing the risk of emotional and behavioural problems and school absences, but there is no evidence to suggest an adverse effect on educational attainment at the GCSE level. Longstanding health conditions or illnesses in children are found to be detrimental to participation in the workforce for single mothers but slightly increase the likelihood that fathers work. However, conditional on working, fathers of such children reduce their hours worked. Finally, caesarean section, particularly a planned caesarean section, can have a significant impact on the incidence of diarrhoea in Pakistani children, but there is no clear evidence of any effect on the incidence of Acute Respiratory Illness

(ARI). Such illnesses contribute to the high rates of child morbidity and mortality and are an economic burden in developing countries where the rates of caesarean section are rising disproportionately.

Overall, these results contribute new knowledge to enhance our understanding of how experiences and the conditions in which we are born, live, and grow impact health and socioeconomic outcomes. This is consistent with research on the determinants of health inequalities (Marmot et al., 2012; Saunders, McHale and Hamelmann, 2017) and the role of health in human capital formation (Bleakley, 2010; Lim et al., 2018). This thesis improves the understanding of how child and parental health can jointly influence the economic trajectories of a child's life.

From a policy perspective, it is important to understand the factors that make children and families more at risk of poor economic outcomes and incorporate these aspects into policy and interventions. Specifically, the findings from this thesis suggest that policies should support and invest in parents in order to improve outcomes for children. For example, mothers who had their child via caesarean in developing countries like Pakistan could benefit from educational interventions that promote the importance of early detection and treatment of diarrhoea. Additionally, all mothers should be educated on the importance of documenting key health indicators during their pregnancy and delivery, and the long-term consequences of caesarean section. Educational interventions for preventative care and health promotion are effective in developing countries, especially when they utilise schools or community health workers (Gilmore and McAuliffe, 2013; Mukamana and Johri, 2016).

If policymakers are interested in removing barriers to work for single mothers, providing appropriate and supplementary childcare or payments for children who require additional support is essential. Additionally, if single mothers of children with longstanding health conditions or illnesses are less likely to work, it is possible they are choosing to focus on their child's development in the absence of a second parent and should be supported through this. Currently in Ireland, parents may receive a Domiciliary Care Allowance

(DCA) if their child has a longstanding disability that allows them to pay for their care. The DCA is a fixed rate of €360 per month, regardless of the level of care required for the child. An alternative model to follow is that of the Nordic countries, where parents of children with disabilities are paid a sum equivalent to the market wage for the assessed hours of care required for each individual child (Von Granitz et al., 2022). The policy in such countries aims to give parents a choice between working and caring for their child by taking into account the impact caretaking has on their work activity. Further research can look at the impact of child health conditions on household income, and whether the DCA is sufficient in compensating for the loss in income or increased childcare costs.

Finally, it is important to acknowledge the contribution and burden for children who have a parent with poor parental health, including young carers. Investing in parents with poor health could have spillover effects on improving children's emotional and behavioural health, as well as their school attendance, in adolescence. Policies that put in place structures for additional support, such as counselling or supplementary tutoring for affected students, could ensure that education is a level playing field. While young carers can be formally recognised by social services in England, this does not necessarily lead to actual support being received, and the availability of educational support depends on the resources available to any particular school. (Leu et al., 2023). Overall, policies and early interventions that support families through health-related challenges could have a significant combined benefit for parents and children.

One of the limitations identified in this study is the absence of information on specific health conditions or complications. Therefore, one aspect for further research is to use detailed information on the health of individuals, such as exact diagnosis, disabilities, severity of conditions, and comorbidities, possibly by linking survey data on demographic characteristics to hospital data. This would allow future research to study how particular illnesses, and their severity, could have a different impact on outcomes. For example, Chapter 3 would benefit from categorising children's conditions into those requiring significant support in daily activities and those that require expensive care. Additionally,

in Chapter 2, information on high-risk pregnancies or delivery complications would help in further categorising caesarean births into necessary cases and elective procedures.

The focus of this thesis is on using available survey responses on health and subjective measures of health, which limits its implications for policies targeted to specific health conditions. However, these survey measures of health or ‘soft data’ can also have the benefit of including individuals who struggle with caregiving and/or illness but cannot access medical care due to costs, time constraints, or difficulties in access (Corsi et al., 2012), and also in removing clinician bias that may exist in medical records (Koran, 1975; Kraemer, 2014). Furthermore, research on subjective health ratings finds that they are good predictors of ill-health, its severity, duration and restrictions (Manderbacka, 1998; Mavaddat et al., 2011; Mutz and Lewis, 2022). Additionally, while the majority of studies on the effects of parental health on child educational outcomes in developed countries use data on relatively rare health shocks and events (Aaskoven, Kjær and Gyrd-Hansen, 2022; Ferrara et al., 2025), Chapter 4 uses data that can observe poor parental health before a health diagnosis or event occurs, capturing anticipation effects.

