# Exploring Inequalities in Child Cognitive Ability, Psychological Well-Being and Risky Health Behaviours

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## Abstract

The aim of this thesis was to analyse household inequalities in child and adolescent outcomes. Using the National Child Development Study, British Cohort Study and Millennium Cohort Study, the first empirical chapter estimated the extent of socioeconomic inequality in child cognitive ability, investigated if the magnitude of these inequalities had changed significantly over time, and decomposed the inequality into its contributing factors. Results showed substantial socioeconomic inequalities in child cognitive ability. There was limited evidence that the magnitude of the relationship had changed over time. Income and parental occupational classification accounted for the majority of income related socioeconomic inequality, with smaller roles for maternal education and family size.

The second empirical chapter estimated the impact of both family size and birth order on child cognitive ability and psychological well-being, using the Millennium Cohort Study. Ordinary Least Squares models indicated a negative conditional association between family size and psychological well-being, but not cognitive ability. Two Stage Least Squares models, using two separate identification strategies, showed no causal effect of family size. For birth order, both Ordinary Least Squares and Nearest Neighbour Matching models showed substantial later born advantages for the certain subscales of psychological well-being, with this relationship in general not shown for cognitive ability.

The third empirical chapter estimated the impact of both maternal labour market supply and non-standard work schedules on adolescent risky health behaviour, using the UK Household Longitudinal Survey dataset. Using a variety of panel data models, there was evidence of a small conditional association between maternal working hours and adolescent drinking, with this relationship not shown for smoking. Two instrumental variable strategies implemented to identify a causal effect were shown to be inappropriate for the research question. For the incidence of non-standard work schedules, there was little evidence of a conditional association for either risky health behaviour.

## Dedication

I dedicate this thesis to the memory of Nain, who made the best toast.

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Firstly, I would like to thank the Health Foundation for providing me with funding for over three years so I could undertake this PhD. Secondly, I would like to say an enormous thank you to my supervisors: Heather Brown, Jing Shen and John Wildman, for all of their encouragement and patience throughout the challenging and often frustrating PhD process. An extra special thank you should go to Heather for her countless hours of reading and commenting on my work in the final stages. Thanks also go to Mark Pearce for acting as an assessor, and Nils Braakmann for both acting as an assessor and discussing ideas with me.

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## Notes and Disclaimers

Although my PhD Studentship was generously sponsored for over three years by the Health Foundation, any opinions expressed in this thesis do not represent the views of the Health Foundation or any of its funders.

In this thesis I used data from the National Child Development Study, the British Cohort Study, the Millennium Cohort Study and the UK Household Longitudinal Survey, all accessed through the UK Data Archive and funded by the Economic and Social Research Council. I analysed the data using Stata v14.1 (Statacorp 2015). Neither the original collectors of the data, the archive or the funders bear any responsibility for the analyses and interpretations presented in this thesis.

In summer 2016 I co-supervised (with Frauke Becker) an MSc student dissertation by Fabienne Thompson entitled "Parental Non-Standard Work Schedules and Adolescent Health Behaviours", based on an original research idea by Heather Brown. Although the research question Fabienne examined was very similar to part of Chapter 6 of this thesis and used the same dataset, the two pieces of work differ substantially.

## Dissemination

<u>Oral Presentations</u>

*"Have socioeconomic inequalities in childhood cognitive scores changed over time? A comparison of three British cohort studies",* European Health Economics Association PhD Student-Supervisor and Early Career Researcher Conference, University of Manchester, **September 2014** - Paper discussed by Florence Jusot, University of Paris-Dauphine

*"Mackenbach's paradox of increasing socioeconomic inequalities in health: do cognitive skills have a role to play?"* CLOSER Conference: The Importance of Early years, Childhood and Adolescence: Evidence from Longitudinal Studies, University College London, **November 2015**

*"The effect of family size and birth order on child cognitive and non-cognitive skill in the UK: evidence from instrumental variable and matching models"*, Health Economics Study Group Winter Meeting, University of Manchester, **January 2016** – Paper discussed by Christoph Kronenberg, University of Duisburg-Essen

<u>Poster Presentations</u>

*"The paradox of socioeconomic health inequalities in the UK: do cognitive scores have a role to play?"* North East Postgraduate Conference, Newcastle University, **October 2014**

*"The causal effect of family size and birth order on child outcomes: new evidence from the UK",* Centre for Longitudinal Studies Cohort Studies Research Conference, **March 2015**

*"Parental non-standard work schedules and adolescent risky health related behaviour in the UK"* York University Workshop on Family and Labour Economics, **September 2016**

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## List of Abbreviations

| | |
|---|---|
| Action on Smoking and Health | **ASH** |
| Average Treatment Effect | **ATE** |
| Avon Longitudinal Survey of Parents and Children | **ASLPAC** |
| Best Linear Unbiased Estimator | **BLUE** |
| British Ability Scales | **BAS** |
| British Births Survey | **BBS** |
| British Cohort Study | **BCS** |
| Centre for Longitudinal Studies Enhancement Resources | **CLOSER** |
| Child Behaviour Checklist | **CBCL** |
| Concentration Curve | **CC** |
| Concentration Index | **CI** |
| Corrected Concentration Index | **CCI** |
| Difference in Differences | **DiD** |
| Directed Acyclic Graph | **DAG** |
| Economic and Social Research Council | **ESRC** |
| Fixed Effects | **FE** |
| First Order Stochastic Dominance | **FSD** |
| Generalised Least Squares | **GLS** |
| Health Survey for England | **HSE** |
| Home Learning Environment | **HLE** |
| Institute for Fiscal Studies | **IFS** |
| Instrumental Variable | **IV** |
| Intersect Unity Principle | **IUP** |
| Inverse Probability Weighting | **IPW** |
| Linear Probability Model | **LPM** |
| Local Average Treatment Effect | **LATE** |
| Local Super Output Area | **LSOA** |
| Longitudinal Survey of Youth | **LSY** |
| Millennium Cohort Study | **MCS** |
| Missing at Random | **MAR** |

| | |
|---|---|
| Missing Completely at Random | **MCAR** |
| Missing Not at Random | **MNAR** |
| Multiple Comparison Approach | **MCA** |
| Multiple Imputation | **MI** |
| National Child Development Study | **NCDS** |
| National Foundation for Educational Research | **NFER** |
| National Institute for Health and Clinical Excellence | **NICE** |
| National Longitudinal Survey of Youth | **NLSY** |
| National Survey of Health and Development | **NSHD** |
| Nearest Neighbour Matching | **NNM** |
| National Statistics Socioeconomic Classification 5 Class | **NSSEC-5** |
| Ordinary Least Squares | **OLS** |
| Organisation for Economic Co-operation and Development | **OECD** |
| Partial Concentration Index | **PCI** |
| Partial Corrected Concentration Index | **PCCI** |
| Perinatal Mortality Study | **PMS** |
| Principal Component Analysis | **PCA** |
| Propensity Score Matching | **PSM** |
| Quantity vs Quality Model | **QQ** |
| Random Effects | **RE** |
| Regression Discontinuity Design | **RDD** |
| Resource Dilution Model | **RD** |
| Second Order Stochastic Dominance | **SSD** |
| Socioeconomic Status | **SES** |
| Standard Deviation | **SD** |
| Strength and Difficulties Questionnaire | **SDQ** |
| Structural Equation Modelling | **SEM** |
| Two Stage Least Squares | **2SLS** |
| UK Household Longitudinal Survey | **UKHLS** |
| United Kingdom | **UK** |

# Chapter 1. Introduction

## 1.1 Research Background

There are well documented levels of social inequality in the United Kingdom (UK). For instance, although overall levels of health are seen to be gradually improving, men in the least deprived areas of the UK can be expected to have 14.6 more disability-free years than their counterparts in the most deprived areas (Smith *et al.,* 2010). Furthermore, despite large increases in education spending over the past half century, there are still significant inequalities in terms of higher education participation relative to family background (Chowdry *et al.,* 2013). Whereas inequalities related to determinants that are freely chosen ("efforts") may be considered legitimate, inequalities related to determinants outside of the control of the individual ("circumstances") are generally considered unacceptable and inequitable, and should in principle be eliminated (Fleurbaey 2008).

This concept of equity is particularly relevant when considering the distribution of child outcomes, as it has been argued that all children should have the same opportunity to achieve their full potential, regardless of their family background (Social Mobility and Child Poverty Commission 2013). However, it is apparent that from a very early age, children differ in a number of different domains according to family background, and are therefore subject to an inequality of opportunity. For instance, the influential Marmot Review into health inequalities in the UK showed there to be persistent and substantial inequalities in a variety of child outcome measures, such as physical and emotional health, cognitive ability and linguistic and social skills (Marmot *et al.,* 2010).

Alongside the acknowledgement that substantial inequalities exist across a variety of child outcomes, it has also been argued that childhood and adolescence is a critical time period for establishing the foundations for a healthy and successful life, and that behaviours begun in adolescence (such as engagement in risky health behaviours) are significant markers for the continued engagement in these activities across the life course. This notion of a significant relationship between early life outcomes and later life outcomes has its roots in the medical literature, in particular the Fetal Origins Hypothesis (Barker 1990), which predicts that the environmental conditions at birth may significantly influence levels of adult disease. However, this idea has been extended by the epidemiological and economic literatures to include a number of other child outcomes, for example health, psychological well-being and cognitive ability.

In particular, several prominent studies (Cunha and Heckman 2007; Conti and Heckman 2012) have argued that the predicted relationship between child outcomes and adult outcomes may be mediated through skill multipliers caused by self-productivity and dynamic complementarity. In this context, self-productivity refers to the notion that skills acquired in one period are likely to persist into future periods, while dynamic complementarity asserts that this increase in skills may raise the productivity of investment in subsequent stages. This relationship has also been examined empirically, with a number of studies having shown early life outcomes to be significantly associated with a range of adult outcomes, such as employment, health, well-being and a number of other social behaviours (Heckman and Carneiro 2003; Blanden *et al.,* 2007; Goodman *et al.,* 2011; Conti *et al.,* 2016). Beyond normative arguments relating to social justice, it has been argued that inequalities in these later life outcomes may also have significant health and economic costs, such as lost years of life and lost economic activity due to illness and disability (Marmot *et al,.* 2010).

As further argued by Marmot *et al.,* (2010), the key to tackling inequalities in child health and development is to tackle their social determinants. These social determinants can be seen as being interacting and multidimensional in nature, and include: the socio-political and social context, neighbourhood level factors such as social cohesion and civic participation, household characteristics such as material circumstances, and individual level determinants such as attitudes and behaviours. In a report for the World Health Organisation (WHO), Currie *et al,.* (2010) have argued that these social determinants are likely to inhibit the ability of young people to achieve their full potential in terms of health, well-being and development, and highlight the need for national and international agencies to strengthen the initiatives that affect young people's health and well-being.

Given that inequalities in child outcomes between individuals and across socioeconomic groups are predicted to appear at a young age and widen over the life cycle, early life interventions have become a mainstay of public policy discourse in relation to the social determinants of health and well-being, with such investments claimed to increase the chances children will successfully navigate the series of transitions they must in order to become successful and self-reliant adults (Bradbury *et al.,* 2011). It has also been acknowledged that there may be specific 'critical' and 'sensitive' periods for different measures of child development. For example, cognitive skills have been shown to be relatively stable by the age of 10, while adolescent interventions may be able to affect other outcomes, such as non-cognitive skill (Cunha and Heckman 2007). As argued by Heckman (2006), and displayed intuitively in Figure 1.1, investments earlier in life are also likely to be more effective than later interventions in terms of returns on human capital, and therefore may offer greater productivity and a reduction in social spending for society in the long run.

Taking note of the potential benefits of early life interventions, in 1999 the Labour government outlined a plan to eliminate child poverty in the UK within a generation, with the flagship policy being the influential Sure Start programme, aimed at developing and enhancing the services provided for households in deprived areas in order to improve the health and well-being of young children. Similar schemes have also been adopted in parts of the United States of America (USA) (the Head Start Programme and the Perry Pre-School Programme), Canada (the Ontario Early Years Programme) and Australia (Head Start Early Learning Programme) in the past 20 years.

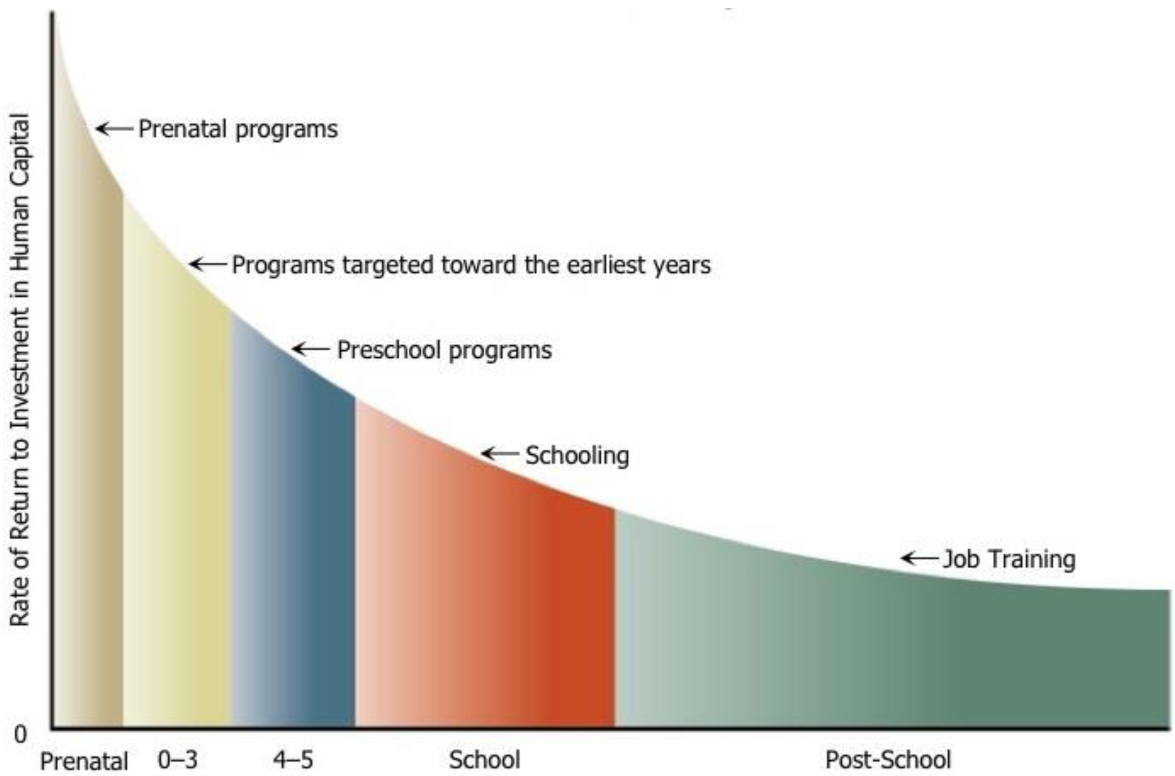


*Figure 1.1- The Heckman curve*

However, despite the acknowledgement that early life factors may be pivotal in determining a range of outcomes across the life course, and the significant investment in early life interventions by a number of governments in recent years, the precise relationship between the various social determinants of inequalities in child outcomes is still an open debate for both academics and public policy makers. The aim of this thesis was to contribute to this debate by exploring the household determinants of inequalities in child and adolescent outcomes, as it has been argued that household conditions and the nature of parental investments may serve as crucial factors that can mitigate inequalities in these outcomes both between individuals and across socioeconomic groups (Cunha and Heckman 2010).

These household determinants can themselves be seen to be interconnecting and multidimensional, and can therefore be separated into variety of 'distal' and 'proximal' characteristics (Gregg *et al.,* 2007). In this context, a distal factor describes a household characteristic that can be seen as being part of the child production function (such as household income, parental employment or family size), which impact child outcomes through proximal (or mediating) factors such as time allocation, parental preferences, attitudes, behaviours and the home environment. An increased knowledge of the way that household characteristics contribute to inequalities in different child and adolescent outcomes should help policy makers in designing effective and efficient interventions to reduce inequalities in early life and across the life course.

**1.2 Thesis Overview**

The remainder of this thesis is broken down into six chapters. Chapter 2 describes the four datasets I used in the empirical analysis. Chapter 3 outlines three difficulties in secondary data analyses: endogeneity, missing data and the use of survey weights; before outlining the potential consequences of these factors on the results and potential solutions. Chapters 4, 5 and 6 present three independent empirical analyses, each concentrating on a different household characteristic which may contribute to inequalities in child and adolescent outcomes. Chapter 7 offers overall conclusions. Summaries of the three empirical chapters are given below.

The first empirical chapter (Chapter 4) investigated socioeconomic inequalities in child cognitive ability in three British birth cohort studies (the NCDS, BCS and MCS), whether the strength of this relationship had changed significantly over time, and the contributing factors to any change in inequality. Using both Ordinary Least Squares (OLS) regression models and Concentration Indices (CI), empirical estimates showed substantial socioeconomic inequalities in the vast majority of child cognitive tests across the three surveys. For the limited number of cognitive tests that could be appropriately compared across cohorts, there was mixed evidence that the level of socioeconomic inequality has changed significantly over time. Decomposition analysis showed that household income and parental occupational classification explained the overwhelming majority of income related socioeconomic inequality, with smaller roles for factors such as maternal education and family size.

The second empirical chapter (Chapter 5) investigated the effect of both family size and birth order in determining child cognitive ability and psychological well-being in the MCS. For family size, estimates from OLS regression models showed a significant conditional association between family size and child psychological well-being. This relationship was not found for child cognitive ability once a full set of controlling characteristics were also included in the empirical specifications. In an attempt to control for the endogeneity of family size, two separate Two Stage Least Squares (2SLS) models were estimated, using the sibling sex composition and the incidence of twin births as two separate identification strategies. Although no causal effect of family size on either outcome measure was found, the results from these models should be treated with caution due to the possibility that unobserved confounding and small sample bias impacted the validity of the identification strategies. For birth order, evidence from both OLS and Nearest Neighbour Matching (NNM) models showed a later born advantage for certain subscales of psychological well-being, with this relationship in general not shown for measures of cognitive ability.

The third empirical chapter (Chapter 6) investigated the association between both maternal labour supply and the incidence of non-standard working schedules and adolescent drinking and smoking, using a sample of adolescents from the UK Household Longitudinal Survey (UKHLS) and a variety of panel data models. Empirical estimates showed evidence of an economically small, yet statistically significant, conditional association between maternal hours worked and the incidence of adolescent drinking, with this result robust to model specifications that controlled for individual level heterogeneity. There was no evidence of a conditional association for adolescent smoking once a full set of controlling characteristics were included in the model specification. Two instrumental variable strategies implemented to identify a ‘true’ causal effect were shown to be inappropriate for the research question. Furthermore, there was no evidence of an economic or statistically significant relationship between maternal non-standard work schedules and adolescent risky health behaviour.

# Chapter 2. Data

In this chapter I provide information regarding the four datasets I used in the empirical analysis of this thesis: the National Child Development Study (NCDS), the British Cohort Study (BCS), the Millennium Cohort Study (MCS) and the UK Household Longitudinal Study (UKHLS), otherwise known as Understanding Society. Issues specifically related to the individual research questions will be discussed in the corresponding empirical chapters.

## 2.1 National Child Development Study

Starting life as the Perinatal Mortality Study (PMS), the NCDS is a birth cohort study that has followed the outcomes of 17416 children born in the first week of March in 1958 in England, Wales and Scotland (Power and Elliott 2006). The reference population is defined as those living in Great Britain at the time of each survey and who were born in the reference week, as well as immigrant children born during the same week who were added while the cohort members attended school. The original aim of the PMS was to identify the risk factors associated with stillbirths and neonatal deaths, due to the high stillbirth rate at the time. Extended into a longitudinal study by the National Children's Bureau in order to supply evidence for the Plowdon enquiry into primary education, a substantial number of the cohort children were further interviewed at ages 7, 11 and 16 in order to examine, amongst other factors, the children's physical, educational and social development.

In addition to parental interviews and examination at these crucial early stages of life, the NCDS has continued to interview the cohort children into adult life. There has been additional data collected when the cohort children were 23, 33, 42, 46, 50 and 55, with a survey at the age of 60 planned for 2018. 9100 cohort members took part at age 50.

The NCDS has several important strengths. Firstly, given that it has attempted to follow every birth in a one week period, it can be seen as a true 'snapshot' of the British population born in 1958. Furthermore, the NCDS has a relatively large size compared to other longitudinal studies, despite constant levels of attrition over time. Although there has been a slight tendency for men and poor educational achievers to leave the study over time, this bias has been shown to be relatively minor (Hawkes and Plewis 2006). The NCDS has also been innovative in linking with other sources of data, such as neighbourhood measures from the census, school leaving examination results and a number of specialist follow-up studies relating to biomedical data. Future work is planned to link the NCDS data to NHS health records and HMRC employment records. Finally, the study has collected data on a random sub sample of the children of the NCDS cohort members, allowing for the study of multiple generations of the same family.

Although the study clearly has many strengths, there are also some associated weaknesses. Firstly, given the time in which it was started, the study is not as ethnically diverse as the current UK population, and therefore there may be a lack of generalisability compared to other modern cohort studies. Secondly, as the survey is not stratified, it may not have sufficient numbers of observations in policy relevant groups such as those growing up in exceptionally deprived circumstances (Bynner and Joshi 2007). Thirdly, due to a lack of a constant funding stream during the first few decades, there was no clear strategy regarding both the timing and the content of each wave, and therefore there are relatively large gaps between some of the waves. Finally, the cohort cannot be seen to be representative of a whole year of births, and therefore seasonal variations in birth outcomes cannot be analysed.

### 2.2 British Cohort Study

Similar to the NCDS, the BCS is a birth cohort study that started life as a study focussing on perinatal mortality, in this case the British Births Survey (BBS) (Elliott and Shepherd 2006). The aim was to compare the results with those from the 1958 PMS. The BBS collected data from a cohort of 16571 children (this time from Northern Ireland as well as England, Scotland and Wales) born during a one week period in 1970, with the data collected by midwifes and linked with data from clinical medical records. This perinatal study was extended to a longitudinal study (through the combined efforts of the University of Bristol and the University of London), and the cohort children were further interviewed at the ages of 5, 10 and 16 to explore their physical, educational and social development. As with the NCDS, the BCS has continued to collect data throughout the life course, with data collected when the cohort children were 26, 30, 34, 38 and 42, with further surveys planned at ages 46 and 50. 9841 cohort members took part at age 42.

Similar to the NCDS, the BCS has several strengths, such as its large sample size and fact that it can be seen as being a true snapshot of the British population born in 1970[1]. Additionally,

[1] The birth survey extended to Northern Ireland (and therefore initially covered the whole of the UK), however the subsequent follow up was restricted to Great Britain

compared to the NCDS, the BCS can be considered more ambitious in terms of data coverage. Although there are several associated weaknesses, such as poor response rate at age 16, it is argued that overall the biases present in the observed sample should be relatively minimal (Bynner and Joshi 2007).

### 2.3 Millennium Cohort Study

The MCS is a birth cohort study made up of a stratified sample of children born between 1st September 2000 and 31st August 2001 in England and Wales, and children born between 24th November 2000 and 11 January 2002 in Scotland and Northern Ireland. The only inclusion criteria was that the children needed to be living in the UK at age 9 months and eligible to receive child benefit (Plewis *et al.,* 2007). In response to the renewed interest in evidence based policy by the Labour government, the MCS was developed as a multidisciplinary study to capture the influence of several markers of early family life on child health and development throughout childhood (Hansen 2014).The MCS cohort children were first surveyed when they were around 9 months of age, and have been further interviewed at ages 3, 5, 7 and 11. The age 14 survey is expected to be released at some point in 2017, with further data collection planned at the age of 17. Although the main unit of observation is the cohort member, information is also collected at the household level. 20646 families were originally contacted, with just under 90% responding. The baseline sample in the first wave was 18827[2].

Given the problems with the older British cohort studies, such as the NCDS and BCS, the MCS was designed to have a number of significant new features while maintaining continuity with the older studies. For instance, the representation of the cohort was broadened to cover a sample of a whole year of births, and where possible, both the mother and the father were interviewed. Furthermore, the sample was stratified in order to make sure that ethnic groups and individuals born in deprived circumstances were sufficiently represented in the initial sample.

As argued by Connelly *et al.,* (2014), the MCS has several other desirable properties. Firstly, the current sample is large (N=13287 at age 11), with levels of attrition relatively low as compared to other UK longitudinal studies. Secondly, the dataset is the first British birth

[2] For a comprehensive description of the survey design, recruitment process and fieldwork please see Dex and Joshi (2005)

cohort study to include all four countries of the UK, meaning that cross country comparisons can be conducted. Thirdly, the dataset has deliberately oversampled children from deprived backgrounds and ethnic minorities, in order to assess the outcomes from these often underrepresented groups. Fourthly, the range of health and cognitive measures present in the MCS allows for the cohort child's health and development to be studied in detail from an ecological perspective. Fifthly, the collection of standardised measures of pregnancy and early childhood outcomes means the MCS is an excellent resource with which to compare to other cohort studies both internationally and nationally, including the three previous UK based cohort studies (1946 Birth Cohort, NCDS and BCS). Finally, the MCS has collected extensive information regarding the cohort member's family, allowing for studies examining the intergenerational transmission of parental factors on child outcomes.

Unlike the NCDS and BCS (which are self-weighting, given that they are snapshots of the British population born in specific weeks in 1958 and 1970), the MCS is a heavily stratified sample. In England, the population were stratified into three strata: an 'ethnic minority' stratum (where the proportion of ethnic minorities in the ward was at least 30% in the 1991 census), a 'disadvantaged' stratum (which contained the poorest 25% wards as predicted by the Child Poverty Index) and an 'advantaged' stratum, which contained children located in the remaining wards. For the rest of UK, the children were only split into the 'disadvantaged' and 'advantaged' strata, as there was not the requisite numbers of children from ethnic minorities to form an 'ethnic minority' stratum.

Given the splitting of the electoral wards into the three strata, the MCS sample was clustered by the characteristics of the particular electoral wards in order to keep fieldwork costs down and to take into account neighbourhood-level effects. The initial MCS sample was randomly selected only within the specific strata and clustering areas, resulting in a disproportionally stratified cluster sample (Plewis *et al.,* 2007). Due to the stratified nature of the sample, it is argued that it is important, where possible, to adjust the data in order to provide accurate estimates and robust standard errors (Connelly 2014). The MCS provides a range of sample design and probability weights in order to correct for MCS cases having unequal probabilities of selection that result from the stratified cluster sample design, which are relatively straightforward to implement.

### 2.4 UK Household Longitudinal Study

The UKHLS is a longitudinal study of national representative private households, designed to capture life in the UK and how it changes over time. The survey (which began collecting data in 2008) replaced the British Household Panel Survey (BHPS), and is part of an international network of studies including the German Socioeconomic Panel, the Swiss Household Panel, and various other household studies from Australia, Canada, South Africa, USA, Korea and China (Buck and McFall 2011). The design of the UKHLS means the survey provides information regarding a wide range of policy relevant factors, for example labour market outcomes such as unemployment, household factors such as marriage, and individual outcomes such as health and well-being.

The total sample in the first wave of the UKHLS was 39802 households, marginally below the target sample of 40000 households. The number of individuals in the total sample of the first wave was 101086, including children. The survey has continued to collect information on an annual basis regarding each household's social and economic circumstance, employment, family life and health, amongst other factors.

In order to achieve such a large sample, various sampling strategies were used. The general population sample was a stratified, clustered sample of the entire residential population of the UK, drawn from the national postcode address file. The Northern Ireland sample was unclustered, with addresses drawn systematically from the Land and Property Agency List. The primary sampling units (PSUs) used in the dataset were stratified by geographical region, population density and ethnic minority density respectively. In the initial sample, 18 addresses were systematically selected from each of the 2640 postal sectors, resulting in an initial sample of 47520 households, rising to 49920 households once the addresses from Northern Ireland were also incorporated. Several other smaller sampling strategies have also been used, including an ethnic minority boost, an innovation panel (used mainly to test novel methods of data collection) and the incorporation of previous BHPS sample members.

There are several distinctive features of the household panel design which give it an advantage as compared to cohort studies. Firstly, while a birth cohort study such as the NCDS or the BCS is representative of one particular cohort, a household panel such as the UKHLS is representative of the whole population, and therefore eliminates the impact of cohort effects. Secondly, following households rather than individuals allows for the investigation of factors that occur at the household level, such as economic welfare, the inter relationships between individuals within the household and changes in household composition.

There are also several key important features specific to UKHLS. For example, it is clearly a very large sample size, allowing researchers to explore issues other longitudinal surveys would be unable to do, such as analysis of small subgroups and regional variation. Secondly, the study specifically focuses on several factors related to ethnicity, diversity and commonality, and boosts the ethnic minority population of the survey. Finally, it is possible to link the UKHLS to several other data sources, including education data (specifically Key Stage 1 and Key Stage 2 results), localised spatial data and various biomedical measures for a sub-sample of the panel.

Like its predecessor, the BHPS, the UKHLS has a very complex sampling design, and subsequently the associated weighting strategy is also complex (Buck and McFall 2011). A variety of household and individual weights are provided by the UKHLS for use in empirical analysis, in order to account for factors such as the probability of selection and non-response, as well as to make the sample distribution a closer match to the UK population distribution.

# Chapter 3. Methodological Issues

In this chapter I outline three methodological issues common to the three empirical chapters: endogeneity, missing data and the use of survey weights. In each case, I discuss the potential consequences of these issues on the results, and the methods used to minimise their impact.

### 3.1 Endogeneity

A chief concern in econometric analysis is endogeneity, defined as inconsistent parameter estimates caused by correlation between the explanatory variables and the error term in an econometric model. There are five commonly encountered situations where endogeneity exists. One cause for endogeneity may be omitted-variable bias. This may occur when an econometric model is unable to include an important factor that is correlated with both the dependant variable and one or more of the explanatory variables. A second cause of endogeneity is reverse causality. This may occur when there is simultaneity between the dependent variable and one or more of the explanatory variables, and therefore the true direction and strength of relationship is not clear. The third cause of endogeneity is measurement error, where one or more of the variables may have an incorrect value associated with it, either due to recall bias or typographical mistakes. The fourth cause of endogeneity is sample selection, where a variable is only observed for a certain subset of the population. Finally, endogeneity can also result from a misspecification of the functional form of the econometric model. In the presence of endogeneity, parameters estimated from regression models may be biased, and should not be interpreted as being true causal effects.

This endogeneity issue can be shown more intuitively using a directed acyclic graph (DAG), which graphically displays the causal pathways in econometric models (Pearl 2000). When endogeneity is not an issue, an estimate of a single explanatory variable $(x)$ on a dependent variable $(y)$ from an econometric model such as OLS can be assumed to be the true estimate, as shown in Figure 3.1:

$$x \longrightarrow y$$

*Figure 3.1- DAG showing the effect of an explanatory variable on an outcome variable with no endogeneity*

However, when endogeneity is present, the error term of the specification ($\varepsilon$) may be significantly associated with the key explanatory variable $x$, as well as the dependent variable $y$, as shown in Figure 3.2. Consequently, there may be both direct and indirect effects stemming from the explanatory variables, meaning that the estimates from these models are likely to be biased and inconsistent. There are several econometric methods that have been developed to control for endogeneity. In the proceeding sub-sections, I discuss two of the methods I used in this thesis to account for endogeneity caused by omitted variable bias or reverse causality: panel data models and instrumental variable (IV) models.

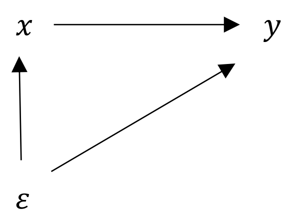


*Figure 3.2- DAG showing the effect of an explanatory variable on an outcome variable in the presence of endogeneity*

### 3.1.1 *Panel data regression analysis*

One method that may be used to control for endogeneity caused by omitted variable bias or reverse causality are panel data models, which I used in Chapter 6. For panel data models, a longitudinal element must be added to the data, as repeated measurements for each individual observation are needed at different time points. Compared to cross sectional regression models, panel data models split the unobserved error term (ε) into two components, individual-specific unobservable effect ($v_i$) and the random error term ($u_{it}$):

$$\varepsilon_{it} = v_i + u_{it} \tag{3.1}$$

While the random error term represents idiosyncratic shocks, the individual-specific unobservable effect refers to the unobserved characteristics of the individual that remain constant over time. Additionally, both $v_i$ and $u_{it}$ are assumed to be random variables from a normal distribution:

$$v_i \sim N(0, \sigma_{v_i}) \tag{3.2}$$

$$u_{it} \sim N(0, \sigma_{u_{it}}) \tag{3.3}$$

Given the presence of an individual specific effect, it is extremely likely that the values of the dependent variable will cluster together for each individual. Such clustering can be accounted for by using the generalised least squares estimator, which allows for the fact that the error term for a particular individual will be correlated over the waves of a panel. The critical issue for panel data analysis is whether the individual-specific unobservable effect is correlated with the set of observed regressors. Failure to correctly account for the correlation between the two factors when estimating such models may lead to inconsistent estimates of the slope coefficients (Jones *et al.,* 2013).

One panel data model that may be used is the random effects GLS model (GLS). Unlike the pooled estimator, which applies a cross sectional regression model to a panel data structure, the GLS model takes into account the fact that there are repeated observations for each individual, and adjusts the error term for autocorrelation. For each observation *i* in time period *t,* the GLS model can be given by:

$$y_{it} = \beta_0 + \beta_1 x_{1it} + \beta_2 x_{2it} + \cdots + \beta_n x_{it} + v_i + u_{it}\ , \tag{3.4}$$

where *i* = 1, 2, … $n$ and *t* = 1,2, … $n$

Let $y_{it}$ represent the *i*th value of the dependent variable $y$ at time $t$. $x_{it}$ represents the *i*th value of the explanatory variable $x$ at time $t$, with the associated coefficient $\beta_1$ . $\beta_0$ is the constant coefficient, the predicted value of $y$ when $x$=0. In addition, $v_i$ represents the time invariant individual specific error term and $u_{it}$ represents the assumed random error term for individual $i$ at time $t$, with $Cov[v_i, u_{it}|X] = 0$ for all $i, t$.

The time invariant individual specific error term ($v_i$) is seen to capture the between-subject variation, the cross sectional variation in the outcome and explanatory variables for each individual. It is also possible to estimate a between effects regression, however this will always be less efficient than a random effects model as it ignores the within variation (Cameron and Trevidi 2009). The random error term ($u_{it}$) is seen to capture the within-subject variation, the variation in the outcome and explanatory variables over time for each individual.

The GLS model can therefore be seen as a weighted average of the within and between estimators, with the weights determined by the proportion of the between variance compared to the overall variance. Thus, the estimates from the GLS model will approach the pooled estimator when the between standard error is significantly smaller than the within standard error, and vice versa.

However, a key aspect of the GLS model is that it explicitly assumes that the unobserved individual level heterogeneity is unrelated to the vector of explanatory variables (Greene 2003). In reality this is usually an extremely strong assumption, and therefore a model specification which removes unobserved individual level heterogeneity completely may be more appropriate in the majority of situations.

Unlike the GLS model, the fixed effects (FE) model does not require the assumption that the individual specific error term is uncorrelated with one or more of the explanatory variables. There are three ways in which to control for these time-invariant unobservable individual effects: first differencing, the least squared dummy variable (LSDV) estimator and the within estimator. In this thesis I used the within estimator, as it is more efficient than first differencing when the error term is homoskedastic and serially uncorrelated, and gives smaller standard errors as compared to the LSDV.

The within estimator removes the individual specific error terms by mean-differencing the data, and then estimating an OLS regression on the mean-differenced data.

For each observation *i* in time period *t,* the FE model can be given by:

$$(y_{it} - \overline{y_i}) = (\beta_0 - \overline{\beta_t}) + \beta_1 (x_{1it} - \overline{x_i}) + \cdots + \beta_n (x_{nt} - \overline{x_i}) + (v_i - \overline{v_i}) + (u_{it} - \overline{u_i}) \quad (3.5)$$

and therefore:

$$\ddot{y}_{it} = \ddot{\beta}_0 + \beta_1 \ddot{x}_{1it} + \cdots + \beta_n \ddot{x}_{nt} + \ddot{u}_{it} \,, \quad (3.6)$$

where *i* = 1, 2, … $n$ and *t* = 1,2, … $n$

Let $\ddot{y}_{it}$ represent the *i*th value of the demeaned dependent variable $y$ at time $t$. $\ddot{x}_{1it}$ represents the *i*th value of the demeaned explanatory variable $x$ at time $t$, with the associated coefficient $\beta_1$ . $\beta_0$ represents the constant coefficient. By definition, the individual specific error term $v_i$ is constant across time, and demeaning this variable will remove it from the regression model. $\ddot{u}_{it}$ represents the idiosyncratic error term for individual $i$ at time $t$. Therefore, estimating an OLS model on the demeaned data leads to consistent estimates of the explanatory variables, even if the unobserved individual specific error term is correlated with one or more of the explanatory variables.

Although consistent, there are several problems associated with the FE model. Firstly, as discussed by Lancaster (2000), when the number of waves or number of observations are small, the estimates from the FE models may be biased, poorly estimated and inconsistent due to the incidental parameters problem (Neyman and Scott 1948). This is due to the fact that the $N$ incidental parameters cannot be estimated if $T_i$ is small, because there are only $T_i$ observations for each individual. This inconsistent estimation of the individual, time invariant fixed effect can spill over to inconsistent estimation of the model parameters (Cameron and Trivedi 2009).

A second problem with the FE model is that although mean differencing the data will remove the individual specific fixed effect from the model and render the empirical estimates consistent, it will also remove time invariant variables of potential interest from the model, for example gender and ethnicity. In order to account for this, other empirical strategies have been suggested.

One approach that has been suggested is the Mundlak methodology (Mundlak 1978), which parametrises $v_i$ by including group means of the time varying explanatory variables as additional explanatory variables in the GLS model, and acts as a proxy fixed effects model:

$$y_{it} = \beta_0 + \beta_1 x_{1it} + \cdots + \beta_n x_{nt} + \varphi_1 \bar{x}_{1it} + \cdots + \varphi_n \bar{x}_{nt} + v_i + u_{it}\ , \tag{3.7}$$

where *i* = 1, 2, … $n$ and *t* = 1,2, … $n$

Let $y_{it}$ represent the *i*th value of the dependent variable $y$ at time $t$. $x_i$ represents the *i*th value of an explanatory variable $x$ at time $t$, with the associated coefficient $\beta$ . $\varepsilon_{it}$ represents the random disturbance term for individual $i$ at time $t$, with a mean value of 0. $\bar{x}_i$ represents the time averaged *i*th value of an explanatory variable $x$ with its associated coefficient $\varphi_1$. Once more, $v_i$ represents the time invariant individual specific error term and $u_{it}$ represents the idiosyncratic error term for individual $i$ at time $t$.

This approach ensures consistent estimation of all within effects, as the deviations from the clustered means should be uncorrelated with the means themselves, the individual error term ($u_{it}$) and any time varying covariates. However, the cluster means themselves can still be correlated with the time invariant individual specific error term ($v_i$), and this may once more produce inconsistent estimates of the between effects (Cameron and Triviedi 2009).

In order to establish which the preferred empirical strategy is, two specification tests can be performed. Firstly, in order to test whether pooled analysis or panel data models are more appropriate, the Breusch-Pagan Lagrange multiplier test (Breusch and Pagan 1979, 1980) can be implemented, which tests for heteroskedasticity in the error term of the pooled OLS model. Under the null hypothesis that the individual-level variance component of the error term is zero, a rejection of the null hypothesis implies that a panel data model is needed.