Moreover, future research relating to Chapter 2 could focus on the impact of caesarean section delivery on the long-term health and economic trajectories of women and children. This could also involve studying the use of healthcare, community support, and education as mediating factors. This would require rich longitudinal data on the health and behaviours of mothers and children, which is currently not available on Pakistan. Despite the benefits of longitudinal studies in addressing questions concerning the impact of risk factors on health outcomes, research on Pakistan has mainly focused on cross-sectional studies as panel survey data collection is expensive and time-intensive (Lynn, Couper and Watson, 2019). However, further research may be possible for similar developing countries such as India using the Young Lives (Younger Cohort) study that collects data on birth delivery method and child health (Barnett et al., 2013).

Chapters 3 and 4 use available longitudinal studies. A common limitation of such data is inconsistency in the questions asked in each wave of the dataset. For example, in

Chapter 3, Wave 6 was excluded from the main analysis due to differences in the questions asked about the work outcomes of parents, making it difficult to compare this outcome consistently across waves. Furthermore, questions on the health of other family members and information on forms of childcare were not consistently asked throughout the waves. Another issue with the data is missing responses. While it is possible to use non-response survey weights to adjust for differences in response rate, and there are available methods for dealing with missing data, such as multiple imputation and Bayesian simulation, the research may suffer from reduced precision and statistical power when dealing with missing responses. Longitudinal studies are costly to conduct, and more effort should be devoted to ensuring the consistency and completeness of responses.

Finally, the timing of the collection of data around key development stages is an important consideration. Ideally, Chapter 4 would use controls for mother and child characteristics around the timing that children took their GCSEs rather than at age 14. However, due to the timing of the collection of the survey, it is not possible to observe any responses, including those on parental health, closer to the time of GCSE examinations. Ideally, the exact timing of diagnosis of health outcomes would also be observed in the datasets, as this may allow researchers to use quasi-experimental methods to look at variation in outcomes before and after diagnosis.

The established Grossman model (Grossman, 1972) views health as the result of an individual's rational choices in allocating time and resources, ignoring the fundamental role of family upbringing and early investments. As a result, there is a large body of economic literature on how one's own health can impact outcomes such as lifetime earnings, work outcomes, and productivity (Gumbau Albert, 2021; Shawa, Hollingsworth and Zucchelli, 2024; Hosseini, Kopecky and Zhao, 2025). Overall, this thesis contributes to the literature on the role of health in the family unit on human capital formation and economic activity using applied microeconomics and survey data. The findings of this thesis support policy recommendations for early and proportional investment in health as a foundation for socioeconomic outcomes, and a means to reduce inequalities (Marmot et al., 2020).

Appendices

Appendix Table 2. 1. Balance table for within-families analysis sample

	(1) Full sample	(2) Sample used for Within Mothers Analysis	(3) Singleton children	(4) Difference (2)-(3)
Any symptoms of ARI	0.45 (0.50)	0.41 (0.49)	0.51 (0.50)	-0.11***
Diarrhoea last two weeks	0.20 (0.40)	0.19 (0.39)	0.21 (0.41)	-0.03***
CS birth	0.15 (0.36)	0.13 (0.34)	0.18 (0.38)	-0.05***
Age of the Child	2.02 (1.42)	2.03 (1.44)	2.00 (1.38)	0.03
Female Child	0.49 (0.50)	0.50 (0.50)	0.48 (0.50)	0.02**
Birth Order: 1	0.23 (0.42)	0.17 (0.37)	0.33 (0.47)	-0.16***
2 to 3	0.38 (0.48)	0.44 (0.50)	0.27 (0.45)	0.17***
4 to 5	0.22 (0.41)	0.22 (0.42)	0.22 (0.41)	0.01
6+	0.17 (0.38)	0.17 (0.37)	0.18 (0.39)	-0.01**
Mother's age at birth: < 20	0.10 (0.30)	0.09 (0.29)	0.11 (0.31)	-0.02***
20 to 34	0.79 (0.41)	0.83 (0.38)	0.73 (0.44)	0.09***
35 to 49	0.11 (0.32)	0.08 (0.28)	0.16 (0.37)	-0.08***
Mother is employed	0.15 (0.36)	0.15 (0.36)	0.15 (0.36)	0.00
Wealth Index : Poorest	0.23 (0.42)	0.25 (0.43)	0.20 (0.40)	0.05***
Poorer	0.20 (0.40)	0.21 (0.40)	0.20 (0.40)	0.01
Middle	0.19 (0.39)	0.20 (0.40)	0.19 (0.39)	0.01
Richer	0.19 (0.39)	0.18 (0.39)	0.20 (0.40)	-0.02**
Richest	0.19 (0.39)	0.17 (0.37)	0.22 (0.41)	-0.05***
Mother has a primary education	0.44 (0.50)	0.42 (0.49)	0.48 (0.50)	-0.05***