Secondly, in order to test whether the GLS model is consistent, the Hausman Test (Hausman 1978) can be implemented, which tests the assumption that the unobserved individual level heterogeneity is uncorrelated with the set of explanatory variables. Under the null hypothesis that the individual level heterogeneity is uncorrelated with the explanatory variables, a rejection of the null hypothesis implies that the FE model should be used rather than GLS, as it is more efficient.

### 3.1.2 *Instrumental variables*

Although panel data models may be able to account for endogeneity caused by omitted variable bias or reverse causality by controlling for unobserved time-invariant individual level heterogeneity, multiple waves of data are not always available for use, and even if they are, panel data methods are still unable to control for *time variant* individual level heterogeneity. A number of alternative methods have also been developed in order to estimate causal effects through directly controlling on both observable and unobservable characteristics, including differences in differences (DiD) estimators, regression discontinuity designs (RDD) and IV methods. Although DiD and RDD estimators require a natural experiment or policy change in order to achieve identification, IV methods exploit random variation in the explanatory variable of interest caused by a variable that is plausibly exogenous to the main equation. I used IV methods in both Chapter 5 and Chapter 6.

To be an appropriate IV in a linear model, an IV, $z$, must satisfy two main conditions. Firstly, the IV, $z$, must be significantly correlated with the suspected endogenous variable $x$:

$$\text{Corr}\ (z, x) \neq 0 \tag{3.8}$$

Secondly, the IV, $z$, must be uncorrelated with the error term, $\varepsilon$ , of the econometric model:

$$\text{Cov}\ (z, \varepsilon\ ) = 0 \tag{3.9}$$

This can once more be displayed intuitively using a DAG. As previously shown in Figure 3.2, the error term, $\varepsilon$, may be associated with the key explanatory variable $x$ as well as the dependent variable $y$, most commonly through omitted variable bias or reverse causality, potentially causing the estimates to be endogenous. However, a valid IV, $z$, offers a solution to this problem, as this variable is correlated significantly with $x$, and not with $\varepsilon$ or $y$, as shown in Figure 3.3. Therefore, if the IV, $z$, is truly uncorrelated with the error term, $\varepsilon$, the endogeneity problem should be eliminated.

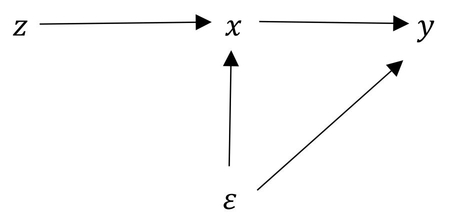


*Figure 3.3- DAG showing an instrumental variable acting as an exogenous form of variation for an explanatory variable in the presence of endogeneity*

The simplest IV estimator is the Wald estimator (Wald 1940, Durbin 1954), which uses a single dummy instrument to estimate a model with one endogenous regressor and no covariates (Angrist and Pischke 2009). With no covariates, the regression model can be shown through two equations:

$$x_{\mathrm{i}} = \beta_0 + \beta_1 z_{1\mathrm{i}} + \varepsilon_{\mathrm{i}} \,, \qquad (3.10)$$

$$y_{\mathrm{i}} = \psi_0 + \psi_1 \hat{x}_{1\mathrm{i}} + \eta_{\mathrm{i}} \,, \qquad (3.11)$$

where *i = 1,2,…n*

In the first stage model, let $x_i$ be the *i*th value of an explanatory variable assumed to be endogenous. $z_{1i}$ is an binary IV significantly correlated to $x_i$, with its associated coefficient $\beta_1$. $\beta_0$ represents the constant coefficient, and $\varepsilon_{\mathrm{i}}$ represents the error term, which is assumed to be randomly distributed.

In the second stage of the model, let $y_{\mathrm{i}}$ be the *i*th value of the dependent variable $y$. $\hat{x}_1$ is a prediction of $x_i$ from the first stage equation, with its associated vector coefficient $\psi_1$. $\psi_0$ represents the constant coefficient, and $\eta_{\mathrm{i}}$ represents the error term, which is assumed to be randomly distributed.

Given the fact that $z_{1\mathrm{i}}$ is a dummy variable that equals 1 with probability $p$, it can be shown that the relationship between the IV and the outcome variable can be given by:

$$cov(y_i, z_i) = \{E[y_i|z_i = 1] - E[y_i|z_i = 0]\}p(1-p) \,, \qquad (3.12)$$

and therefore the estimate of $\hat{x}_1$ can be shown as:

$$\psi_1 = \frac{E[y_i|z_i = 1] - E[y_i|z_i = 0]}{E[x_i|z_i = 1] - E[x_i|z_i = 0]} = \frac{A}{B} \tag{3.13}$$

The numerator, given by $A$, is the mean difference of $y$ in the group of individuals for which $z_i = 1$ and the group for which $z_i = 0$, which measures the causal effect of $z_i$ on $y_i$. The denominator, given by $B$, is the mean difference of $x$ in the group of individuals for which $z_i = 1$ and the group for which $z_i = 0$, which measures the causal effect of $x_i$ on $y_i$. The causal parameter is therefore the ratio of the two differences, known as indirect least squares.

If additional covariates are included in the model specification, the simplest and most commonly used technique is the 2SLS model (Angrist *et al.,* 1995). This model is made up of two consecutive OLS regressions, with the additional exogenous covariates included in both the first stage and second stage equations. Whereas a 'just-identified' model indicates that there are the same number of endogenous variables and IVs, the 2SLS model allows for 'over-identified' models, where there are more IVs than endogenous variables.

However, despite the appealing nature of IV estimators such as 2SLS, there are several associated problems with this method. Firstly, in practice it can be extremely difficult to identify a valid IV strategy, as the criteria for validity discussed previous is extremely strict. Secondly, as discussed in detail by Bound *et al.,* (1995), having a 'weak' instrument (an instrument that is not sufficiently correlated with the endogenous variable) may significantly impact the consistency and efficiency of the estimates from 2SLS models. Amongst others, Cragg and Donald (1993) and Stock and Yogo (2002) have proposed formal tests for the weakness of IVs, both with critical values for the first stage F-statistic of the two stage models. In application, having a partial first stage F-statistic of less than 10 is generally considered the rule of thumb cut-off point for a weak instrument. Due to the potential weakness of IV, in certain cases it may in fact be better to use a biased OLS estimate rather than a consistent estimate using IV with weak instruments (Cerulli 2015).

Thirdly, as argued by Nelson and Startz (1990) and Staiger and Stock (1997), IV models will be biased in finite samples. Staiger and Stock (1997) have compared the finite sample bias of IV estimators to the relative bias of the OLS estimator, concluding that the inverse of the first stage partial F-statistic can be used as an estimate of the relative bias of IV estimators. For instance, in the case that the F-statistic is equal to 10 (the previously discussed rule of thumb cut-off point), the finite sample bias of a correctly specified IV estimator will be roughly 10% of the bias from the OLS model.

Finally, testing the relationship between the instrument ($z$) and the error term ($\varepsilon$) is notoriously difficult in practice. Formally, testing this condition requires an over identified setting (where this is access to more than one IV for the endogenous variable), a relatively rare occurrence given the problems in finding a single IV for an endogenous variable. Furthermore, even if there is an over identified setting, statistical tests for exogeneity (such as those developed by Sargan 1958 and Hansen 1982) can only test the joint exogeneity of all the available IV strategies, not each individual IV.

The parameters identified from IV models should be interpreted as the local average treatment effect (LATE) (Angrist *et al.,* 1996) rather than an average treatment effect (ATE) for the whole population or the average treatment effect on the treated (ATET). This distinction is essential, as the ATE calculated using different instruments and sub-populations are specific to those instruments and sub-populations, and should not be extrapolated to the whole population.

To clarify the theory underpinning the LATE, assume a simplified model with a binary outcome variable $y$, a binary, endogenous treatment variable $x$ and a binary IV $z$, which is significantly associated with $x$. In this context, the LATE framework partitions the population into four potential statuses, as shown in Figure 3.4:

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">$z = 0$</td></tr>
<tr><td>$x = 0$</td><td>$x = 1$</td></tr>
<tr><td rowspan="2">$z = 1$</td><td>$x = 0$</td><td>Never-taker</td><td>Defier</td></tr>
<tr><td>$x = 1$</td><td>Complier</td><td>Always-taker</td></tr>
</table>

*Figure 3.4- Potential Statuses of the Population in the context of the LATE*

- Never-taker: an individual who, independent of $z$, does not take the treatment $x$
- Defier: an individual who take the treatment $x$ when $z = 0$, but does not take the treatment $x$ when $z = 1$
- Complier: an individual who takes the treatment $x$ when $z = 1$, but does not take the treatment $x$ when $z = 0$
- Always-taker: an individual who, independent of $z$, takes the treatment $x$

As it is not possible to know if a given individual in the sample is a never-taker, defier, complier or always-taker, there is a missing observation issue. Under the assumption that the effect of the treatment is heterogonous across the sample, it can be proved that the Wald estimator is equal to the ATE in the sub-group of compliers only, and therefore the LATE can be shown as:

$$LATE = \frac{\overline{y_1} - \overline{y_0}}{\overline{z_1} - \overline{z}_0} = \psi_1 \tag{3.14}$$

The numerator represents the difference between the averages of $y$ in the sub-sample of compliers. The denominator represents the difference between the frequency of treated individuals amongst the compliers having $z = 1$ and the frequency of the untreated individuals amongst the compliers having $z = 0$.

However, the use of the LATE calculated from IV models has some disadvantages. Firstly, the effect of the LATE is the ATE for the non-observable compliant sub-population, and therefore is not generalisable to the whole population. Although this non-observable sub-population can often be regarded as the population of interest, it means that generating policy relevant conclusions using IV methods can be challenging.

Secondly, as the LATE calculates the ATE for the compliant sub-population, this effect will be different depending on the instrument being used. Although this means that the estimates from two different instruments are not directly comparable, as argued by Angrist and Fernandez-Val (2010), differences in estimates from different IV strategies need not signal a failure of the exclusion restriction. Instead, these differences may be attributable to differences in the types of people who are affected by the underlying experiments implicit in any IV identification strategy.

### 3.2 Missing Data

The vast majority of secondary datasets, especially longitudinal designs, have a certain degree of missing data, most commonly due to attrition or non-response. Attrition refers to the loss of sample members over time. Sample members may drop out of surveys for a number of reasons, including moving house, lack of availability or a lack of interest. Non-response refers to individuals not answering certain questions in the survey. Sample members may not respond to certain questions for a number of reasons, for example not understanding the question, not being able to recall the answer, or not wanting to answer due to the sensitive nature of the question.

As argued by Rubin (1976), there are several assumptions that one may make regarding the mechanisms driving the levels of missing data. If the mechanism does not depend on the values or potential values of the variables included, then the data can be regarded as missing completely at random (MCAR). Alternatively, data can be regarded as being missing at random (MAR) if the probability of data being missing for a variable is not a function of that variable conditional on some other variables in the design. In both the MCAR and MAR cases, the missingness can be referred to as ignorable, as such missingness should not lead to bias in the empirical estimates. However, if the mechanism generating the missing data is not MCAR or MAR, the data can be seen as being missing not at random (MNAR), which if ignored may lead to less precise estimation and inference.

The most common approach in microeconometric studies is to undertake a complete case analysis, where analysis involves using only data from those subjects for whom all of the variables involved in the analysis are observed (Cameron and Trivedi 2009). This is also the default setting in the majority of statistical packages where there is missing data present. However, this method may lead to sample selection bias if those observations in the complete case analysis differ significantly from those with incomplete records. Therefore, the results may not be generalisable at the population level. Due to this common issue, a number of techniques have been designed to partially account for missing data, including imputation methods and inverse probability weighting (IPW).

Imputation involves imputing the missing values of the dataset using information from the other observed covariates in the model. Mean imputation involves replacing missing observations with the average of the available values. Although simple to implement and mean preserving, this method is rarely used, as it may significantly impact the distribution of the data and will also impact the covariance and correlation with other variables. Multiple imputation (MI) involves imputing the missing values multiple times, using a variety of variables seen to be related to the missingness. MI can therefore improve the efficiency of the estimates, and in certain settings may completely remove the bias present in the estimates. However, although flexible, the MI approach comes attached with a significant number of assumptions. Firstly, the MI method only gives completely unbiased estimates when the imputation model is correctly specified. Secondly, it can be difficult to implement MI methods when there is a complicated pattern of missing data.

An alternative method that has been commonly used in microeconometric studies is IPW. This method involves performing a complete case analysis, but weighting the complete cases by the inverse probability of them being a complete case. Those who have a large chance of being observed are given a smaller weight, while those who have a smaller chance of being observed are given a larger weight, in an attempt to compensate for missing observations with similar characteristics. Modelling this 'missingness' may be easier than modelling the partially observed variables. However, there are several problems associated with this method. Firstly, IPW can be relatively inefficient compared to other methods, such as MI. Secondly, it is difficult to use in settings where there is a complicated pattern of missing data.

In order to check the robustness of the results to missing data in this thesis, I used IPW models in each empirical chapter, due to the ease of computation compared to MI, the difficulties in implementing MI if the missing variables are binary or categorical, and the fact that modelling missing data on multiple explanatory variables simultaneously requires additional assumptions regarding the joint distribution of these missing variables (Carpenter,. *et al* 2006). As outlined by Bartlett (2012), the implementation of IPWs is a two-procedure. Firstly, a logit regression model must be estimated, regressing the probability of being fully observed on a number of variables predicted to influence missingness. Secondly, the inverse of the predicted values calculated from these logit models are then used as the probability weights in the full estimation sample.

Specifically related to analysis using panel data, there may also be bias in the empirical estimates if there are drop-outs from the panel over time which are related directly to the variables of interest. A simple variable addition test can be used to diagnose attrition bias in panel data regressions, such as the test proposed by Verbeek and Nijman (1992). This test involves adding a test variable, which reflects non-response, to the original regression model and testing its statistical significance. The test variables then can be used as: 1) an indicator of whether the individual responds in the subsequent wave; 2) an indicator of whether the individual responds in all waves; and 3) to count the total number of waves for each respondent (Jones *et al.,* 2013). If non-response is random, indicators of individual's pattern of survey response should not be associated with the outcome of interest after controlling for the observed covariates.

### 3.3 Survey Weights

While certain datasets (such as the NCDS and BCS) can be seen as a random snapshots of a population at a given time point, and therefore in theory an unbiased sample for that specific time period, the majority have more complex, stratified survey designs (such as the MCS and UKHLS), and therefore usually come attached with a variety of survey weights. However, the use of survey weights in econometric analysis is a fiercely debated topic, and are still a major source of confusion and frustration for many experienced applied empirical researchers (Angrist and Pischke 2009).

On one hand, there are several reasons why sample weights should be integrated into regression analysis. For example, weighted coefficients may be able to increase the precision of the empirical estimates by correcting for heteroskedasticity, achieve consistent estimates by correcting for endogenous sampling, identify the correct partial effects in the presence of heterogeneous effects or adjust bias caused by differential non response (Wooldridge 2010).

However, as argued by Solon *et al.,* (2015), if the aim of the multivariate analysis is to estimate causal effects (for example the causal effect of income on health) rather than generate nationally representative descriptive statistics (for example the average level of health in each income quintile in the UK), the answer is less clear cut, as it is usually this causal relationship which is of interest. For instance, it has also been argued that using weights in regression may not be necessary if the sampling probability is exogenous to the model, and that using survey weights may often produce less precise estimates of the regression parameters (Dickens 1990; Wooldridge 1999). Furthermore, if the model is seen to be good approximation of the data-generating process, weighted models are likely to be less efficient that unweighted models.

Overall, it is recommended that, where possible, researchers should estimate econometric models both with and without sample weights and report both sets of estimates, in order to determine if the weights significantly impact the empirical results, and therefore merit inclusion. Furthermore, Solon *et al.,* (2015) have argued that the use of robust standard errors is advisable in all circumstances, in order to account for potential heteroskedasticity. In order to check the robustness of the empirical estimates to survey weights in this thesis, I estimated both weighted and unweighted econometric models wherever possible, and used robust standard errors.

# Chapter 4. The Socioeconomic Distribution of Child Cognitive Ability in Three British Cohort Studies

## 4.1 Introduction

Amongst the large literature that has investigated the role that early life characteristics play in predicting adult outcomes, a significant proportion has examined the specific role of child cognitive ability. In this context, cognitive ability represents conscious intellectual effort reflected in the child's use of language or numeracy skills[3]. Theoretical literature from the economics field predicts that early life cognitive ability may have distinct effects on economic, social and health outcomes across the life cycle, with these effects driven by factors such as self-productivity, dynamic complementarity and multiplier effects (Cunha and Heckman 2007). The relative importance of such cognitive skills is also likely to increase over time in the UK, given the gradual decline in the supply of jobs in the manufacturing and production industries.

A number of empirical studies concerning the association between cognitive skills and adult outcomes confirm the theoretical predictions of Cunha and Heckman (2007). For instance, studies using US datasets have found that cognitive test scores are extremely good predictors for wage levels, occupational choice and risky health related behaviours such as drinking and smoking (Heckman and Carneiro 2003; Cunha *et al.,* 2006 and Heckman *et al.,* 2006). Such patterns have also been found using UK data. For instance, McIntosh and Vignoles (2001), Machin *et al.,* (2001), and Schoon (2010) all show that basic literacy and numeracy skills are significantly correlated with employment rates and wages in later life.

While it is clear that the level of child cognitive ability itself may be an important marker for a variety of later life outcomes, a number of studies have shown that there are also substantial socioeconomic inequalities in child cognitive ability in the UK (Duncan *et al.,* 1994; Blau 1999; Feinstein 2003; Dickerson and Popli 2016). There are both normative and practical reasons why one may be concerned about such socioeconomic inequalities in child cognitive ability. Firstly, socioeconomic inequalities in child outcomes such as cognitive ability can be seen as a matter of social justice. Unequal opportunities caused by

[3] The American Psychological Association formally defines cognitive ability as "the ability to understand complex ideas, to adapt effectively to the environment, to learn from experience, to engage in various forms of reasoning and to overcome obstacles by taking thought" (Neisser *et al.,* 1996).

circumstances at birth beyond the control of the individual are viewed as being fundamentally unfair, with such unfairness potentially leading to social conflict (Stewart 2009). Due to this moral obligation to give every child a strong start in life, and the acknowledgement that individuals with a higher level of cognitive ability may be able to make stronger contributions to society through increased economic productivity, a number of organisations (for example The British Government and the Organisation for Economic Cooperation and Development) have made it a priority to reduce levels of socioeconomic inequality in child outcomes such as cognitive ability. More generally, the UK Child Poverty Act has committed to end child poverty by 2020.

Secondly, it has been argued that the relationship between socioeconomic status (SES) and child outcomes such as cognitive ability may play a significant role in intergenerational income persistence (Blanden *et al.,* 2007), alongside other transmission mechanisms such as education attainment (Gregg and Machin 1999). Defined as the strength of relationship between the income level of the parent and their children, low levels of intergenerational income mobility (i.e. a strong correlation between the levels of income) indicate that those born to relatively low income households may have more restricted life chances compared to those from high income households, and therefore may not achieve their full potential. This is particularly policy relevant in a UK setting, where the level of intergenerational mobility is relatively low compared to other developed countries (Solon 2002).

Thirdly, authors such as Lynch and Davey Smith (2005) and Mackenbach (2010) have argued that inequalities in early life outcomes such as cognitive ability may also help to drive socioeconomic health inequalities. Building on such arguments, Mackenbach (2012) has theorised that changes in personal characteristics, for example cognitive ability, may be able to help explain the paradoxical persistence of socioeconomic health inequalities in developed countries such as the UK. Specifically, the author has argued that over time, the lower social strata has become more exclusively composed of individuals with personal characteristics, such as cognitive ability and personality profiles, that increase the risks of ill health. Due to decades of upward intergenerational social mobility, it follows that opportunities for social selection may have made lower social groups more homogenous with regard to child characteristics such as cognitive ability, therefore widening socioeconomic inequalities in health.