Child Ever breastfed	0.97 (0.17)	0.97 (0.17)	0.97 (0.17)	-0.00
Mother smokes/ uses tobacco	0.08 (0.27)	0.08 (0.27)	0.07 (0.25)	0.01***
Punjab	0.34 (0.47)	0.34 (0.47)	0.33 (0.47)	0.01
Sindh	0.22 (0.41)	0.22 (0.41)	0.21 (0.41)	0.01
KPK	0.20 (0.40)	0.19 (0.39)	0.21 (0.41)	-0.02***
Baluchistan	0.15 (0.36)	0.15 (0.36)	0.15 (0.36)	-0.00
Gilgit Baltistan	0.05 (0.22)	0.05 (0.21)	0.05 (0.22)	-0.00
FATA	0.05 (0.21)	0.05 (0.22)	0.04 (0.20)	0.01*
Urban Area	0.44 (0.50)	0.42 (0.49)	0.47 (0.50)	-0.05***
Number of ANC visits	3.66 (3.38)	3.27 (3.12)	3.95 (3.53)	-0.68***
Observations	20657	12624	8033	20657

*, **, *** indicate significance at 10%, 5%, and 1% levels.

Appendix Table 2. 2. OLS estimation: using sample studied in within-families analysis

	(1) Any Symptoms of ARI	(2) Diarrhoea
Births delivered by Caesarean	0.024 (0.022)	0.033** (0.016)
Observations	12624	12624
R-squared	0.045	0.092
Mean of Dep. Variable	0.433	0.196
Region FE	No	No
Region-year FE	Yes	Yes

Standard errors in parentheses

All regressions include year of birth and month of survey fixed effects. The standard errors are clustered at the community level.

Child and Maternal controls include child sex, birth order, mother's age at birth, household income quintile, maternal education, and maternal employment. All controls additionally include maternal health behaviors: breastfeeding history, number of antenatal care visits, and smoking behaviour.

* p < 0.10, ** p < 0.05, *** p < 0.01

Appendix Table 2. 3. OLS estimation using sample studies in IV analysis

	(1)	(2)
	Any Symptoms of ARI	Diarrhoea
Births delivered by Caesarean	0.030	0.048**
	(0.026)	(0.024)
Observations	6636	6636
R-squared	0.034	0.032
Mean of Dep. Variable	0.484	0.265

Standard errors in parentheses

All regressions include region-trends, year of birth, and month of survey fixed effects. The standard errors are clustered at the community level.

All regression include controls: child sex, birth order, mother's age at birth, household income quintile, maternal education, maternal employment, breastfeeding , number of antenatal care visits, and smoking behaviour.

* p < 0.10, ** p < 0.05, *** p < 0.01

Appendix Table 2. 4. IV analysis: adjusting for illness in older sibling)

	(1)	(2)
	Any Symptoms of ARI	Diarrhoea
Births delivered by Caesarean	0.0084	0.0223
	(0.030)	(0.030)
Older Siblings- Any Symptoms of ARI	0.3875***	
	(0.016)	
Older Sibling has Diarrhoea		0.2934***
		(0.026)
Observations	6636	6636
R-squared	0.1470	0.0527
First stage Coef.	0.8280	0.8280
	(0.0165)	(0.0165)
Kleibergen-Paap rk Wald F statistic	2319.9600	2309.6670

Standard errors in parentheses

First stage regresses the instrument on Births by Caesarean

All regressions include year of birth, month of survey and region fixed effects. The standard errors are clustered at the community level.

Controls include child sex, birth order, mother's age at birth, household income quintile, maternal education, and maternal employment, breastfeeding, number of antenatal visits, and smoking behaviour, and older siblings report of ARI or diarrhoea

* p < 0.05, ** p < 0.01, *** p < 0.001

Appendix Table 2. 5. Balance table comparing 2012/2013 and 2017/2018 sample (used for timing of decision analysis)

	(1) Full sample	(2) 2017/2018 Survey Sample	(3) 2012/2013 Survey Sample	(4) Diff (2)-(3)
Any symptoms of ARI	0.45 (0.50)	0.46 (0.50)	0.43 (0.50)	0.03***
Diarrhoea last two weeks	0.20 (0.40)	0.18 (0.39)	0.21 (0.41)	-0.03***
CS Births	0.15 (0.36)	0.18 (0.39)	0.12 (0.33)	0.06***
Age of the Child	2.02 (1.42)	2.01 (1.43)	2.04 (1.41)	-0.03
Female Child	0.49 (0.50)	0.49 (0.50)	0.49 (0.50)	0.00
Birth Order: 1	0.23 (0.42)	0.24 (0.42)	0.23 (0.42)	0.01
2 to 3	0.38 (0.48)	0.39 (0.49)	0.37 (0.48)	0.02***
4 to 5	0.22 (0.41)	0.22 (0.41)	0.22 (0.41)	-0.00
6+	0.17 (0.38)	0.15 (0.36)	0.19 (0.39)	-0.03***
Mother's age at birth: < 20	0.10 (0.30)	0.10 (0.30)	0.09 (0.29)	0.01**
20 to 34	0.79 (0.41)	0.79 (0.41)	0.79 (0.41)	-0.00
35 to 49	0.11 (0.32)	0.11 (0.31)	0.12 (0.32)	-0.01
Mother is employed	0.15 (0.36)	0.12 (0.32)	0.19 (0.39)	-0.07***
Wealth Index : Poorest	0.23 (0.42)	0.23 (0.42)	0.23 (0.42)	0.00
Poorer	0.20 (0.40)	0.21 (0.41)	0.20 (0.40)	0.01
Middle	0.19 (0.39)	0.19 (0.39)	0.19 (0.40)	-0.00
Richer	0.19 (0.39)	0.19 (0.39)	0.19 (0.39)	-0.00
Richest	0.19 (0.39)	0.19 (0.39)	0.19 (0.39)	-0.00
Mother has a primary education	0.44 (0.50)	0.45 (0.50)	0.44 (0.50)	0.02**
Child Ever Breastfed	0.97	0.97	0.97	-0.01**