Although a number of studies have documented the change in child health inequalities over time (Marmot *et al.,* 2010), the same cannot be said about cognitive ability. Despite there being an established literature regarding the level of socioeconomic inequality of child cognitive ability, and the key role that cognitive skills may play in both generating social mobility and socioeconomic health inequalities, relatively few studies have specifically investigated whether these socioeconomic inequalities have significantly changed over time in the UK. This is despite the huge cultural and environmental changes that have occurred in recent years, for example higher levels of socioeconomic inequality, increased investment in the education system and the changing composition of the labour market. Furthermore, several government policies to reduce levels of social exclusion (such as the influential Sure Start scheme), have been developed over the past 20 years. If such policies have indeed been effective, this may have also had a significant impact in the level of socioeconomic inequality in child outcomes such as cognitive ability.

Given this gap in the evidence base, this chapter had three main aims. Firstly, I aimed to estimate the level of socioeconomic inequality in cognitive ability in the NCDS, BCS and MCS, using both regression methods and the concentration index (CI), a measure of socioeconomic inequality mainly used in the context of health and health care utilisation which is rarely used in the context of other child outcomes such as cognitive ability. Secondly, I aimed to investigate whether the level of socioeconomic inequality has changed significantly between the NCDS and the MCS, using dominance analysis between the associated concentration curves (CC). Finally, I aimed to investigate the determinants of socioeconomic inequality using the decomposition methods of Wagstaff *et al.,* (2003), and also considered whether these determinants have changed significantly over time.

## 4.2 Previous Work

### 4.2.1 *Socioeconomic inequalities in child cognitive ability*

Due to the variety of household and longitudinal datasets available, the majority of the previous empirical work regarding the relationship between SES and child cognitive ability has been carried out in the UK and the USA. Although a significant empirical literature has investigated the relationship between measures of SES and other child outcomes, for example years of schooling (Duncan *et al.,* 1998), completion of higher education (Carneiro and Heckman 2002) and health (Khanam *et al.,* 2009), in the interests of space I focus specifically on studies looking directly at the relationship between SES and child cognitive ability. The vast majority of studies which have examined the relationship between SES and child cognitive ability have found evidence of socioeconomic inequalities, despite differences in the setting, methodology and measurement of both cognitive ability and SES. A selection of the more notable studies are discussed below.

Duncan *et al.,* (1994) used data from the USA based Panel Study of Income Dynamics (PSID) to estimate the impact that family income and persistent poverty status have on child IQ level, measured at age 5. Using linear regression analysis and controlling for a wide range of confounding characteristics including the home environment and neighbourhood factors, the results showed that an increase in income of $10,000 was associated with an increase in IQ at age 5 of 0.15 SD. Furthermore, the authors found that the impact of persistent poverty was roughly twice as large as the effect of transient poverty, and that the association was mediated by maternal depressive symptoms and the home learning environment.

Utilising a sample of children (N=6864) from the USA based National Longitudinal Survey of Youth (NLSY), Blau (1999) estimated the effect of family income on a range of child outcomes, including cognitive and behavioural development. Utilising a variety of panel data models in order to partially control for the endogeneity of income, results showed both current income and permanent income to be associated with child cognitive ability. However, the magnitude of this effect was found to be relatively small when a number of controlling characteristics were included in the empirical specification, implying that a range of factors associated with both income and child cognitive ability may have explained a significant proportion of the correlation. A number of other empirical studies (for instance Parcel and Menaghan 1990; Hill and O'Neill 1994; Korenmann *et al.,* 1995 and Smith *et al.,* 1997) have also investigated the relationship using the NLSY but less sophisticated econometric methods, with the findings mostly in line with those from Blau (1999).

In a highly influential and UK based study, Feinstein (2003) used a sub-sample of children (N=1194) from the BCS to show the long shadow that parental SES (as measured by parental occupational classification) has on child development (as measured by the wide range of cognitive tests available in the BCS). Empirical results showed that children from lower socioeconomic backgrounds had lower cognitive scores in later childhood, even if they had high cognitive scores in early childhood, with children from higher socioeconomic backgrounds showing significantly more upward mobility. Although it has been argued that a certain proportion of the disadvantages displayed in this study (in particular the phenomena of lower ability children from higher social classes overtaking high ability children from a lower social class at a very early age) may in fact be attributed to regression to the mean (Jerrim and Vignoles 2013), the significant socioeconomic inequalities in cognitive ability are still apparent.

In a rare cross country comparison, Aughinbaugh and Gittleman (2003) examined the effect of household income on levels of child development in sub-samples of children from both the NLSY (N=2380) and the NCDS (N=2080). Similar to the studies of Duncan *et al.,* (1994) and Blau (1999), results across both cohort studies showed a remarkably similar statistically significant association between levels of income and child cognitive ability, despite significant differences in factors such as health care provision, racial composition and educational institutions. However, this effect was found to be relatively small (a $10,000 increase in income associated with a 0.05-0.08 SD change in cognitive ability) compared to other family background variables such as the home learning environment.

Goodman and Gregg (2010) used a variety of British studies to analyse the gap between the rich and poor in terms of educational attainment, including the MCS, Avon Longitudinal Study of Parents and Children (ALSPAC) and the Longitudinal Survey of Youth (LSY). Using parental occupational classification as their measure of SES and a wide range of measures of cognitive ability, results showed those children from households in the lowest quintile of a combined measure of SES had cognitive scores 23% lower than those in the highest quintile at the age of 3, with this level of inequality rising to 27% at age 5. Further analysis showed that a significant proportion of the gap in test scores between the richest and the poorest children could be explained by parenting behaviours and the cognitive ability of the parent, implying that this may be a potential pathway through which socioeconomic inequalities may be reduced.

Unlike the vast majority of the UK based literature, Violato *et al.,* (2010) focused on the relationship between parental income and cognitive ability using both cross sectional and panel data regression methods. Once more utilising the rich MCS data, empirical estimates from both random effects and fixed effects model specifications showed that although family income was significantly associated with measures of child cognitive ability at age 5 (a one unit increase in logged permanent income was associated with an 0.1 SD increase in cognitive ability), the magnitude and precision of this estimate significantly diminished whilst controlling for a variety of other factors. The authors also acknowledged that family income was likely to be acting as a proxy for a broader range of socioeconomic factors, and therefore may not have a strictly causal interpretation.

Rather than estimating a conditional association between a measure of SES and child cognitive ability, Milligan and Stabile (2011) exploited exogenous changes in child benefits in Canada to estimate the causal impact of household income on child cognitive ability using IV methods. Utilising the National Longitudinal Survey of Canadian Youth (NLSCY), results showed a relatively small causal effect of income on both maths and reading test scores in the full sample (a $1000 increase in income corresponding to a 0.03-0.07 SD increase in cognitive ability), with these effects larger among boys and those from families with low levels of educational attainment.

Several other studies in this literature have also attempted to account for endogeneity and estimate a causal effect of income on child cognitive ability, with these studies in general generating mixed results. For instance, Loken (2010) used the 1970s Norwegian oil boom as an instrument to find no causal relationship between income and measures of child cognitive ability, while Loken *et al.,* (2012) used the same natural experiment to find a small positive causal effect of income at the lower end of the income distribution. Furthermore, Dahl and Locher (2012) used non-linear changes in Earned Income Tax Credit in the USA to show that a $10,000 increase in income increased standardised cognitive ability by between 2-3%. However, the conclusions from this study are disputed, as Lundstrom (2017) has shown that a coding error when calculating the income variable may in fact explain a significant proportion of the estimates.

Most recently, Dickerson and Popli (2016) used the MCS to identify the relationship between persistent poverty and various measures of child cognitive ability from ages 3-7. Using structural equation modelling (SEM) methods in order to identify both the direct and indirect effects of poverty on cognitive development, empirical estimates showed that children born into poverty have a significant disadvantage in terms of cognitive ability after controlling for various background characteristics and measures of parental investment. The authors further noted the potential important role of parenting skills and investment, and also showed that poverty crucially has a cumulative negative effect. However, as argued by the authors, disentangling the effect of income from other household factors and treating the estimates as causal may be difficult, given that children in poor households often have young, less educated and single mothers.

Although not discussed in detail, there have also been several other important contributions to this empirical literature. For instance, Wolfe (1982), Brooks-Gunn and Duncan (1997), Klebanov *et al.,* (1998), Duncan *et al.,* (1998), Taylor *et al.,* (2004) have analysed the relationship between SES and child cognitive ability using US data, while McCulloch and Joshi (2001), Gregg *et al.,* (2007), Barnes *et al.,* (2010), Kiernan and Mensah (2009; 2011) and Schoon *et al.,* (2012) have analysed the relationship using data from the UK. All of these studies showed a significant association between measures of SES and child cognitive ability.

One common feature of this empirical literature is the use of purely regression based methods, with very few empirical studies having utilised more sophisticated measures of socioeconomic inequality, such as the concentration index (CI). As Wagstaff *et al.,* (1991) have argued, the CI can be regarded as one of the most appropriate empirical measures of socioeconomic inequality, as it reflects the experiences of the entire population, is sensitive to changes in the distribution of the population across socioeconomic groups and summarises the extent of inequality in a single measure that can be compared across groups.

Only two other published empirical studies have used the CI in the context of non-health child outcomes. The first of these was Maika *et al.,* (2013), who analysed the change in socioeconomic inequality in child cognitive ability between 2000 and 2007 in the Indonesian Family Life Survey. Empirical results showed that although the burden of poorer cognitive function was consistently higher among the disadvantaged, this level of disadvantage decreased over time. Decomposition analysis showed household income and parental education to be the largest contributing factors to the overall level of income related socioeconomic inequality.

The second study to use the CI in child non-health outcomes was that of Vallejo-Torres *et al.,* (2014), who investigated income-related inequality in a measure of psychological wellbeing, along with several other health measures, in five years of pooled data from the Health Survey for England. The results showed a significant level of socioeconomic inequality in child psychological well-being, with these inequalities being larger than those found in late adolescence and also larger than several domains of physical and mental health.

### 4.2.2 *Comparing socioeconomic inequalities in child cognitive ability over time*

As well as the level of socioeconomic inequality, in this empirical chapter I was also concerned about whether the level of socioeconomic inequality has changed over time. Although measuring the degree of socioeconomic inequality in cognitive ability has been a relatively prominent research area for a number of years, very few published studies have explicitly attempted to measure the changes in the socioeconomic inequalities in cognitive ability across time, with the few that have generating mixed results. To my knowledge, only five empirical studies have either directly or indirectly examined whether socioeconomic inequalities in cognitive ability have significantly changed over time in the UK[4].

Blanden and Machin (2007) considered the indirect relationship between parental income and a range of child outcomes (including cognitive test scores, non-cognitive ability and degree attainment) in a variety of British datasets (NCDS, BCS, MCS, British Household Panel Survey) in the context of changing social mobility. Using both OLS and 2SLS models, the authors found little evidence that the relationships between these intermediate variables had significantly changed from the older studies (for example the NCDS and BCS) to the more recent MCS and British Household Panel Survey. However, the results from the 2SLS models should be treated with caution, due to the fact that the variables used to instrument income were measure of parental education, employment status and housing tenure at age 16. Although it is almost certain that these variables will be highly correlated with household income, it is extremely unlikely that these variables will be exogenous to the main equation, as one may expect a large vector of unobservable factors to be related to both education level and income, such as underlying ability.

Schoon (2010) investigated the relationship between family socioeconomic background (measured by parental occupation), general cognitive ability and academic attainment, using the 1946 National Survey of Health and Development, the NCDS and the BCS. General measures of cognitive ability were calculated through principal components analysis (PCA) and SEM methods, with the author finding that the association between social background and cognitive ability marginally increased between 1946 and 1970 cohorts, despite the

[4] Reardon (2011), Duncan and Murnane (2011) and Michelmore and Dynarski (2017) have examined the widening achievement gap between the rich and poor in the USA in the past fifty years, whereas Maika *et al.,* (2013) have investigated changes in the inequality of cognitive ability in an Indonesian sample from 2000-2007. However, due to the different institutional contexts of these studies and the interests of space, these studies are not discussed in greater detail.

introduction of the 1944 Education Act aimed at increasing educational opportunities irrespective of socioeconomic background.

Blanden and Machin (2010) compared the inequality in cognitive ability between the second and third waves of the MCS with the children of respondents of the original NCDS and BCS birth cohorts. In all cohorts, the authors found a significant association between parental income levels and child cognitive ability, with these income related cognitive ability gaps once more relatively stable over time. Although this cross-cohort comparison allowed the authors to compare children using the exact same cognitive test, the time range examined was relatively short (1991-2005) and the children of the NCDS and BCS samples were relatively small in comparison to the MCS sample.

The most prominent study in this small literature is that of Gregg and Macmillan (2010), who analysed the relationship between standardised family income and cognitive ability across groups of cohorts from both the late 1950s (NCDS) and the 1990s (the ALSPAC study and a sample from the BHPS). In contrast to Blanden and Machin (2007), using OLS methods the authors found a small, yet consistent narrowing of the social gradient in the relationship between family background and cognitive ability between the older cohorts (such as the NCDS and the BCS) and the newer youth cohorts (such as the ALSPAC and BHPS). The authors attributed this change of relationship to changes in the UK education system over time, such as increased spending on education as a share of GDP.

The most recent study to investigate the changing relationship of socioeconomic disparities in child cognitive ability over time was Connelly (2013), who used the NCDS, BCS and MCS to examine changes over time using SEM methods. Using a latent measure of SES calculated using information on parental occupational classification and parental education, the author found no significant change in the degree of socioeconomic inequality between the three cohort studies. The latent measure of cognitive ability used in the study was a combined measure of cognitive ability created using PCA. Although PCA methods allowed the authors to combine various cognitive test into a single measure, and have also been used in several high profile publications utilising the British cohort studies (for instance Feinstein 2003 and Galindo-Rueda and Vignoles 2005), this combined measure does not take into account that different cognitive tests may have radically different socioeconomic distributions, and therefore may underestimate or overestimate the level of socioeconomic inequality, depending on the measure of cognitive ability in question.

Although they did not explicitly examine the socioeconomic distribution of child cognitive ability over time, at this point it is also worth mentioning the recent studies of Goisis *et al,.*(2017a) and Goisis *et al,.*(2017b), as both studies utilised the NCDS, BCS and MCS to compare child cognitive test scores over time. In the first of their studies (Goisis *et al,.* 2017a), the authors examined the changing relationship between birth weight and child cognitive ability (as measured by verbal ability at age 10/11) in the three separate cohort studies. Using pooled linear regression models, results showed a marginal narrowing of the relationship between birth weight and child cognitive ability over time from the NCDS and BCS to the MCS.

In the second of their studies (Goisis *et al.,* 2017b), the authors examined the changing relationship between maternal age and child cognitive ability (once more measured by verbal ability at age 10/11) in the three separate cohort studies. Again using pooled linear regression methods, results showed that the relationship changed from negative in the NCDS and BCS to positive in the MCS, potentially driven by changes in parental characteristics relative to maternal age such as levels of education and household income.

Given the previous literature, in this chapter I contribute to the applied empirical literature in two main ways. Firstly, I contribute to the literature investigating the relationship between SES and child cognitive ability, with this being the third empirical study (after Maika *et al.,* 2013 and Vallejo-Torres *et al.,* 2014) to apply the CI methodology and use the decomposition methods of Wagstaff *et al.,* (2003) in the context of child non-health outcomes such as cognitive ability.

Secondly, I contribute to the small literature comparing socioeconomic inequalities in child cognitive ability over time, with this being the first to use dominance analysis, which allows for the difference in the level of socioeconomic inequality to be estimated, given the different sampling structures of the NCDS and the MCS. Although Connelly (2013) also examined the relationship between SES and child cognitive ability over time using both the NCDS and the MCS datasets, this chapter differs from that study in a number of ways. For instance, rather than latent measures of SES and child cognitive ability, I use two distinct measures of SES (parental occupation classification and household income) and a range of measures of cognitive ability in empirical analysis. Furthermore, I use a variety of empirical methodologies related to the CI that are not explored by Connelly (2013).

In examining the socioeconomic gradient in child cognitive ability over time, I am also the first to indirectly empirically test the hypothesis proposed by Mackenbach (2012), who has argued that the changing composition of the social strata may help explain the paradoxical persistence of socioeconomic inequalities in health in developed countries such as the UK.

### 4.3 Theoretical Considerations

There are three main hypotheses that I test in the empirical analysis:

a) Are there socioeconomic inequalities in child cognitive ability in the NCDS, BCS and MCS?
b) Has the level of income related socioeconomic inequality in child cognitive ability changed significantly from children born in 1958 to children born in 2000?
c) Have the contributing factors to the level of income related socioeconomic inequality in child cognitive ability changed significantly from children born in 1958 to children born in 2000?

In sub-sections 4.3.1 and 4.3.2 below, I outline the theoretical reasoning behind these hypotheses.

#### 4.3.1 *Socioeconomic inequality in child cognitive ability*

There are a number of reasons why there may be significant levels of socioeconomic inequality in child cognitive ability. For instance, theories developed in the economic literature, most famously those of Becker (1981) and Becker and Tomes (1986), have proposed that the outcomes of children are a direct consequence of both the endowments that parents transfer (either biological or personality traits) and also the level of investment of the parents. A key aspect of such models is that parents care about the capabilities and success of their children, and therefore dictate both the level of economic resources (through the level of labour supplied) and how these resources are shared amongst the household. Given that parents attempt to maximise their household utility subject to both their time and budget constraints, those households with larger budgets will invest higher levels of resources into their children, generating disparities in such outcomes between those in different socioeconomic groups.

Alongside such economic theories, which focus on household investment, a number of alternative theories have been proposed from the sociological and developmental psychology literatures which instead relate to non-monetary investment. For instance, the 'parental stress' theory asserts that the increased stress of being in poverty diminishes the ability of parents to be supportive and consistent with their children (McLoyd 1990), and that this unsupportive and inconsistent parenting in turn impacts the social, cognitive and emotional development in children. This in turn may impact educational development and social opportunities in later life, depending on how the child responds to this environment (Parker *et al.,* 1988). An alternative theory that has been presented is the 'role model' theory, which focuses on values, norms and behaviours developed by those parents in poverty (Mayer 1997). Specifically, the theory argues that due to being in poverty, low-income parents develop dysfunctional behaviours, and it is such behaviours that influence the cognitive and social-psychological development of a child.

### 4.3.2 *Changes in the level of socioeconomic inequality in child cognitive ability over time*

Although there are several reasons why one may expect there to be significant socioeconomic inequalities in child cognitive ability in all three cohort studies, the case for changing socioeconomic inequalities in cognitive ability over time is less clear cut. There are reasons to believe that socioeconomic inequalities in child cognitive ability should have decreased over time. For instance, the past fifty years have seen a substantial amount of social progress the UK, with increased relative incomes allowing UK citizens to have greater spending power, and absolute child poverty generally being in decline since the 1980s, and halving since 1997 (Social Mobility Commission 2016). Despite being threatened with funding cuts in recent years, in general there has also been significant, widespread investment in the British education system over the past century, with real spending rising from around £25 billion per year in 1965 to around £99 billion per year in 2010 (Institute for Fiscal Studies 2015), despite pupil numbers only increasing by just over 10% in the same time period.

Recent generations of children have also been subject to several other welfare reforms, for example the influential Sure Start initiative, which was introduced by the 1997 Labour government as a multi-departmental programme of early intervention for the under-fours. This initiative was specifically created to reduce inequalities in early life child outcomes such as health, well-being and school readiness (Rutter 2006), with Melhuish *et al.,* (2010) finding the scheme to have had some beneficial effects in the short term. Empirical analysis of the long-term effects of the programme on child outcomes is ongoing.