	(0.17)	(0.18)	(0.16)	
Mother smokes/ uses tobacco	0.08	0.09	0.07	0.02***
	(0.27)	(0.28)	(0.25)	
Punjab	0.34	0.34	0.34	0.00
	(0.47)	(0.47)	(0.47)	
Sindh	0.22	0.22	0.21	0.00
	(0.41)	(0.41)	(0.41)	
KPK	0.20	0.20	0.20	0.01
	(0.40)	(0.40)	(0.40)	
Baluchistan	0.15	0.14	0.16	-0.02***
	(0.36)	(0.35)	(0.37)	
Gilgit Baltistan	0.05	0.00	0.09	-0.09***
	(0.22)	(0.00)	(0.29)	
FATA	0.05	0.10	0.00	0.10***
	(0.21)	(0.30)	(0.00)	
Urban Area	0.44	0.46	0.43	0.03***
	(0.50)	(0.50)	(0.49)	
No. of ANC visits	3.66	3.94	3.40	0.54***
	(3.38)	(3.25)	(3.47)	
Observations	20657	9834	10823	20657

*, **, *** indicate significance at 10%, 5%, and 1% levels.

Appendix Table 2. 6. Probit (average marginal effects): Any symptoms of Acute Respiratory Illness (ARI)

	(1) No Controls	(2) Child & Maternal Controls	(3) All Controls	(4) All Controls	(5) All Controls + Female Interaction
Births delivered by Caesarean	0.043*** (0.014)	0.028* (0.015)	0.031** (0.015)	0.029* (0.015)	0.036** (0.017)
Caesarean*Female					-0.016 (0.025)
Observations	20657	20657	20657	20657	20657

Standard errors in parentheses

All regressions include year of birth and month of survey fixed effects. The standard errors are clustered at the community level.

Child and Maternal controls include child sex, birth order, mother's age at birth, household income quintile, maternal education, and maternal employment. All controls additionally include maternal health behaviors: breastfeeding, number of antenatal care visits, and smoking behaviour.

* p < 0.10, ** p < 0.05, *** p < 0.01

Appendix Table 2. 7: Probit (average marginal effects): Diarrhoea

	(1) No Controls	(2) Child & Maternal Controls	(3) All Controls	(4) All Controls	(5) All Controls + Female Interaction
Births delivered by Caesarean	0.026** (0.011)	0.035*** (0.012)	0.036*** (0.012)	0.035*** (0.011)	0.051*** (0.014)
Caesarean*Female					-0.035* (0.018)
Observations	20657	20657	20657	20667	20657

Standard errors in parentheses

All regressions include year of birth and month of survey fixed effects. The standard errors are clustered at the community level.

Child and Maternal controls include child sex, birth order, mother's age at birth, household income quintile, maternal education, and maternal employment. All controls additionally include maternal health behaviors: breastfeeding, number of antenatal care visits, and smoking behaviour.

* p < 0.10, ** p < 0.05, *** p < 0.01

Appendix Table 2. 8: Negative Binomial Regression: Number of symptoms of Acute Respiratory Illness (ARI)

	(1) No Controls	(2) Child & Maternal Controls	(3) All Controls	(4) All Controls	(5) All Controls + Female Interaction
Births delivered by Caesarean	0.037 (0.045)	0.026 (0.044)	0.037 (0.045)	0.029 (0.045)	0.071 (0.054)
Caesarean*Female					-0.089 (0.080)
Observations	20657	20657	20657	20657	20657

Standard errors in parentheses

All regressions include year of birth and month of survey fixed effects. The standard errors are clustered at the community level.

Child and Maternal controls include child sex, birth order, mother's age at birth, household income quintile, maternal education, and maternal employment. All controls additionally include maternal health behaviors: breastfeeding, number of antenatal care visits, and smoking behaviour.

* p < 0.10, ** p < 0.05, *** p < 0.01

Appendix Table 2. 9. Oster robustness test for Caesarean delivery and ARI					
	(2)	(3)	(4)	(5)	(6)
	Model 2	Model 3	Model 4	Model 5	Model 6
Births delivered by Caesarean	0.040*** (0.010)	0.026*** (0.010)	0.024** (0.010)	0.027*** (0.010)	0.026** (0.010)
Observations	20657	20657	20657	20657	20657
R-squared	0.045	0.024	0.031	0.036	0.044
Delta	1.902	5.437	2.060	1.633	1.926
Beta adj.	0.013	0.034	0.014	0.010	0.014
t-stat	2.794	-0.801	0.987	1.631	1.242
p-value	0.005	0.423	0.324	0.103	0.214

δ represents the relative strength of selection on unobservables vs. observables needed to nullify the effect. Bias-adjusted β is calculated assuming $\max R^2 = 1.3 \times R^2$ from full model.