Despite the reported increase in levels of social progress, increasing investments in the education system and the introduction of welfare reforms such as Sure Start, there are also reasons to believe that socioeconomic inequalities in child cognitive ability may have in fact increased over time (Reardon 2011). Firstly, there has been a significant increase in levels of income inequality over the past 50 years. For example, a 2010 report from the Institute of Fiscal Studies (IFS 2010) showed that although levels of relative income may have increased in recent years, levels of income inequality (as measured by the Gini coefficient) have significantly increased in the UK over time, from around 0.25 between 1965 and 1969 (when the children of the NCDS cohort undertook their cognitive assessment) to around 0.35 between 2007-2010 (when the children of the MCS cohort undertook their cognitive assessments), as shown in Figure 4.1. Given the predicted strong relationship between SES and child cognitive ability, it is possible that this increase in income inequality may also be reflected in such outcomes.

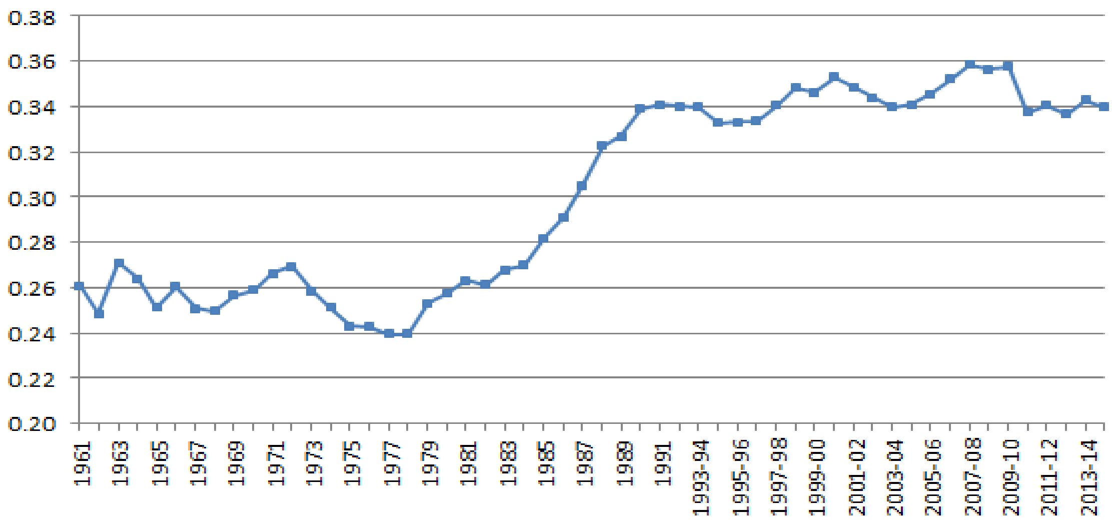


*Figure 4.1- UK Gini coefficient from 1961-2013/14*

Secondly, Reardon (2011) argues that family investment patterns may have changed differentially during the last century, with high income families investing more time and resources into children's cognitive development than their lower income counterparts. Although Guryan *et al.,* (2008) have shown that this may be a conceivable path through which socioeconomic inequalities may manifest themselves, there is very little empirical literature with which to confirm the hypothesis of changing investment patterns over time. A notable exception to this is the study of Kornrich and Furstenberg (2013), who found that spending on children as a proportion of household income rose 14.5% from 1973 to 2007 in a sample of households from the US Consumer Expenditure Survey. Importantly, the authors also noted that the inequality in investment also increased in same time period, in line with increasing levels of income inequality in the USA.

Reardon (2011) has also argued that income related socioeconomic inequalities in child cognitive ability may have increased through an increase in residential segregation by income. Reardon and Bischoff (2011) have shown that increasing income inequalities may result in high income and low income families residing spatially far from each other, which may in turn lead an increase in school segregation by income. There is however currently very little empirical evidence with which to test this hypothesis.

Finally, it has been argued that increasing levels of parental education may drive increasing socioeconomic inequalities in child cognitive ability over time, given the strong relationship between education and income and increasing levels of inequality in education. Blanden *et al.,* (2003) and Blanden and Machin (2004) have shown that despite the significant investments in higher education during the same time period from the UK government, for various measures of educational attainment (both staying on at school past the compulsory age and engagement in higher education), socioeconomic educational inequalities have increased over time in the UK. For instance, Blanden *et al.,* (2003) showed that the gap in the probability of receiving a degree between the top income and bottom parental income quintiles increased from 0.14 to 0.37 in the years 1981-1999.

### 4.3.3 *Empirical implications*

From the various theoretical models discussed in sub-section 4.3.1, one can clearly relate how measures of SES may be related to child cognitive ability, mediated either through household investment decisions, parental psychological well-being or parental attitudes and behaviours. Given that SES is a multi-faceted concept, it is important for robustness to assess the extent of inequality using different measures of SES, as the extent of inequality may be heterogeneous across such measures. Consequently, in the empirical analysis, I measured socioeconomic inequality through both parental occupational classification in OLS models, and household income in the calculation of the CIs. This choice of empirical methodology will be further discussed in sub-section 4.5.2.

Notwithstanding the likely endogenous relationship between measures of SES and child cognitive ability, in the empirical analysis of this chapter I did not attempt to identify a causal effect, and the estimates should instead be interpreted as conditional associations. There was no appropriate IV strategy or policy change that could be used to identify a causal parameter across the different cohort studies, and the lack of comparable cognitive tests within the individual cohort studies meant that I could not use panel data methods to control for unobserved individual level heterogeneity. Taking into account the previous studies that have attempted to measure the 'true' causal effect of measures of SES on child outcomes (Milligan and Stabile 2011; Loken *et al* 2012), it is therefore possible that not accounting for endogeneity will overestimate the true impact of SES.

It is *a priori* unclear whether the level of socioeconomic inequality in cognitive ability should have increased or decreased over time in the UK, and it is therefore an empirical question as to whether the factors related to increased educational spending and welfare reforms or the factors related to increased income inequalities dominate. Due to the limited number of comparable variables available across the cohort studies, I was unable to evaluate the majority of the pathways through which it has been predicted that income related socioeconomic inequality may have changed over time. The exception to this was the level of maternal education, as there are proxy measures of this variable (specifically if the mother stayed in school beyond the minimum age) available in the NCDS, BCS and MCS. I used the decomposition methods outlined by Wagstaff *et al.,* (2003) to analyse to what extent maternal education contributes to income related socioeconomic inequalities in child cognitive ability, and whether the magnitude of this relationship has changed over time.

**4.4 Estimation Strategy**

Informed by both the past theoretical and empirical literature, I used a number of econometric techniques to: 1) estimate the level of socioeconomic inequality in child cognitive ability in the NCDS, BCS and MCS; 2) identify if the magnitude of this socioeconomic inequality had changed significantly over time; and 3) identify if the contributing factors to this socioeconomic inequality had changed over time.

To investigate the level of socioeconomic inequality in the three cohort studies, I first estimated OLS regression models, using parental occupational classification as a broad measure of social class[5]. To compliment this, I estimated CIs for the NCDS and MCS, which had the required information on income needed for this specific estimation strategy.

In order to compare the level of socioeconomic inequality over time, I used dominance analysis, which uses information from the CC associated with the CI, for the few cognitive test scores that were generally comparable across the NCDS and MCS. The CI and CC are defined in detail in the proceeding sub-sections. Finally, in order to identify if the contributing factors to the level of income related socioeconomic inequality had changed over time, I used decomposition methods developed by Wagstaff *et al.,* (2003), which take into account both the correlation and socioeconomic distribution of contributing factors to the overall level of socioeconomic inequality.

### 4.4.1 *Ordinary least squares model*

The starting point of this analysis was an OLS regression model. The OLS model estimates the effect that a one unit increase in a predictor variable has on a dependent variable whilst holding a number of other variables constant by minimising the sum of the squared residuals, and can be seen as the best linear unbiased estimator (BLUE) given a set of classical assumptions, as outlined by the Gauss-Markov theorem (Gauss 1887; Markov 1899). The OLS specification I used in this chapter can be formally presented as:

$$CA_i = \beta_0 + \beta_1 SES_i + \beta_2 \boldsymbol{x}_{ji} + \varepsilon_i \, , \tag{4.1}$$

where $i$ = *1,2,…n*

In this equation, let $CA_i$ represent a standardised measure of child cognitive ability for child $i$. $SES_i$ is a measure of SES, measured in this case by parental occupational classification, with its associated vector coefficient $\beta_1$. $\boldsymbol{x}_{ji}$ represents a vector of individual and household characteristics assumed to be confounders, with their associated parameter coefficients $\beta_2$. $\varepsilon_i$ represents the error term, which is assumed to be randomly distributed. This OLS error term may be made up of several factors, including omitted variables, measurement error and reverse causality (Wooldridge 2010). I implemented the OLS models using the *regress*

[5] A number of other studies in this literature have also used parental occupational classification as a measure of SES, including Feinstein (2003), Goodman and Gregg (2010) and Schoon (2010).

command. In the NCDS and BCS, I used robust standard errors, whereas in the MCS I calculated standard errors using the Taylor-Linearization method[6] through the *svy* prefix.

### 4.4.2 *Concentration index*

An alternative method to OLS regression in measuring socioeconomic inequality is the CI, a measure which is usually applied to health variables. The CI has its roots in measures of pure income inequality, namely the Gini coefficient (Gini 1921). The Gini coefficient measures relative inequality in the distribution of income across the population, so that the level of income inequality can be compared across different populations and across time[7]. The Gini coefficient is bound between 0 and 1. A value of 1 represents a situation where there is one person holding all of the income. Conversely, a value of 0 represents a situation in which every person in the population has an equal amount of income. The Gini coefficient can be illustrated by the Lorenz curve (Lorenz 1905; Kakwani 1977), as shown in Figure 4.2.

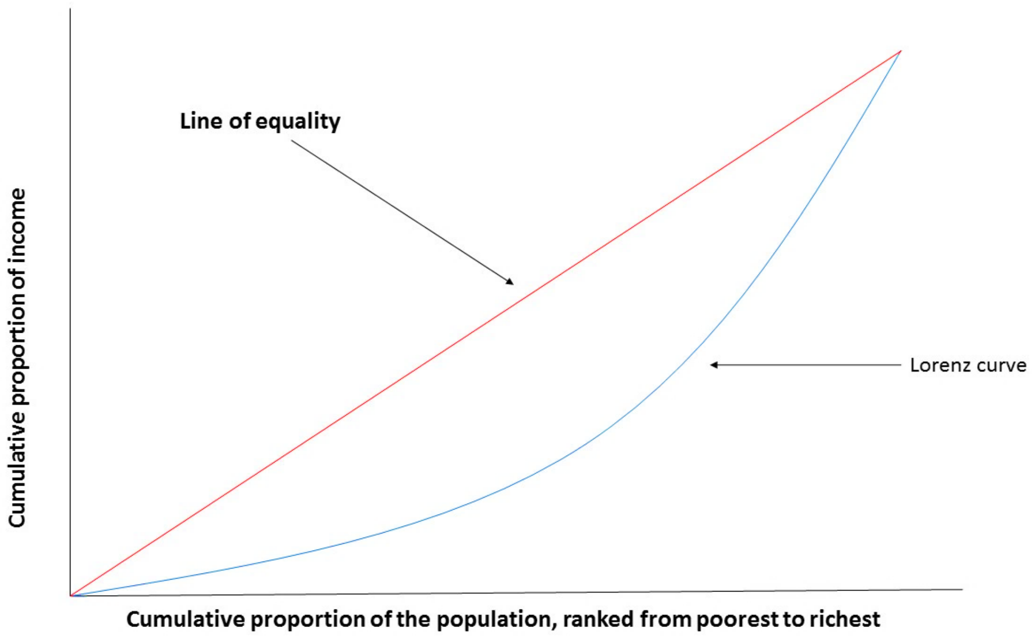


*Figure 4.2- Lorenz curve*

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[6] This is the default setting when implementing survey weights in a stratified sample such as the MCS.
[7] The Gini coefficient is shown as:

$$Gini = \frac{2}{n\mu}\sum_{i=1}^{n} y_i R_i - 1 ,$$

where $y_i$ represents income and $R_i$ represents the socioeconomic fractional rank within the population of a member of the population $i$. Furthermore, $n$ represents the total number of people within the population, and $u$ represents the mean of the ranking variable.

The Lorenz curve plots the cumulative proportion of income (y-axis) against the cumulative proportion of the population, starting with the poorest person (x-axis). The 45° line from the origin represents the line of equality, at which point the Gini coefficient would equal 0 (the red line). The Lorenz curve (the blue line) shows the distribution of income, with a larger area between the line of equality and the Lorenz curve indicating a larger level of income inequality[8].

While the Gini coefficient measures pure income inequality within a population, the CI measures socioeconomic inequality in health variables. The CI can be calculated in two ways. Firstly, the CI can be presented as the following formula:

$$CI = \frac{2}{n\mu}\sum_{i=1}^{n} CA_i R_i - 1\,, \tag{4.2}$$

with $n$ representing the total number of people within the population, $u$ representing the mean of the total income and $R_i$ representing the socioeconomic fractional rank within the population of a member of the population $i$. The socioeconomic variable most commonly used to rank the population is income. Compared to other measures of SES such as education levels, housing tenure and parental occupational classification, income can rank individuals within the population more precisely, as it is a continuous variable.

As well as the formula method shown in equation 4.2, a point estimate of the CI can also be calculated through the 'convenient regression' method. Firstly, an OLS regression equation must be estimated in order to calculate the linear correlation between the health variable and the fractional rank of the socioeconomic variable. Given that $CA_i$ and $R_i$ are variables representing child cognitive ability and fractional rank of the socioeconomic variable for individual $i$ respectively, it follows that the equation of interest is:

---

[8] The Gini coefficient can also be derived from the Lorenz curve, through the calculation of the area below the Lorenz Curve. More formally, given that *p* represents the cumulative proportion of the population (x-axis) and *L(p)* represents the cumulative proportion of income (y-axis), the Gini coefficient can be calculated through the equation below, and therefore can be seen twice the area in between the line of equality and the Lorenz curve:

$$Gini = 1 - 2\int_0^1 Lh\,(p)dp$$

$$CA_i = \beta_0 + \beta_1 R_i + \varepsilon_i \ , \tag{4.3}$$

where $\beta_1$ is the vector coefficient associated with $R_i$, $\beta_0$ is the constant term and $\varepsilon_i$ the error term with mean and variance equal to 0. Using the parameters from equation 4.3, the CI can be calculated by:

$$CI = \frac{2\sigma_r^2}{\beta_0 + \ \beta_1 \mu_r} \beta_1 \ , \tag{4.4}$$

where $\sigma_r^2$ is the variance of the fractional rank of the socioeconomic variable $R_i$ and $\mu_r$ is the mean value of the fractional rank of the same socioeconomic variable.

Whichever way it is calculated, like the Gini coefficient, a CI value of 0 indicates no socioeconomic related inequality. However, unlike the Gini coefficient, the CI is bound between -1 and 1 rather than 0 and 1. A value of 1 represents a situation where the whole health variable is consumed by the richest person in the population (pro-rich inequality). Conversely, a value of -1 represents a situation where the whole health variable is consumed by the poorest person in the population (pro-poor inequality). In the interests of space, the process of calculating the standard error of the CI is shown in Appendix 4A.

Wagstaff *et al.,* (1991) have suggested that the CI is one of the best measures of health inequality (along with the Slope Index of Inequality and the Relative Index of Inequality), as it meets the three basic requirements of a health inequality index:

i. It reflects the socioeconomic dimension to inequalities in health
ii. It reflects the experience of the entire population
iii. It is sensitive to changes in the distribution of the population across socioeconomic groups

As well as being one of the best measures of health inequality, the CI also has an intuitive interpretation. Koolman and van Doorslaer (2004) have shown that the CI can be used to calculate the proportion of health that needs to be redistributed in order to eliminate the rank predicted socioeconomic inequalities in health. The authors estimated the proportion of total health that should be redistributed from the richest half of the population to the poorest half of the population in order to eliminate inequality (a CI of 0) to be:

$$R_i = \frac{300}{4}\beta_1 = 75 \cdot CI\ , \tag{4.5}$$

with $\beta_1$ being the estimate of the CI from equation 4.3. This redistributive interpretation makes clear that the indices have ratio scale properties, implying that when the CI doubles in value, so too does the degree of socioeconomic inequality.

Although the above discussion implies that the CI is an association between the outcome variable and the fractional income rank, Koolman and van Doorslaer (2004) have argued that the CI is in fact more complex. The authors mention findings from Milanovic (1997), which showed, through a series of steps, that the relationship between the CI and the Pearson correlation coefficient ($\rho$) can be given as:

$$CI = \frac{12\sigma_r^2}{\sqrt{3}} \frac{\sigma_y}{y} \rho(y, r)\ , \tag{4.6}$$

where $\sigma_y$ and $\sigma_r$ represent the standard deviations (SD) of the outcome and ranking variables respectively.

In relatively large samples, the first term will almost always be a constant value, meaning that the difference between the CI and the correlation coefficient only depends on the second term, which represents the variation in the outcome variable. Therefore, this equation implies that even if the correlation between the two variables is identical, income related inequality will be higher for an outcome variable with greater variability. Therefore, the CI takes into account both the strength of association and the distribution of the variable. In the context of this chapter, higher scores in the cognitive tests are associated with higher cognitive function, meaning that positive values of the concentration index indicate that children with a higher cognitive function are concentrated amongst the rich, and vice versa.

#### 4.4.3 *The partial concentration index*

Although the CI captures the level of association between SES and an outcome variable, one is often interested in income-related inequalities after standardising for correlates of income (O'Donnell *et al.,* 2008). Gravelle (2003) has argued that if, for example, income has a positive effect on health and age has a negative effect on health, a better average health of the rich could be due to both the direct positive effect of income and the fact that rich people are younger and therefore healthier, hence overstating the extent of the socioeconomic inequality. Therefore, it is common in health economics, public health and epidemiological studies to standardise such estimates (Wagstaff and van Doorslaer 2000), which can be done either directly or indirectly. This standardised CI is also known as a 'partial' CI (PCI).

Direct standardisation involves generating predicted values of the health variable purged of the influence of demographics across socioeconomic groups, and then computing the CI for this single standardised value (O'Donnell *et al.,* 2008). Therefore, the directly standardised CI may also be thought of as a CI of standardised health. Indirect standardisation involves removing the effects of health affecting confounding variables and other controlling variables. A standardising variable in this context is defined as a variable to which it is impossible to alter its direct effect on the dependent variable of interest, or its joint distribution with income. Regression decomposition methods (Wagstaff *et al.,* 2003) can be used to make such standardisations, as the contributions of the standardising variables simply need to be deducted from total inequality. This is seen as being equivalent to the two-step approach to standardisation (van Doorslaer *et al.,* 2004).

Alternatively, O'Donnell *et al.,* (2008) have suggested that, if one wishes to standardise for the full correlation with confounders but no controlling variables, a short cut method of calculating an indirectly standardised concentration index is to include the standardising variables directly into the regression equation. Given that $CA_i$ and $R_i$ are once again variables representing child cognitive ability and the fractional rank of the socioeconomic variable for individual $i$, it follows that the model of interest is:

$$CA_i = \beta_0 + \widehat{\beta_1} R_i + \beta_2 \boldsymbol{x}_{ji} + \varepsilon_i \,, \tag{4.7}$$

where $\boldsymbol{x}_{ji}$ represents a vector of controlling variables related to individual $i$ with their associated coefficients $\beta_2$, $\widehat{\beta_1}$ is the parameter coefficient associated with the matrix $R_i$, $\beta_0$ is the constant term and $\varepsilon_i$ the unbiased error term. Therefore, the PCI can be shown as:

$$PCI = \frac{2\sigma_r^2}{\beta_0 + \widehat{\beta_1}\mu_r} \widehat{\beta_1} \tag{4.8}$$

This equation is almost identical to equation 4.4, except the standardised estimate $\widehat{\beta_1}$ replaces the unstandardised estimate $\beta_1$.