Full model includes month and year fixed effects, region-trend dummies, and full set of controls.

Appendix Table 2. 10. Oster robustness test for Caesarean delivery and diarrhoea					
	(2)	(3)	(4)	(5)	(6)
	Model 2	Model 3	Model 4	Model 5	Model 6
Births delivered by Caesarean	0.006 (0.008)	0.010 (0.008)	0.024*** (0.008)	0.024*** (0.008)	0.024*** (0.008)
Observations	20,657	20,657	20,657	20,657	20,657
R-squared	0.057	0.041	0.045	0.049	0.052
Delta (δ)	-274.120	1.269	2.586	409.964	-612.743
Bias-adjusted β	0.026	0.001	0.006	0.025	0.025
t-stat	-2.625	1.073	2.162	-0.108	-0.140
p-value	0.009	0.283	0.031	0.914	0.888

δ represents the relative strength of selection on unobservables vs. observables needed to nullify the effect. Bias-adjusted β is calculated assuming $\max R^2 = 1.3 \times R^2$ from full model. Full model includes month and year fixed effects, region-trend dummies, and full set of controls.

Appendix Table 2. 11. Cox regression hazard model

	Coef.	St. Err.	t- value	p- value	[95% Conf Interval]	Sig
Births delivered by Caesarean	1.188	.112	1.83	.068	.988 1.429	*
Female Child	.952	.06	-0.78	.438	.841 1.078	
Birth Order Number	1.087	.018	4.97	0	1.052 1.123	***
Mother's age at birth	.726	.058	-3.99	0	.621 .85	***
Wealth index	.894	.027	-3.74	0	.843 .948	***
Mother has primary education	.778	.065	-3.02	.003	.661 .916	***
Mother is employed	1.205	.099	2.28	.022	1.027 1.415	**
Mother smokes/ uses tobacco	.903	.097	-0.95	.343	.731 1.115	
Region : base Punjab	1	.	.	.	.	.
Sindh	.923	.082	-0.90	.369	.776 1.099	
KPK	.76	.076	-2.74	.006	.625 .925	***
Baluchistan	1.255	.155	1.84	.066	.985 1.599	*
GB	.875	.134	-0.87	.386	.648 1.183	
FATA	.239	.069	-4.99	0	.136 .419	***
Mean dependent var	853.192	SD dependent var	544.890			
Pseudo r-squared	0.012	Number of obs	21796			
Chi-square	197.748	Prob > chi2	0.000			
Akaike crit. (AIC)	23429.469	Bayesian crit. (BIC)	23629.206			

Appendix Table 2. 12. Average marginal effects from logistic regression on early child death (under 12 months)

	(1) Marginal Effects
Births delivered by Caesarean	0.008 (0.007)
Female Child	-0.008 (0.005)
Birth Order Number	0.006*** (0.001)
Mother's age at birth (years)	-0.028*** (0.007)
Wealth index	-0.006*** (0.002)
Mother has a primary level education	-0.012* (0.007)
Mother is employed	0.015** (0.007)
Mother smokes/ uses tobacco	-0.009 (0.009)
Observations	22031

Standard errors in parentheses

Average marginal effects (dy/dx) from a logistic regression. All regressions include region and year of birth fixed effects. Standard errors clustered at the community level.

Control variables include child sex, birth order, mother's age at birth, education, wealth, employment, and tobacco use.

* p < 0.10, ** p < 0.05, *** p < 0.01

Appendix Table 3. 1 OLS LPM and RE Probit estimates (average marginal effects) on parental employment (all covariates)