As well as the unstandardised CIs, I estimated PCIs for all applicable cognitive test scores in the NCDS and MCS. I standardised the CIs using a small number of comparable confounding variables which cannot be considered policy relevant, including child gender, polynomials of maternal age, ethnicity and region. Although this is a relatively small number of variables, it is very similar to the list used by Vallejo-Torres *et al.,* (2014) in the context of child behavioural issues.

### 4.4.4 *Correction of the concentration index*

As noted by Wagstaff (2005) and Erreygers (2009), the interpretation of the CI when the dependent variable of interest is not an unbounded variable (such as expenditure and years of life) is problematic, as the CI will no longer be bound between -1 and 1, but between μ-1 and 1-μ, where μ represents the mean of the dependent variable of interest. Using the standard CI on variables which are not unbounded therefore means that the inequalities may not be comparable across groups, as the value will critically depend on the mean value. Therefore, in analysis I used the correction presented by Erreygers (2009)[9], which can be shown as:

[9] Wagstaff (2005) has also developed a correction procedure for the CI, however this correction is only appropriate in the context of binary variables.

$$CI_{Erreygers} = CI\frac{4\bar{h}}{h^{max} - h^{min}}, \tag{4.9}$$

where $\bar{h}$ represents the mean of the health care variable, $h^{max}$ represents the maximum value, and $h^{min}$ represents the minimum value. This corrected CI technically measures 'quasi-absolute inequalities' rather than relative inequality as it is translation invariant, similar to the generalised concentration index (Kjellsson and Gerdtham 2013). I calculated the various CIs using the *glcurve* (Jenkins 2008) and *conindex* (O'Donnell *et al.,* 2016) commands.

### 4.4.5 *Concentration curve*

Similar to the Gini coefficient and its associated Lorenz curve, the CI can be illustrated with the CC. The CC plots the cumulative proportion of health (y-axis) against the cumulative proportion of the population as ranked by a measure of SES, starting with the lowest socioeconomic position (x-axis). An example of this is shown in Figure 4.3. The 45˚ degree line from the origin is the line of equality, at which point the CI would equal 0 (the red line). The CC (the blue line) shows the socioeconomic distribution of the health variable.

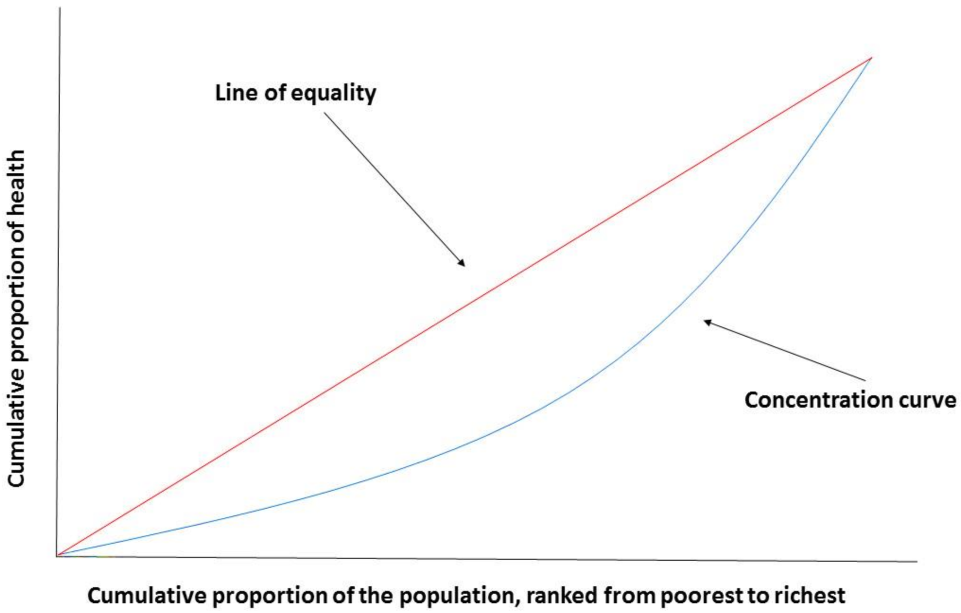


*Figure 4.3- Concentration Curve*

In the same way that the Gini coefficient can be derived from the Lorenz curve, the CI can also be derived from the CC, as shown below:

$$CI = 1 - 2\int_0^1 Lh\,(p)dp \tag{4.10}$$

The CI is twice the area between the line of equality and the CC. This once more implies that a larger area between the line of equality and the CC curve indicates a larger level of income related socioeconomic health inequalities.

Several aspects of the CC are worth noting. Firstly, inequalities can favour both the worse-off and the better-off, as they can lie both over and under the line of equality. Secondly, socioeconomic equality may apply if the CC coincides with the line of equality. Thirdly, unlike Lorenz curves, CCs may have inflection points and increase monotonically. Finally, CCs measure relative inequalities, implying that a proportionate increase or decrease in health will leave socioeconomic inequality unchanged (van Doorslaer and van Ourti 2012). In this chapter I calculated the various CCs using the *glcurve* command.

### 4.4.6 *Dominance analysis*

While the CI and the associated CC may give an indication of the level of socioeconomic inequality in cognitive ability, point estimates from CI calculations are not sufficient to establish statistically significant differences, as the different CIs are calculated from survey data, and therefore may be subject to sampling variability (O'Donnell *et al.,* 2008).

The few previous studies that have compared socioeconomic inequalities in cognitive ability over time have relied purely on regression based methods. For example, Gregg and Macmillan (2010) first pooled individuals from different cohort studies (for example the NCDS and the ALSPAC), and then estimated a joint model including an interaction term between the cohort and the measure of SES, in their case the income quintile. The authors argued that if this interaction term was statistically significant, the cohort estimates can be assumed to be significantly different from each other. However, using such regression based methodologies with the NCDS, BCS and MCS is complicated by the fact that the MCS is structured very differently to the NCDS and the BCS. While the two earlier cohort studies were made up of children born during particular weeks in 1958 and 1970 respectively, the MCS is a heavily stratified sample, which oversamples those from particular socioeconomically deprived areas and those from ethnic minorities.

In order to empirically test if socioeconomic inequalities in cognitive ability have significantly increased over time in this empirical chapter, I conducted dominance analysis between the estimated CCs for the comparable measures of child cognitive ability. CCs from different variables and time periods can be plotted on the same graph, and can therefore be compared to establish if one CC dominates another (Wagstaff *et al.,* 1991). An example of CC dominance is shown in Figure 4.4.

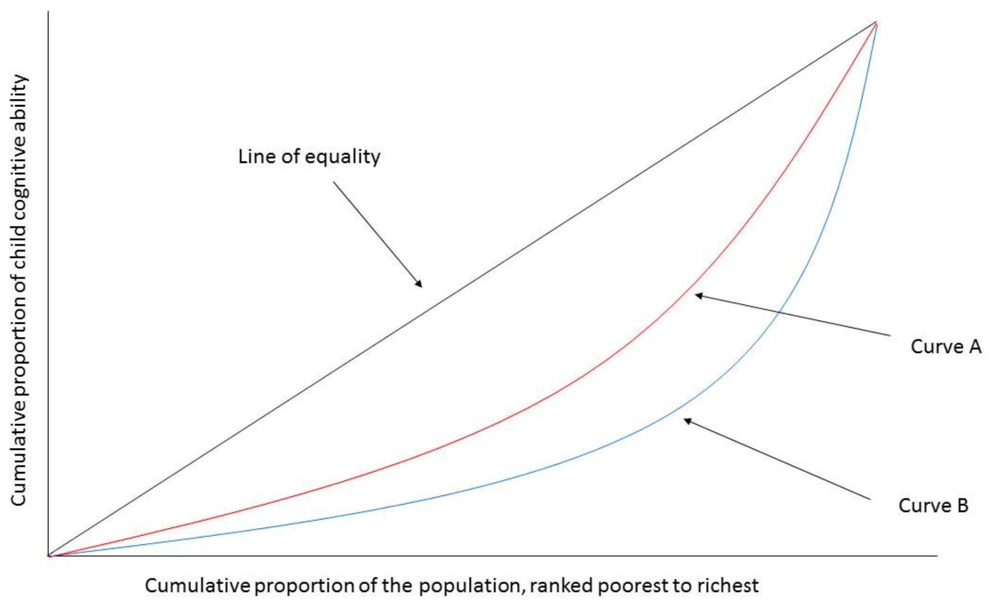


*Figure 4.4- Concentration Curve Dominance*

In this case, it appears that Curve A 'dominates' Curve B, as it lies above Curve B at every point along the distribution. A visual inspection of a particular CC against another, such as the one shown in Figure 4.4, can give a general impression unto whether one concentration curve 'dominates' another. However, this is not sufficient to conclude whether this apparent dominance is statistically significant, as the standard errors of the concentration curve coordinates must be calculated along with the point estimates (van Doorslaer and van Ourti

2012). In this chapter I accounted for the stratified sampling structure of the MCS by calculating the weighted fractional rank rather than the standard fractional rank of the socioeconomic ranking variable and using the survey weights in the regression equation to produce corrected standard errors. I used the *dominance* ado file provided by O'Donnell (2008) to implement the dominance analysis.

#### 4.4.7 *Decision rules for dominance analysis*

Two main decision rules exist regarding CC dominance, with the theoretical basis of these decision rules relating back to social welfare theory. The first decision rule that can be used is to reject the null hypothesis of non-dominance if there is at least one significant difference between the ordinates of the curves in one direction, and no significant differences in the opposite direction (Beach and Richmond 1985). This is equivalent to first order stochastic dominance (FSD) in decision theory. Howes (1996) has suggested that the use of conventional critical values may over-reject the null hypothesis, as there is no correction for the fact that multiple comparisons are being made. Therefore, the 'Multiple Comparison Approach' (MCA) (Dardanoni and Forcina 1999) has been developed, which uses the same decision rule, but uses critical values from the studentized maximum modulus in order to account for the multiple comparisons being made simultaneously (Bishop *et al.,* 1992).

Alternatively, a number of studies (Howes 1996; Sahn and Stifel 2000) have argued that in order for dominance to be accepted, significant differences must be shown between ordinates at all quantile points, consistent with the 'Intersect Unity Principle' (IUP) (Kaur *et al.,* 1994, Howes 1996). This is equivalent to second order stochastic dominance (SSD) in decision theory. As suggested by Dardanoni and Forcina (1999), Monte Carlo simulations show that although the stricter, more conservative IUP decision rule (analogous to SSD) reduces the probability of rejecting non-dominance compared to FSD, it also significantly reduces the power of detecting dominance when true.

The decision rules listed above also depend on the number of comparison points used and the level of statistical significance. The convention in the literature is to make comparisons at 19 different quantiles (evenly spaced between 0.05 and 0.95) (O'Donnell and Wagstaff 2008). In this chapter I used 19 comparison points, at both the 5% and 1% significance levels. I also used both the MCA and the IUP decision rules for comparison, in order to examine first and second order stochastic dominance respectively.

#### 4.4.8 ***Decomposition of concentration index***

As well as satisfying the three basic requirements of an inequality index (Wagstaff *et al.,* 1991), a further advantage of the CI is that the inequality can be partitioned into the determinants which contribute to the observed inequality (Wagstaff *et al.,* 2003; van Doorslaer and Jones 2003)[10]. Decomposition analysis divides the observed inequality into separate contributions, in which each contribution is the product of the sensitivity of the variable of interest with respect to the impact the determinant has on the dependent variable and the degree of income-related inequality in that factor (O'Donnell *et al.,* 2008). Therefore, with decomposition analysis one can measure the total level of inequality by the contribution from each of the explanatory variables. This may be useful for policymakers looking to identify policy instruments that can be used to reduce levels of socioeconomic inequality (van Doorslaer *et al.,* 2004).

What sets decomposition analysis apart from traditional regression analysis is that it takes into account both the correlation of the underlying determinants and the dependent variable and the socioeconomic distribution of these determinants. Therefore, if a determinant has a strong correlation with the dependent variable yet is distributed equally across the socioeconomic distribution, it will not contribute to the inequality shown in the concentration index. Furthermore, if a determinant is distributed unequally across socioeconomic groups but is not significantly correlated with the dependent variable, then it will also not contribute to the inequality shown by the CI. For example, a variable such as gender may well be significantly correlated with certain measures of child cognitive ability, but should be evenly distributed across the socioeconomic distribution, and therefore not contribute to any observed socioeconomic inequality.

As suggested by Wagstaff *et al.,* (2003), the decomposition of the CI can be seen as portioning the total level of inequality into a determinist component and a residual component. The deterministic component can be seen as the portion of total inequality that can be explained by the determinants. There are several steps involved in calculating this deterministic component. Firstly, the impact of the determinant on the dependent variable

[10] The CI can also be decomposed by population subgroup, which reveals the between-group inequality and the within group inequality, so that the overall CI is represented as the sum of the between-group and within-group inequality. I did not use this approach is this chapter.

is measured through the use of an OLS regression model. The OLS model used in the calculation of the deterministic components can be represented as:

$$CA_i = \alpha_0 + \beta_1 \boldsymbol{x}_{ji} + \varepsilon_i \;, \tag{4.11}$$

where $CA_i$ represents a measure of cognitive ability of child $i$, $\boldsymbol{x}_{ji}$ represents a vector of determinants with their associated parameter coefficients $\beta_1$, $\alpha_0$ is the constant term and $\varepsilon_i$ the unbiased error term.

Secondly, the socioeconomic distribution of each individual determinant is calculated using the CI. Thirdly, the error term from the OLS regression model shown in equation 4.7 is used to compute the residual component in the decomposition:

$$E_i = \frac{2}{n} \sum_{i=1}^{n} \varepsilon_i R_i \;, \tag{4.12}$$

where $E_i$ represents the residual component of the CI within the decomposition analysis, $R_i$ represents the fractional rank of the individual in the income distribution and $\varepsilon_i$ represents the unbiased error term.

Formally this can be seen as an estimate of the generalised CI rather than the regular CI, as the mean of the error term is not included. This distinction is necessary because the classical assumptions of the OLS model imply that the mean of the error term is zero. In a well specified model, this residual component should tend to zero. Jones and Lopez-Nicholas (2006) and Walsh and Cullinan (2015) have noted that the residual term of the decomposition is the part of the CI that is not explained by the regressors' contribution within the regression, and may instead be explained by unobservable heterogeneity.

It follows that the three components discussed in equations 4.11 and 4.12 can then be combined in order to give a formal representation of the decomposition analysis:

$$CI = \sum_j \left(\frac{\beta_{1j}x_j}{\mu}\right)CI_j + \frac{E_i}{\mu}, \tag{4.13}$$

where $\sum_j \left(\frac{\beta_{1j}x_j}{\mu}\right)CI_j$ represents the contribution of the deterministic component and $\frac{E_i}{\mu}$ represents the contribution of the residual component. In order to determine the percentage of the total inequality contributed by each determinant, the contribution of the individual component is divided by the overall CI and multiplied by 100.

Rather than the elasticity and CI of each individual component, the most important parts of the decomposition analysis are the contribution and percentage contribution, as they allow one to understand the factors which explain the level of socioeconomic inequality. However, there are three aspects of these terms that must be taken into account when interpreting empirical estimates from decomposition analysis.

Firstly, a determinant can contribute both positively and negatively to the total level of inequality shown in the CI (Yiengprugsawan *et al.,* 2010). If a determinant contributes positively to pro-rich socioeconomic inequality, then both $\beta_{1j}$ and $CI_j$ must be positive. This implies that socioeconomic inequality would be reduced if there was no correlation between the determinant and the outcome variable, or the variable was equally distributed across the socioeconomic distribution. Conversely, if either of $\beta_{1j}$ or $CI_j$ are negative then the contribution will also be negative. A negative contribution implies that that the overall level of socioeconomic inequality would be larger without the contribution of this determinant (Speybroeck *et al.,* 2010).

Secondly, it is possible that the predicted CI (the sum of the individual determinants of the decomposition) is larger than the actual CI, due to the contribution of the residual term being the opposite direction of the CI, potentially due to misspecification of the underlying OLS regression model. Although this scenario is a relatively common phenomenon in the literature, and therefore is not treated as an anomaly, it is worth considering this when interpreting the coefficients from these models.

Finally, although these decomposition methods can be considered useful for estimating the linear associations between the outcome variable and a range of factors associated with SES and evaluating the individual contribution of these factors to socioeconomic inequalities, it is important to note that the decomposition cannot be a considered structural model or infer a direction of causality (Shen *et al.,* 2013). I implemented the decomposition analysis in this chapter using an adapted version of the code provided by O'Donnell *et al.,* (2008).

### 4.5 Data and Variables

The data for the empirical analysis in this chapter was taken from the NCDS, BCS and MCS, which were all described in detail in Chapter 2. Given the research question at hand, these datasets seemed to be the most appropriate for analysis from those available for use in the UK, as they have large sample sizes and have a range of cognitive ability measures available for use, including a small number of generally comparable cognitive tests across the different cohort studies.

While the NCDS and BCS can be seen as self-weighting, the MCS has a complex survey design. To control for this, I adjusted the MCS data using the *pttyp2, weight2* and *covwt2*, *dovwt2* and *eovwt2* weights for analysis. The *pttyp2* weight adjusts the data for the number of strata within the particular country, *weight2* adjusts the data for the fact that the analysis is conducted on the whole of the UK and the *covwt2*, *dovwt2* and *eovwt2* weights adjust the data for the fact that this analysis is conducted on the third, fourth and fifth wave of MCS data respectively, and reflects the level of non-random attrition that may have occurred across these waves of data.

#### 4.5.1 *Dependent variables*

A key aspect of the NCDS, BCS and MCS is that they each provide a number of high quality child cognitive assessments. The full battery of cognitive tests available for use in the NCDS, BCS and MCS are shown in Table 4.1. All cognitive tests were standardised to have a mean of 0 and a SD of 1 for analysis. For a full description of each of the cognitive tests, please see Appendix 4B.