	(1)	(2)	(3)	(4)	(5)	(6)
	Cohabiting Mother LPM	Cohabiting Mother RE	Single Mother LPM	Single Mother RE	Father LPM	Father RE
Child has longstanding condition	-0.010	-0.011	-	-	0.016***	0.017***
	(0.007)	(0.007)	0.053**	0.049**	(0.005)	(0.006)
Child is male	0.003	0.001	0.040*	0.039*	0.000	-0.001
	(0.009)	(0.009)	(0.021)	(0.021)	(0.005)	(0.005)
Low birthweight	0.011	0.014	-0.026	-0.026	-0.036	-0.024
	(0.029)	(0.029)	(0.064)	(0.056)	(0.024)	(0.016)
Child was in NICU	-0.018	-0.015	-0.066*	-0.062*	0.005	0.006
	(0.014)	(0.015)	(0.036)	(0.036)	(0.009)	(0.008)
Child was premature	-0.003	-0.011	-0.003	-0.003	0.005	-0.000
	(0.026)	(0.026)	(0.051)	(0.055)	(0.020)	(0.015)
Parental Age	0.003	0.000	0.027*	0.025*	0.020***	0.011***
	(0.008)	(0.007)	(0.014)	(0.014)	(0.005)	(0.003)
Parental age squared	0.006	0.009	-0.020	-0.017	-0.024***	-
						0.014***
	(0.011)	(0.010)	(0.022)	(0.023)	(0.006)	(0.003)
Parent has degree	0.073***	0.070***	0.062**	0.065**	0.014***	0.017***
	(0.009)	(0.008)	(0.027)	(0.026)	(0.005)	(0.006)
Parent completed secondary school	0.148***	0.132***	0.181***	0.193***	0.079***	0.049***
	(0.018)	(0.016)	(0.026)	(0.029)	(0.011)	(0.006)
Parent born in Ireland	0.069***	0.064***	0.083***	0.085***	0.033***	0.027***
	(0.012)	(0.011)	(0.026)	(0.026)	(0.007)	(0.006)
Parent's Health						
Omitted. Excellent						
Very Good	-0.007	-0.007	-0.017	-0.016	-0.000	-0.001
	(0.006)	(0.006)	(0.020)	(0.023)	(0.005)	(0.005)
Good	-0.017**	-0.017**	-0.035	-0.033	-0.007	-0.007
	(0.008)	(0.008)	(0.024)	(0.025)	(0.006)	(0.006)
Fair	-0.060***	-0.056***	-0.055	-0.057	-0.072***	-
						0.060***
	(0.016)	(0.014)	(0.038)	(0.036)	(0.014)	(0.012)
Poor	-0.137***	-0.136***	-0.080	-0.082	-0.225***	-
						0.172***
	(0.040)	(0.039)	(0.077)	(0.074)	-0.000	-0.001
Urban area	-0.017***	-0.017***	0.023	0.026*	-0.027***	-
						0.027***
	(0.005)	(0.005)	(0.016)	(0.016)	(0.004)	(0.004)
Number of older siblings	-0.025***	-0.026***	-0.021*	-0.020	0.014***	0.014***
	(0.004)	(0.004)	(0.012)	(0.012)	(0.003)	(0.003)
Number of younger siblings	-0.047***	-0.047***	-	-	0.007**	0.009***
			0.047***	0.054***		
	(0.005)	(0.004)	(0.018)	(0.019)	(0.003)	(0.003)

Income Quintile						
Omitted 1 st Quintile						
2 nd	0.097***	0.096***	0.141***	0.140***	0.180***	0.168***
	(0.011)	(0.011)	(0.023)	(0.022)	(0.013)	(0.013)
3 rd	0.192***	0.186***	0.403***	0.393***	0.290***	0.279***
	(0.012)	(0.012)	(0.029)	(0.028)	(0.013)	(0.013)
4 th	0.322***	0.321***	0.457***	0.469***	0.337***	0.324***
	(0.012)	(0.012)	(0.032)	(0.036)	(0.013)	(0.013)
5 th	0.374***	0.380***	0.442***	0.483***	0.347***	0.337***
	(0.013)	(0.013)	(0.039)	(0.051)	(0.013)	(0.013)
Log-Likelihood	-9465.38		-		-	
			1168.98		4184.49	
Wald Chi ²	1822.16		356.50		1281.51	
Panel ICC	0.69		0.49		0.49	
Observations	20916	20916	2376	2376	18245	18245
Standard errors in parentheses						
* p < 0.10, ** p < 0.05, *** p < 0.01						

Appendix Table 3. 2. Heckman model of hours worked with Random Effects

Hours worked, conditional on being employed				
	(1)	(2)	(3)	
	Cohabiting	Single	Father	
	Mother	Mothers	Hours	
	Hours	Hours	Worked	
	Worked	Worked		
Child has longstanding condition	0.154	-1.121	-0.495***	
	(0.208)	(0.726)	(0.179)	
Child is male	0.219	-1.023	0.241	
	(0.254)	(0.720)	(0.233)	
Low birthweight	-1.425	0.399	-1.159	
	(0.914)	(1.858)	(0.840)	
Child was placed in NICU	0.597	-0.818	-0.344	
	(0.414)	(1.169)	(0.382)	
Child was premature	2.040**	3.584*	-0.024	
	(0.821)	(1.874)	(0.768)	
Number of older siblings	-0.971***	-2.120***	0.486***	
	(0.128)	(0.477)	(0.109)	
Number of younger siblings	-1.414***	-1.288**	0.264**	
	(0.124)	(0.650)	(0.107)	
Parent's age	0.279	1.465**	0.624***	
	(0.224)	(0.623)	(0.146)	
Parent's age squared	-0.001	-0.015	-0.008***	
	(0.003)	(0.009)	(0.002)	
Parent has degree	2.690***	4.664***	-0.762***	
	(0.232)	(0.917)	(0.219)	
Parent completed secondary school	2.424***	2.876*	-0.731*	
	(0.706)	(1.476)	(0.391)	
Parent's current health (Omitted: Excellent)				