In this chapter I was concerned not only by the level of socioeconomic inequality in child cognitive ability, but also whether the strength of relationship has changed significantly over time. Analysing the strength of the relationship over time requires generally comparable cognitive tests across the separate cohort studies. The test scores concerning the same measure of cognitive ability at the same age are described in Table 4.2.

| Table 4.1- Child cognitive tests in the NCDS, BCS and MCS | | | |
|---|---|---|---|
| **Study** | **Cognitive Test** | **Authors** | **Variable(s) Used** |
| **NCDS** | Southgate Reading Test (Age 7) | Southgate (1962) | *n92* |
| | Copying Designs Test (7) | NCDS | *n457* |
| | Drawing-A-Man Test (7) | Goodenough (1926) | *n1840* |
| | Problem Arithmetic Test (7) | Pringle *et al.,* (1966) | *n90* |
| | General Ability Test (Age 11) | Douglas (1964) | *n914, n917* |
| | Reading Comprehensive Test (11) | NFER (1969) | *n923* |
| | NFER Arithmetic Test (11) | NFER (1969) | *n926* |
| | NFER Copying Test (11) | NFER (1969) | *n929* |
| **BCS** | Human Figure Drawing Test (Age 5) | Goodenough (1926) | *f121* |
| | Copying Designs Test (5) | Rutter *et al.,* (1970) | *f119* |
| | English Picture Vocabulary Test (5) | Brimer and Dunn (1962) | *BD2READ* |
| | Complete-A-Profile Test (5) | Goodenough (1926) | *f118* |
| | Friendly Maths Test (Age 10) | NCDS | *BD3MATHS* |
| | Shortened Edinburgh Reading Test (10) | Thompson Unit (1978) | *BD3RREAD* |
| | BAS Word Definitions (10) | Elliott *et al.,* (1979) | *i3504- i3540* |
| | BAS Recall Digits (10) | Elliott *et al.,* (1979) | *i3541- i3574* |
| | BAS Similarities (10) | Elliott *et al.,* (1979) | *i4201- i4221* |
| | BAS Matrices (10) | Elliott *et al.,* (1979) | *i3617- i3644* |
| **MCS** | BAS Picture Similarities (Age 5) | Elliott *et al.,* (1979) | *ccpsco00* |
| | BAS Naming Vocabulary (5) | Elliott *et al.,* (1979) | *cdnvabil* |
| | BAS Pattern Construction (5) | Elliott *et al.,* (1979) | *cccsco00* |
| | BAS Word Reading (7) | Elliott *et al.,* (1979) | *DCWRSD00* |
| | BAS Pattern Construction (7) | Elliott *et al.,* (1979) | *DCWRSD00* |
| | NFER Progress in Maths (7) | NFER (1969) | *MATHS7SA* |
| | BAS Verbal Similarities Age (11) | Elliott *et al.,* (1979) | *EVSTSCO* |

**Table 4.2- Generally comparable cognitive tests**

| National Child Development Study | | Millennium Cohort Study | |
|---|---|---|---|
| Problem Arithmetic Test<br>Age 7<br>*(Pringle et al., 1966)* | 10 problems graded in level of difficulty, which could either be read by the children themselves or read to them by a teacher. One mark is awarded for each correct answer, and is therefore scored between 0 and 10. | NFER Progress in Maths Test<br>Age 7<br>*(NFER 2007)* | Covers topics such as numbers, shapes, measurement and data handling. Although there are 20 test items, the test is scored out of 12, 16 or 20 depending on the scores from the initial 7 test items. |
| Verbal Subset of the General Ability Test<br>Age 11<br>*(Pigeon 1964)* | Children are presented with an example set of four words that were lined logically, semantically or phonologically. The child is then presented with another set of three words, and asked to fill in the missing item from a choice of five alternatives. | BAS II Verbal Similarities Test<br>Age 11<br>*(Elliot et al., 1997)* | A series of questions where three linked items are read out to the child by the interviewer. The child is then asked to describe the main link between them. The test is designed to measure the child's ability to identify and describe similarities between items. |
| **British Cohort Study** | | **Millennium Cohort Study** | |
| *English Picture Vocabulary Test*<br>*Age 5*<br>*(Brimer and Dunn 1962)* | Children are presented with 56 sets of four pictures with a particular word associated with each of the four pictures. The child must indicate the one picture that corresponds to the given word. | *BAS Naming Vocabulary*<br>*Age 5*<br>*Elliott et al., (1979)* | The child is shown 36 pictures of objects and is asked to name them e.g. a picture of a shoe, chair or a pair of scissors. The number of items answered depends on his/her performance, and therefore the scores are scaled. |

The first set of cognitive tests I considered for cross-cohort comparison were measures of maths ability at age 7. In the NCDS, this was measured by the Problem Arithmetic Test (Pringle *et al.,* 1966), while in the MCS, this was measured by the Progress in Maths Test. Both measures contain individual items chosen from the National Foundation of Education Research. Comparing the distributions of the different measures showed both to be relatively normally distributed, and therefore the two measures were considered for comparison.

The second set of cognitive tests I considered for comparison were measures of reading ability at age 7 in the NCDS and MCS. In the NCDS, this was measured by the Southgate Reading Test (Southgate 1962), while in the MCS, this was measured by the British Ability Scale (BAS) Word Reading sub-scale (Elliott *et al.,* 1997). Although the BAS Word Reading sub-scale was shown to be relatively normally distributed, the Southgate Reading Test was shown to be extremely negatively skewed, as displayed in Figure 4.5.

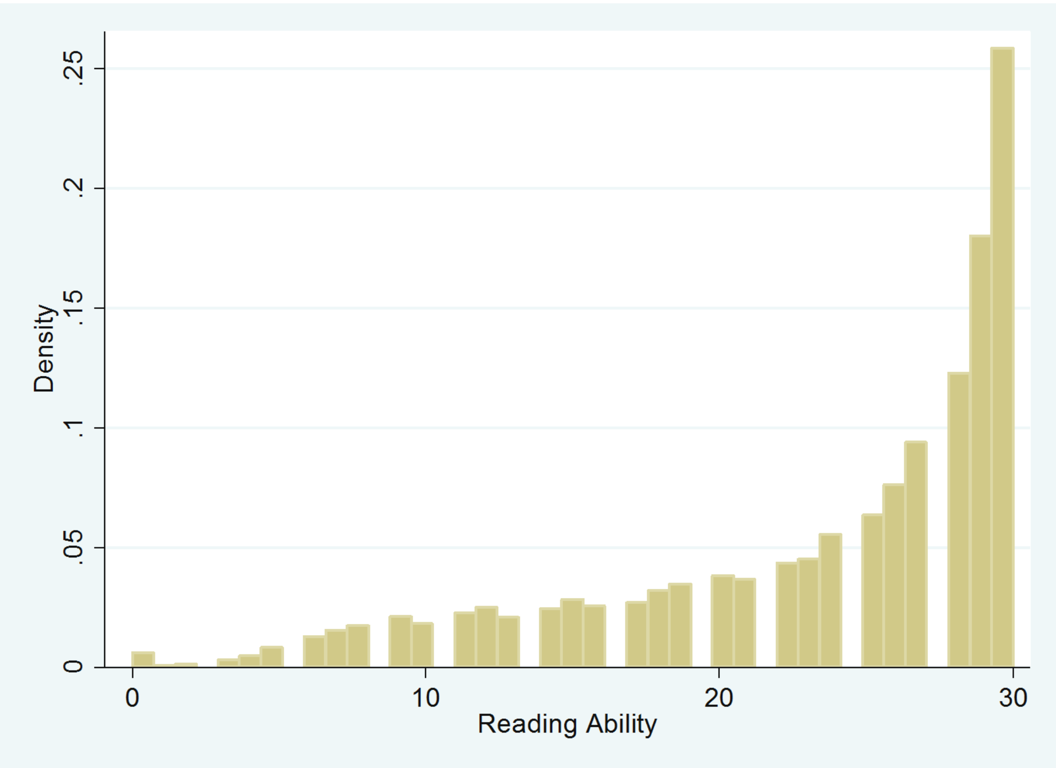


*Figure 4.5- Distribution of the Southgate Reading Test*

As argued by Shepherd (2012), this skewness was almost certainly due to the test being originally designed to differentiate 'backward' readers. Therefore, the test was unable to extend the above average reader at this age, and consequently has a low ceiling. Due to the skewness of the distribution, the Southgate Reading Test was not considered appropriate for comparison across cohorts.

The third set of the generally comparable tests I considered were measures of verbal ability at age 11. In the NCDS, this was measured by the Verbal Subset of the General Ability Test (Pigeon 1964), while in the MCS this was measured by the BAS Verbal Similarities sub-scale (Elliott *et al.,* 1997). A comparison of the distributions showed both measures to be relatively normally distributed, and therefore the two measures were considered appropriate for comparison. These specific measures were also used by Goisis *et al,.* (2017a) and Goisis *et al,.*(2017b) when conducting cross-cohort comparisons between the NCDS and MCS.

The final set of generally comparable tests I considered were measures of vocabulary ability at age 5 in the BCS and MCS. In the BCS, this was measured by the English Picture Vocabulary Test (Brimer and Dunn (1962), while in the MCS this was measured by the BAS Naming Vocabulary (Elliott *et al.,* 1997). Once more, a comparison of the distributions showed both measures to be relatively normally distributed, and therefore applicable for cross-cohort comparison.

As shown by the various cognitive tests from the NCDS and the MCS described in Table 4.2, even if the cognitive tests are generally comparable between the cohort studies, the tests were collected in different ways and on different scales. With these differences in mind, other studies comparing the cognitive tests between the different cohorts, for instance Gregg and Macmillan (2010) and Goisis *et al.,* (2017a, 2017b), have standardised the cognitive tests to mean 0, SD 1 for cross-cohort comparison. When using the CI, I took into account the different scales from the cognitive tests through the use of the Erreygers CI (2009) rather than the standard CI, which does not take into account the bounds of the dependent variable.

### 4.5.2 *Key explanatory variables*

SES can be seen as a composite measure (Baker 2014), and therefore can be measured in a number of different ways, including family income, parental occupation, housing tenure and parental education[11]. The two measures of SES I used in this empirical chapter were parental occupational classification and household income. The advantage of using parental occupational classification as the measure of SES is that it is relatively stable, and may therefore be a good indicator of permanent socioeconomic position. In the context of this empirical chapter, the main advantage of using household income is the fact that it is a broadly continuous measure, and therefore applicable for use in the CI, which ranks individuals according to their socioeconomic position.

I also considered using parental educational attainment as a measure of SES to compare inequalities between the cohort studies, as the age at which mother left full time education was collected in approximately the same manner in the NCDS, BCS and MCS. However, as argued by Feinstein *et al,.* (2008), although years of schooling can be considered a 'functional proxy' for the level of education, this basic measure does not fully take account of the type or quality of educational attainment, and it is the level of qualification rather than the years of schooling that will lead to socioeconomic dividends through signalling effects.

One issue pertaining to cross-cohort comparisons such as this chapter is the fact that the different studies collect apparently similar variables in very different ways. This is exemplified in the ways in which information concerning parental occupational classification and household income has been collected in the NCDS, BCS and MCS. For instance, in both the NCDS and the BCS, the question regarding occupational classification refers to the father (also referred to as the 'male head'). However, in the MCS, there are survey questions relating to both the mother and father, enabling the calculation of the highest occupational classification in the family, which may be a more appropriate measure to use in modern society, given the significant increase in the number of women in the labour market over time.

The measures of income are also collected in different ways in the NCDS, BCS and MCS. In the empirical analysis, I attempted, where possible, to capture a measure of permanent household income, in order to minimise potential biases from short term income shocks. Blau (1999) has argued that the effect of current income levels may be relatively small compared to that of a permanent income measure.

[11] For a comprehensive review of measuring SES in relation to child development, please see Hauser (1994).

For the NCDS, the measure of income I used was the 'Permanent Parental Income' variable provided by the Centre for Longitudinal Studies and originally funded by the Economic and Social Research Council (ESRC) in order to aid research into income dynamics and health inequalities (Taylor 2000). This income variable was created because although the NCDS contains extremely detailed and high quality information on a variety of child and family outcomes throughout childhood, the family income of the child was only collected at the age of 16. Although this variable has been used in studies relating to child cognitive ability, for example by Gregg and Macmillan (2010), there are several associated problems. Firstly, Benzeval *et al.,* (1997) have argued that such a measure may not be an accurate reflection of living standards in earlier childhood, when the cognitive tests are undertaken. Secondly, earnings are grouped into a small number of bands, with the highest band having no upper limit. Although work has been undertaken in order to convert this banded measure into a continuous one (Blanden and Gregg 2004), this analysis resulted in only 77 unique income categories being generated. Thirdly, the interview for the third wave of the NCDS happened to be conducted during the 'Three-Day Week' of 1974, and there is therefore confusion unto whether the respondents were reporting their usual salary or the reduced figure (Micklewright 1988).

In order to overcome these problems, Taylor (2000) has calculated a measure of permanent income, using information on parental characteristics deemed to have a permanent impact on family income levels, such as parental years of education, parental occupational class and whether parents were absent during childhood. In an estimated income equation, the above measures were used as key explanatory variables, along with controls for parents' age and region, similar to the study of Dearden *et al.,* (1997). Using the grouped dependent variable technique of Stewart (1983), a total measure of log family income was calculated, with this measure taking into account the bounded nature of the income question.

However, there are several issues associated with this measure of income in the NCDS. Firstly, this method assumes that factors such as occupational class and parental education only affect child outcomes indirectly through income, which may be considered a strong assumption. Secondly, cohort members with missing information on parental occupational class and cohort members with no natural parents in wave 3 of the survey were not given a value and therefore excluded from analysis. Although the estimated values of non-natural parents were imputed using the mean difference between the reported mother's and father's age at birth, there may be concerns that the missing information regarding parental occupational class may bias the empirical estimates using the income measure. However, detailed studies of non-response in the NCDS, such as Nathan (1999) and Hawkes and Plewis (2006), have shown that no significant bias is generated from this missing data, and descriptive statistics, as displayed in Table 4.3, show that the distribution of fathers' social class at 1960 (as measured by the NSSEC-5) does not significantly change between the full sample and the sample in which there is missing data on the income variable.

**Table 4.3- Distribution of parental occupation in the NCDS**

| | Full Estimation Sample | | Income Estimation Sample | |
|---|---|---|---|---|
| | Observations | % | Observations | % |
| Managerial/Professional | 566 | 5.18 | 361 | 4.89 |
| Lower Managerial/Higher Technical | 1602 | 14.67 | 1,088 | 14.75 |
| Intermediate Occupations | 6144 | 56.26 | 4,169 | 56.53 |
| Small Employers/Own Account | 1927 | 17.64 | 1,303 | 17.67 |
| Lower Supervisory/Technical | 682 | 6.24 | 454 | 6.16 |
| Total | 10921 | 100 | 7375 | 100 |

Although a measure of permanent income has been generated in the NCDS, no such measure of income has been generated in the BCS. The income measure in the BCS was collected in a single income, banded manner and was also only collected at the ages of 10 and 16. Micklewright and Schnef (2010) have argued that the reliability of single income questions such as the one used in the BCS could be brought into question, as such questions may be poor at capturing income when one individual is asked to report the income for the whole household. Although a significant amount of work has been undertaken to generate a measure of income comparable to the NCDS at the age of 16 (Blanden and Gregg 2004), it is once more unclear how representative such a measure would be in the earlier waves. Due to the absence of an appropriate measure of income, I did not consider the BCS for analysis using the CI, and therefore I could not use this study when comparing the level of socioeconomic inequality in cognitive ability over time, despite the comparability of the vocabulary ability cognitive test at age 5.

For the MCS, the measure of income I used was equivalised family income, calculated from information in waves 3-5, when the cohort children were 5, 7 and 11 respectively. Similar to the measure of income in the NCDS, the original income question in all three of the waves required the main respondent to choose from a number of income bands. Rather than using these measures, I used the CLS provided OECD equivalised measures for all three waves, found in the MCS list of derived variables. The OECD equivalence formula (Haagerors *et al.,* 1994) can be given by:

$$\frac{Household\ Income}{1 + (0.5 * Additional\ Adults) + (0.3 * Number\ of\ Children)} \tag{4.14}$$

This particular equivalence method assigns a value of 1 to the household head, 0.5 to every additional adult, and 0.3 to each child. For instance, a family of two adults and two children is given a value of 2.1, and a single parent family with four children is given a value of 2.2. The total level of household income is then divided by this value to create an equivalised income measure.

To account for the fact that a permanent income measure combines the income measures from different waves of data over a span of six years, I also adjusted these measures for inflation. This was calculated using wave 3 as the base year (2006) and the end of year Great Britain inflation rates (ONS 2016). Following this, I calculated income measures for the separate waves. The income measure used in the $4^{th}$ wave (when the cohort children are 7) was the average income across the $3^{rd}$ and $4^{th}$ waves. The income measure used in the $5^{th}$ wave of data (when the cohort children are 11) was the average income across the $3^{rd}$, $4^{th}$ and $5^{th}$ waves.

As demonstrated above, although unavoidable, the income measures for the different cohort studies were collected in different ways, complicating direct cross-cohort comparisons. Previous studies that have used measures of income in cross-cohort comparisons, such as Blanden and Machin (2004; 2010) and Gregg and MacMillan (2010), either standardised the calculated income measures to mean 0, SD 1 (in an attempt to ensure that changes in income inequality or the variance of income across the cohorts did not drive the results) or converted the income measure into quintiles. Due to the fact that I used the CI as the empirical strategy in this chapter, the income of the cohort children was ranked in the calculation, converting household income into an ordinal measure rather than a cardinal scale.

### 4.5.3 *Other explanatory variables*

I also included a number of variables that may attenuate the relationship between SES and child cognitive ability in the various regression models. The different surveys have collected information regarding similar variables in a variety of ways, and as a consequence the variables I included were relatively limited. My choice of explanatory variables was also partially guided by the studies of Goisis *et al.,* (2017a; 2017b), who have used the NCDS, BCS and MCS to examine the changes in relationship between birth weight and cognitive ability (2017a) and maternal age and cognitive ability (2017b) over time respectively.

The first child characteristic I included was a dummy variable for gender, as boys and girls may excel at different aspects of cognitive ability. Several empirical studies, including Hedges and Nowell (1995), Weiss *et al.,* (2003) and Halpern (2013), have shown that there may be significant gender differences in child cognitive test scores, with the extent of the difference dependent on the cognitive assessment in question. A further child characteristic I controlled for was ethnicity, as several studies (for instance Todd and Wolpin 2007) have shown that there may be significant ethnic disparities in child cognitive ability. It is particularly important to control for ethnicity in the context of cross-cohort comparisons, as the MCS is substantially more ethnically diverse than both the NCDS and BCS. I also included categorical variables for region, in order to account for potential spatial variation in child outcomes, which may occur due to localised educational policies (Taylor *et al.,* 2013).

Several empirical studies, including Black *et al.,* (2005) have shown that early life factors, such as having a low birth weight and being a preterm birth, may also be significantly associated with a number of short and long-term factors, including child cognitive ability. Furthermore, Goisis *et al.,* (2017a) found that there has been a decreasing association over time in the relationship between low birth weight and cognitive ability, with a significantly higher level of correlation in the NCDS than the MCS. Although the impact of such early life factors may not be strictly causal, it is thought that such factors may proxy for the early environment experienced by the child.

These two early life variables are also likely to be highly correlated due to the fact that one of the distinctive determinants of a low birth weight is being a preterm birth. However, it is important to control for both factors, as although being a preterm birth may also be picked up by variation in birth weight, there are other issues that may contribute to a low birth weight, for instance genetics and maternal behaviours such as smoking cigarettes and drinking alcohol. I included low birth weight as a dummy variable with the value of 1 if the cohort child weighs below 2500g at birth, and 0 otherwise, and preterm birth as a dummy variable with the value of 1 if gestational age is lower than 259 days (37 weeks) and 0 otherwise.

As well as child characteristics, I also included a small number of maternal characteristics in the empirical models. The first maternal characteristic I controlled for was maternal age. As Fergusson and Lynskey (1993) have shown, maternal age may affect child outcomes through two main pathways. Firstly, children of younger mothers are more likely to be born into poorly educated, socially disadvantaged families. Secondly, the same children are also less likely to be exposed to stable home environment. Furthermore, Goisis *et al.,* (2017b) have shown that the relationship between maternal age and cognitive ability has changed over time, with the correlation negative in the NCDS and positive in the MCS. Ideally, I would have liked to also include paternal age, but the inclusion of this variable would have resulted in a large amount of missing data across the three cohort studies. To capture any non-linear effects of maternal age, I entered this variable into the model in both a linear and quadratic form. I also included a dummy variable for marital status, which acts as a proxy variable for the stability of the household environment. In the NCDS and BCS this was measured as whether or not the mother was married, and in the MCS this was measured as whether or not the mother was married, cohabiting or single.

I also considered two markers of maternal health related behaviour: whether the mother smoked at all during pregnancy and whether the mother breastfed the child at any point. As Fergusson and Lloyd (1991) have shown, although the relationship between smoking in pregnancy and child cognitive ability may not be strictly causal, it may mediate itself through the home environment. Horwood and Fergusson (1998) have shown that although the relationship between breastfeeding and cognitive ability may be small, it is long lived and may extend into late childhood. I included both as dummy variables, taking the value of 1 if the mother engages in the respective activities, and 0 otherwise.

Finally, I controlled for three further sociodemographic variables. The first of these was family size, as a number of studies (including Hanushak 1992) have shown that this measure to be associated with a number of child outcomes, including cognitive ability. Although there is significant debate about whether this relationship is causal (this issue is discussed in great detail in Chapter 5), I included this variable to further account for the potential impact of family structure on child cognitive ability.