Very Good	0.095 (0.172)	-1.292* (0.739)	0.321** (0.153)
Good	0.215 (0.233)	-1.973** (0.882)	0.320 (0.204)
Fair	-0.215 (0.482)	-0.159 (1.419)	0.972** (0.417)
Poor	-0.474 (1.547)	-0.698 (2.676)	-2.456 (2.091)
Urban Region	-0.364*** (0.124)	-0.149 (0.537)	-0.359*** (0.116)
Income Quintile (Omitted: Lowest)	0.000 (.)	0.000 (.)	0.000 (.)
2nd	2.367*** (0.441)	0.814 (0.975)	1.610*** (0.408)
3rd	3.679*** (0.431)	3.518*** (1.093)	2.052*** (0.409)
4th	5.383*** (0.429)	8.252*** (1.211)	2.926*** (0.404)
Highest	7.212*** (0.447)	11.584*** (1.369)	3.769*** (0.413)
Constant	16.680*** (3.908)	-8.597 (10.682)	33.967*** (2.941)
Probit model of selection into employment			
	Cohabiting Mother Employed	Single Mother Employed	Father Employed
Parent born in Ireland	0.679*** (0.064)	0.581*** (0.133)	0.619*** (0.137)
Child has longstanding condition	-0.045 (0.041)	-0.245** (0.102)	0.165*** (0.055)
Child is Male	-0.005 (0.051)	0.195* (0.108)	0.004 (0.051)
Low birthweight	0.069 (0.164)	-0.245 (0.312)	-0.327* (0.194)
Child was placed in NICU	-0.122 (0.084)	-0.315* (0.183)	0.073 (0.087)
Child was premature	-0.177 (0.145)	-0.270 (0.257)	-0.014 (0.165)
Number of older siblings	-0.243*** (0.023)	-0.290*** (0.060)	-0.045 (0.039)
Number of younger siblings	-0.368*** (0.026)	-0.294*** (0.093)	-0.126*** (0.037)
Parent's age	0.102** (0.042)	0.267*** (0.071)	0.219*** (0.039)
Parent's age squared	-0.000 (0.001)	-0.003** (0.001)	-0.003*** (0.000)
Parent has degree	0.746*** (0.052)	0.626*** (0.128)	0.556*** (0.116)
Parent completed secondary school	0.927***	1.111***	0.723***

	(0.111)	(0.158)	(0.120)
Parent's current health (Omitted: Excellent)			
Very good	-0.030 (0.037)	-0.096 (0.099)	-0.019 (0.048)
Good	-0.127*** (0.045)	-0.263** (0.116)	-0.126** (0.054)
Fair	-0.360*** (0.083)	-0.337* (0.172)	-0.601*** (0.090)
Poor	-0.948*** (0.215)	-0.318 (0.401)	-1.525*** (0.268)
Urban Region	-0.089*** (0.029)	0.159** (0.080)	-0.271*** (0.041)
Income Quintile (Omitted: Lowest)	0.000 (.)	0.000 (.)	0.000 (.)
2nd	0.481*** (0.059)	0.611*** (0.102)	0.780*** (0.060)
3rd	0.961*** (0.063)	1.635*** (0.144)	1.581*** (0.074)
4th	1.695*** (0.071)	2.020*** (0.202)	2.186*** (0.089)
Highest	2.087*** (0.082)	2.086*** (0.299)	2.388*** (0.103)
Constant	-3.567*** (0.715)	-6.912*** (1.138)	-3.574*** (0.725)
var(ϵ_i) in hours worked equation	45.994*** (1.075)	63.867*** (5.828)	45.570*** (1.599)
correlation between error terms in selection equation and outcome equation : corr(u_i, ϵ_i)	-0.056*** (0.021)	0.146 (0.127)	-0.161*** (0.018)
variance of hours worked : var(H[i])	62.055*** (1.877)	56.274*** (7.731)	49.926*** (1.616)
variance of probability of working : var(E[i])	2.706*** (0.130)	1.508*** (0.221)	1.367*** (0.128)
corr(E[i], H[i])	0.440*** (0.023)	0.503*** (0.114)	0.344*** (0.073)
Observations	20916	2376	18245
p value	0.000	0.000	0.000
Wald test	331.289	72.973	83.361

Standard errors in parentheses. Controls included in selection equation as in Table 3.5 All controls in selection equation are included in outcome equation except for parent born in Ireland * p < 0.10, ** p < 0.05, *** p < 0.01

Appendix Table 4. 1. Main Analysis: GCSE results; Achieved 5 GCSEs A*-C (all covariates)

	(1)	(2)
	All controls	All controls + FE
Wave 6 At least one parent has poor health	-0.032*	-0.015
	(0.018)	(0.030)
Highest Education Level of parents: Ref: None		
GCSE or Equivalent	-0.000	0.019
	(0.053)	(0.080)
Upper Secondary/A levels	0.062	0.021
	(0.056)	(0.083)
Higher Education	0.111**	0.077
	(0.054)	(0.081)
Overseas Qualifications	0.137	0.103
	(0.106)	(0.140)
Poor Child Health	-0.028	-0.037
	(0.021)	(0.032)
Low Birthweight (<2.5kg)	-0.043	-0.025
	(0.036)	(0.056)
Premature Birth (<37 weeks gestation)	0.009	-0.034
	(0.036)	(0.055)
Child Ethnicity: Ref: White		
Mixed	-0.040	-0.054
	(0.035)	(0.054)
Indian	0.060	0.117
	(0.037)	(0.072)
Pakistani and Bangladeshi	0.107**	0.153*
	(0.045)	(0.084)
Black or Black British	0.032	0.073
	(0.049)	(0.090)
Other Ethnic group (inc Chinese, Other)	0.041	0.009
	(0.055)	(0.142)
Mother smoked during pregnancy	-0.052***	-0.039*
	(0.016)	(0.023)
Child is male	-0.101***	-0.099***
	(0.013)	(0.019)
Mother's Age at Birth: Ref: 12 to 19		
20 to 29	0.029	0.093*
	(0.040)	(0.056)
30 to 39	0.079**	0.126**
	(0.040)	(0.056)
40 plus	0.139**	0.233***
	(0.057)	(0.076)
Single Parent Household	-0.019	-0.048

	(0.024)	(0.034)
At least one parent is employed	0.073**	0.069
	(0.034)	(0.052)
OECD Below 60% Median Income	-0.092***	-0.112**
	(0.029)	(0.044)
MCS adjusted family size	-0.012	-0.014
	(0.014)	(0.021)
Prior KS2 achievement		
Ref: Low		
Average prior KS2 achievement	0.310***	0.347***
	(0.029)	(0.039)
High prior KS2 achievement	0.681***	0.700***
	(0.027)	(0.036)
Observations	3694	3694
R-Squared	0.374	0.627
Mean of Dep. Variable	0.707	0.707
Academic Year FE	No	Yes
School FE	Yes	Yes

Standard errors in parentheses are cluster robust at school level. ... * p < 0.10, ** p < 0.05, *** p < 0.01

Appendix Table 4. 2. Main Analysis: GCSE results Attainment 8 (all covariates)

	(2)	(4)
	All controls	All controls + FE
Wave 6 At least one parent has poor health	-1.330**	-1.037
	(0.621)	(0.920)
Highest Education Level of parents: Ref: None		
GCSE or Equivalent	-2.528	-0.919
	(1.591)	(2.245)
Upper Secondary/A levels	0.176	0.648
	(1.685)	(2.313)
Higher Education	3.589**	3.464
	(1.623)	(2.259)
Overseas Qualifications	-0.810	-0.380
	(3.375)	(5.035)
Poor Child Health	-2.130***	-2.364**
	(0.710)	(1.068)
Low Birthweight (<2.5kg)	-3.038***	-1.486
	(1.118)	(1.654)
Premature Birth (<37 weeks gestation)	1.577	0.618
	(1.154)	(1.705)
Child Ethnicity: Ref: White		
Mixed	-0.700	-1.712
	(1.412)	(1.778)
Indian	3.931**	6.206**
	(1.616)	(2.831)
Pakistani and Bangladeshi	4.063***	0.258

	(1.559)	(2.788)
Black or Black British	0.220	2.242
	(1.323)	(2.388)
Other Ethnic group (inc Chinese, Other)	5.987***	0.720
	(2.217)	(5.054)
Mother smoked during pregnancy	-2.924***	-2.529***
	(0.527)	(0.721)
Child is male	-4.049***	-3.708***
	(0.477)	(0.677)
Mother's Age at Birth:		
Ref: 12 to 19		
20 to 29	-0.178	0.968
	(1.042)	(1.407)
30 to 39	2.032*	2.437*
	(1.057)	(1.452)
40 plus	2.448	3.784
	(2.135)	(2.755)
Single Parent Household	-0.975	-1.552
	(0.802)	(1.099)
At least one parent is employed	2.119*	1.669
	(1.193)	(1.517)
OECD Below 60% Median Income	-3.228***	-2.163*
	(0.955)	(1.175)
MCS adjusted family size	0.145	0.225
	(0.537)	(0.764)
Prior KS2 achievement		
Ref: Low		
Average prior KS2 achievement	13.007***	12.923***
	(1.282)	(1.383)
High prior KS2 achievement	30.624***	29.278***
	(1.331)	(1.495)
Observations	3694	3694
R-Squared	0.511	0.748
Mean of Dep. Variable	52.511	52.511
Academic Year FE	No	Yes
School FE	Yes	Yes

Standard errors in parentheses are cluster robust at school level. * p < 0.10, ** p < 0.05, *** p < 0.01

Appendix B

Ethics Approval

Ethics approval for the research in this thesis was deemed unnecessary because the data analysed is secondary data, not NHS data, and cannot be traced back to identifiable individuals.

Joint Authorship

We certify that Rubab Ahmed was involved in the conception and design of the work in Chapter 3 titled: “Child health and parental labour supply: Evidence from the Growing Up in Ireland (GUI) cohort study”. She has made significant contributions to the data cleaning, data analysis and its interpretation. She is the primary contributor to the empirical design, drafting and critical revision of the chapter.

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