The second sociodemographic variable I included was maternal employment. A number of studies (such as Waldfogel *et al.,* 2002), have shown that maternal employment may be associated with child outcomes such as cognitive ability through a number of pathways, such as maternal allocation of time or the resources available to the household. It is again particularly important to include such variables in the context of cross-cohort comparisons, given the significant changes in maternal employment levels in the UK over time. I included this variable as a dummy taking the value of 1 if the mother is employed and 0 otherwise[12].

The final variable I controlled for was a proxy measure of maternal education. A number of authors, for example Carneiro *et al.,* (2013), have shown that maternal education levels may be significantly associated with child outcomes, with this association potentially mediated through maternal achievement beliefs or the ability to provide a stimulating home environment for their children (Davis-Kean 2005). Once more, it is particularly important to include this variable in the analysis, given the increases in levels of maternal education over time. Due to data limitations, I included this measure as a dummy variable taking the value of 1 if the mother stayed in formal education past the minimum school leaving age at the time, and 0 otherwise.

Clearly, there are a wide range of other controlling variables that I would have also wanted to include in empirical analysis, such as a variety of household measures relating to the home learning environment. However, due to the different survey structures, finding comparable variables for such measures was difficult, and therefore this was unfortunately not possible. Definitions for the variables that were included in the empirical analysis are shown in Tables 4.4-4.6.

### 4.5.4 *Missing data*

Aside from the missing income data discussed previously, there were relatively large amounts of missing cognitive test score data (n=1639), as well as a smaller amounts of missing data for maternal age (n=772) and breastfeeding (n=742) in the NCDS.

[12] The relationship between maternal employment and child outcomes is discussed in greater detail in Chapter 6, in the context of adolescent risky health behaviours.

## Table 4.4- Variable labels and definitions for empirical analysis in the NCDS

| Variable Name | Description | NCDS Variable(s) used |
|---|---|---|
| ***Key Explanatory Variables*** | | |
| *PARENTAL OCCUPATION* | Father's occupational classification. 1 = Managerial/Professional, 2 = Intermediate, 3 = Semi/Self-Employed, 4 = Lower Supervisory and Technical, 5 = Semi-routine/routine. | *n190* |
| *INCOME* | *Predicted log permanent family income* | *p_faminc* |
| ***Child Characteristics*** | | |
| *GENDER* | 0 = Child is female, 1 = Child is male | *n622* |
| *ETHNICITY* | 0 = Child is Non-White, 1 = Child is White | *n1612* |
| *NORTH* | 0 = Child does not live in North, 1 = Child lives in North | *n1region* |
| *NORTH_WEST* | 0 = Child does not live in the North West, 1 = Child lives in the North West | *n1region* |
| *EAST_YORKSHIRE* | 0 = Child does not live in the East Riding or West Yorkshire, 1 = Child lives in East Riding or West Yorkshire | *n1region* |
| *NORTH_MIDLANDS* | 0 = Child does not live in Yorkshire/Humber, 1 = Child lives in Yorkshire | *n1region* |
| *MIDLANDS* | 0 = Child does not live in Midlands, 1 = Child lives in Midlands | *n1region* |
| *EAST* | 0 = Child does not live in East England, 1 = Child lives in East England | *n1region* |
| *SOUTH_EAST* | 0 = Child does not live in South East, 1 = Child lives in South East | *n1region* |
| *SOUTH* | 0 = Child does not live in the South, 1 = Child lives in the South | *n1region* |
| *SOUTH_WEST* | 0 = Child does not live in the South West, 1 = Child lives in the South West | *n1region* |
| *WALES* | 0 = Child does not live in Wales, 1 = Child lives in Wales | *n1region* |
| *SCOTLAND* | 0 = Child does not live in Scotland, 1 = Child lives in Scotland | *n1region* |
| *FAMILY_SIZE* | Number of children in the household | *n1117, n99* |
| *LOW_BIRTH_ WEIGHT* | 0 = Child weighed over 2500 grams at birth, 1 = Child weighed under 2500 grams at birth | *n574* |
| *PRE_TERM* | 0 = Gestational age lower than 37 weeks, 1 = Gestational age higher than 37 weeks | *n497* |
| ***Maternal Characteristics*** | | |
| *MATERNAL AGE* | Mother's age at birth in years. | *n553* |
| *(MATERNAL AGE)$^2$* | As above, but squared. | *n553* |
| *BREASTFEEDING* | Binary measure of breastfeeding. 0 = Never breastfed, 1 = Ever breastfed | *n222* |
| *SMOKING_PREG* | Binary measure of smoking in pregnancy. 0 = Did not Smoke, 1 = Smoked | *n502* |
| | | *n503* |
| *MARRIED* | 0 = Mother is not married/cohabiting, 1 = Mother is married/cohabiting | *n545* |
| ***Socioeconomic Characteristics*** | | |
| *MATERNAL_EDUCATION* | Binary measure of whether mother stayed at school beyond the minimum age | n537 |
| *MATERNAL_EMPLOYMENT* | Dummy variable for maternal employment. 0 = Unemployed, 1 = Employed | *n542* |

## Table 4.5- Variable labels and definitions for empirical analysis in the BCS

| Variable Name | Description | BCS Variable(s) used |
|---|---|---|
| ***Key Explanatory Variables*** | | |
| *PARENTAL OCCUPATION* | Father's occupational classification. 1 = Managerial/Professional, 2 = Intermediate, 3 = Semi/Self-Employed, 4 = Lower Supervisory and Technical, 5 = Semi-routine/routine. | *a0014* |
| ***Child Characteristics*** | | |
| *GENDER* | 0 = Child is female, 1 = Child is male | *a0255* |
| *ETHNICITY* | 0 = Child is Non-White, 1 = Child is White | *e247* |
| *NORTH* | 0 = Child does not live in North, 1 = Child lives in North | *BD1REGN* |
| *YORKSHIRE_HUMBERSIDE* | 0 = Child does not live in Yorkshire or Humberside, 1 = Child lives in Yorkshire or Humberside | *BD1REGN* |
| *EAST_MIDLANDS* | 0 = Child does not live in the East Midlands, 1 = Child lives in East Midlands | *BD1REGN* |
| *EAST_ANGLIA* | 0 = Child does not live in East Anglia, 1 = Child lives in East Anglia | *BD1REGN* |
| *SOUTH_EAST* | 0 = Child does not live in the South East, 1 = Child lives in the South East | *BD1REGN* |
| *SOUTH_WEST* | 0 = Child does not live in the South West, 1 = Child lives in the South West | *BD1REGN* |
| *WEST_MIDLANDS* | 0 = Child does not live in West Midlands, 1 = Child lives in West Midlands | *BD1REGN* |
| *NORTH_WEST* | 0 = Child does not live in the North West, 1 = Child lives in the North West | *BD1REGN* |
| *WALES* | 0 = Child does not live in Wales, 1 = Child lives in Wales | *BD1REGN* |
| *SCOTLAND* | 0 = Child does not live in Scotland, 1 = Child lives in Scotland | *BD1REGN* |
| *NORTHERN_IRELAND* | 0 = Child does not live in Northern Ireland, 1 = Child lives in Northern Ireland | *BD1REGN* |
| *FAMILY_SIZE* | Number of children in the household | *e006, e007* |
| *LOW_BIRTH_ WEIGHT* | 0 = Child weighed over 2500 grams at birth, 1 = Child weighed under 2500 grams at birth | *a0278* |
| *PRE_TERM* | 0 = Gestational age lower than 37 weeks, 1 = Gestational age higher than 37 weeks | *a0195a* |
| ***Maternal Characteristics*** | | |
| *MATERNAL AGE* | Mother's age at birth in years. | *a0005a* |
| *(MATERNAL AGE)*$^2$ | As above, but squared. | *a0005a* |
| *BREASTFEEDING* | Binary measure of breastfeeding. 0 = Never breastfed, 1 = Ever breastfed | e020 |
| *SMOKING_PREG* | Binary measure of smoking in pregnancy. 0 = Did not Smoke, 1 = Smoked | a0043b |
| *MARRIED* | 0 = Mother is not married/cohabiting, 1 = Mother is married/cohabiting | *a0012* |
| ***Socioeconomic Characteristics*** | | |
| *MATERNAL_EDUCATION* | Binary measure of whether mother stayed at school beyond the minimum age | a0009 |
| *MATERNAL_EMPLOYMENT* | Dummy variable for maternal employment. 0 = Unemployed, 1 = Employed | e205 |

## Table 4.6- Variable labels and definitions for empirical analysis in the MCS

| Variable Name | Description | NCDS Variable(s) used |
|---|---|---|
| ***Key Explanatory Variables*** | | |
| *PARENTAL OCCUPATION* | Highest occupation in the family. 1 = Managerial/Professional, 2 = Intermediate, 3 = Semi/Self-Employed, 4 = Lower Supervisory and Technical, 5 = Semi-routine/routine. | *CMD05C00*<br>*CPD05C00* |
| *INCOME* | Equivalised Income | *CDOEDE00* |
| ***Child Characteristics*** | | |
| *GENDER* | 0 = Child is female, 1 = Child is male | *ahcsexa0* |
| *ETHNICITY* | 0 = Child is Non-White, 1 is White | *AMD06E00* |
| *LONDON* | 0 = Child does not live in London, 1 = Child lives in London | *ADREGN00* |
| *NORTH_EAST* | 0 = Child does not live in the North East, 1 = Child lives in the North East | *ADREGN00* |
| *NORTH_WEST* | 0 = Child does not live in the North West, 1 = Child lives in the North West | *ADREGN00* |
| *YORSHIRE_HUMBER* | 0 = Child does not live in Yorkshire/Humber, 1 = Child lives in Yorkshire/Humber | *ADREGN00* |
| *EAST_MIDLANDS* | 0 = Child does not live in East Midlands, 1 = Child lives in East Midlands | *ADREGN00* |
| *WEST_MIDLANDS* | 0 = Child does not live in West Midlands, 1 = Child lives in West Midlands | *ADREGN00* |
| *EAST_ENGLAND* | 0 = Child does not live in East England, 1 = Child lives in East England | *ADREGN00* |
| *SOUTH_EAST* | 0 = Child does not live in the South East, 1 = Child lives in the South East | *ADREGN00* |
| *SOUTH_WEST* | 0 = Child does not live in the South West, 1 = Child lives in the South West | *ADREGN00* |
| *WALES* | 0 = Child does not live in Wales, 1 = Child lives in Wales | *ADREGN00* |
| *SCOTLAND* | 0 = Child does not live in Scotland, 1 = Child lives in Scotland | *ADREGN00* |
| *NORTHERN_IRELAND* | 0 = Child does not live in Northern Ireland, 1 = Child lives in Northern Ireland | *ADREGN00* |
| *FAMILY_SIZE* | Number of children in the household | *CDTOTS00,* |
| *LOW_BIRTH_ WEIGHT* | 0 = Child weighed over 2500 grams at birth, 1 = Child weighed under 2500 grams at birth | *ADBWGTA0* |
| *PRE_TERM* | 0 = Gestational age lower than 37 weeks, 1 = Gestational age higher than 37 | *ADGESTA0* |
| ***Maternal Characteristics*** | | |
| *MATERNAL AGE* | Mother's age at birth in years. | *AMDRES00* |
| *(MATERNAL AGE)$^2$* | As above, but squared. | *AMDRES00* |
| *BREASTFEEDING* | Binary measure of breastfeeding. 0 = Never breastfed, 1 = Ever breastfed | *ambfeva0* |
| *SMOKING_PREG* | Binary measure of smoking in pregnancy. 0 = Did not Smoke, 1 = Smoked | *amcipr00* |
| *MARRIED* | 0 = Mother is not married/cohabiting, 1 = Mother is married/cohabiting | *amfcin00* |
| ***Socioeconomic Characteristics*** | | |
| *MATERNAL_EDUCATION* | Binary measure of whether mother stayed at school beyond the minimum age | *cmacqu00* |
| *MATERNAL_EMPLOYMENT* | Dummy variable for maternal employment. 0 = Unemployed, 1 = Employed | *CMDWRK00* |

There were also significant levels of missing data stemming from the ethnicity variable, with around 17% of the individuals (n=2563) not responding to this question. In order to check that the inclusion of the ethnicity variable did not significantly bias the empirical results, I estimated the OLS models with and without the inclusion of the ethnicity variable and compared the results. I also implemented IPW models to check that missing data from other variables did not influencing the interpretation the empirical estimates.

Overall, the level of missing data in the BCS was minimal. The only variables for which there were significant levels of missing data were the measure of parental occupational classification (n=789) as well as several of the cognitive tests[13]. In order to check that the missing data did not significantly influence the interpretation of the results, I once more estimated models weighted by the inverse probability of being in the estimation sample. There was relatively little missing data in the MCS sample. Despite the fact that the implementation of the sampling survey weights in the MCS should fully adjust for non-response (Plewis *et al.,* 2007), as a robustness check I estimated IPW models.

### 4.5.5 *Descriptive relationships*

Descriptive statistics for the full estimation samples in three cohort studies (taken at age 7 in the NCDS and age 5 in the BCS and MCS) are shown in Tables 4.7- 4.9. In the interests of space, the descriptive statistics of the estimation samples used at other ages are shown in Appendix 4C. All of the measures of child cognitive ability were standardised for empirical analysis, meaning that all of these variables had a mean value of 0 and a SD of 1 in the full estimation samples.

As shown in Table 4.10 on page 76, there has been a significant change in the number of parents in each of the broad occupational classification categories over time, with many more individuals in both the highest and lowest occupational classifications in the MCS compared to the NCDS and BCS. Goos and Manning (2007) have argued that this change is due to the decline in 'routine' jobs, which used to make up a substantial share of the UK job market.

[13] Due to the significant amount of missing data in several of the cognitive tests, list wise deletion was not implemented, due to the significant levels of missing data this would cause for the other cognitive tests. For this reason, the sample sizes in the vocabulary test at age 5 and maths ability, reading ability, BAS matrices and BAS spelling tests at age 10 are lower than the full estimation sample.

**Table 4.7- Descriptive statistics of the full estimation sample (N=10921) in the NCDS (Age 7)**

| Variable | Mean | Std Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Maths Ability | 0 | 1 | -2.05 | 1.96 |
| Reading Ability | 0 | 1 | -3.27 | 0.93 |
| Draw A Man | 0 | 1 | -3.37 | 4.12 |
| Copying Ability | 0 | 1 | -3.50 | 2.49 |
| Parental Occupation | 3.07 | 0.88 | 1 | 5 |
| Boy | 0.51 | 0.50 | 0 | 1 |
| North | 0.08 | 0.26 | 0 | 1 |
| North West | 0.13 | 0.34 | 0 | 1 |
| East Riding of Yorkshire | 0.08 | 0.28 | 0 | 1 |
| North Midlands | 0.08 | 0.27 | 0 | 1 |
| Midlands | 0.10 | 0.30 | 0 | 1 |
| East | 0.08 | 0.27 | 0 | 1 |
| South East | 0.16 | 0.37 | 0 | 1 |
| South | 0.06 | 0.24 | 0 | 1 |
| South West | 0.06 | 0.24 | 0 | 1 |
| Wales | 0.05 | 0.23 | 0 | 1 |
| Scotland | 0.11 | 0.32 | 0 | 1 |
| Family Size | 3.10 | 1.62 | 1 | 14 |
| Low Birth Weight | 0.04 | 0.21 | 0 | 1 |
| Preterm Birth | 0.04 | 0.19 | 0 | 1 |
| Maternal Age | 27.53 | 5.62 | 14 | 47 |
| (Maternal Age)$^2$ | 789.26 | 326.64 | 196 | 2209 |
| Breastfeeding | 0.69 | 0.46 | 0 | 1 |
| Smoking in Pregnancy | 0.33 | 0.47 | 0 | 1 |
| Married | 0.97 | 0.16 | 0 | 1 |
| Maternal Education | 0.25 | 0.43 | 0 | 1 |
| Maternal Employment | 0.32 | 0.47 | 0 | 1 |

**Table 4.8- Descriptive statistics of the full estimation sample (N=11167) in the BCS (Age 5)**

| Variable | Mean | Std Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Drawing Ability | 0 | 1 | -3.91 | 3.15 |
| Copying Ability | 0 | 1 | -2.38 | 1.66 |
| Vocabulary Ability* | 0 | 1 | -2.94 | 1.91 |
| Profile Ability | 0 | 1 | -1.73 | 2.28 |
| Parental Occupation | 3.04 | 0.85 | 1.00 | 5.00 |
| Boy | 0.52 | 0.50 | 0.00 | 1.00 |
| North | 0.06 | 0.24 | 0 | 1 |
| Yorkshire/Humberside | 0.09 | 0.29 | 0 | 1 |
| East Midlands | 0.07 | 0.25 | 0 | 1 |
| East Anglia | 0.04 | 0.19 | 0 | 1 |
| South East | 0.27 | 0.45 | 0 | 1 |
| South West | 0.07 | 0.26 | 0 | 1 |
| West Midlands | 0.11 | 0.31 | 0 | 1 |
| North West | 0.13 | 0.34 | 0 | 1 |
| Wales | 0.06 | 0.23 | 0 | 1 |
| Scotland | 0.09 | 0.28 | 0 | 1 |
| Family Size | 2.57 | 1.13 | 1 | 14 |
| Low Birth Weight | 0.05 | 0.22 | 0 | 1 |
| Preterm Birth | 0.05 | 0.22 | 0 | 1 |
| Maternal Age | 26.16 | 5.34 | 15 | 52 |
| (Maternal Age)$^2$ | 712.84 | 302.96 | 225 | 2704 |
| Breastfeeding | 0.37 | 0.48 | 0 | 1 |
| Smoking in Pregnancy | 0.40 | 0.49 | 0 | 1 |
| Married | 0.98 | 0.14 | 0 | 1 |
| Maternal Education | 0.35 | 0.48 | 0 | 1 |
| Maternal Employment | 0.44 | 0.50 | 0 | 1 |

*Please note that the number of observations for the Vocabulary Ability is 8616 rather than 11167

**Table 4.9- Descriptive Statistics of the Full Estimation Sample (N=13614) in the MCS (Age 5)**

| Variable | Mean | Std Deviation | Minimum | Maximum |
|---|---|---|---|---|
| BAS Similarities | 0 | 1 | -4.47 | 2.05 |
| BAS Vocabulary | 0 | 1 | -5.96 | 3.82 |
| BAS Pattern Construction | 0 | 1 | -2.34 | 9.30 |
| Parental Occupation | 2.58 | 1.69 | 1 | 5 |
| Income | 0 | 1 | -1.59 | 4.25 |
| Boy | 0.51 | 0.50 | 0 | 1 |
| North East | 0.03 | 0.16 | 0 | 1 |
| North West | 0.07 | 0.26 | 0 | 1 |
| Yorkshire and Humber | 0.07 | 0.25 | 0 | 1 |
| East Midlands | 0.05 | 0.22 | 0 | 1 |
| West Midlands | 0.07 | 0.25 | 0 | 1 |
| East of England | 0.07 | 0.25 | 0 | 1 |
| London | 0.11 | 0.32 | 0 | 1 |
| South East | 0.10 | 0.29 | 0 | 1 |
| South West | 0.05 | 0.22 | 0 | 1 |
| Wales | 0.15 | 0.35 | 0 | 1 |
| Scotland | 0.13 | 0.33 | 0 | 1 |
| Northern Ireland | 0.11 | 0.31 | 0 | 1 |
| Family Size | 2.39 | 1.05 | 1 | 13 |
| Low Birth Weight | 0.07 | 0.26 | 0 | 1 |
| Preterm Birth | 0.08 | 0.27 | 0 | 1 |
| Maternal Age | 28.88 | 5.74 | 14 | 51 |
| (Maternal Age)$^2$ | 866.85 | 331.31 | 196 | 2601 |
| Breastfeeding | 0.70 | 0.46 | 0 | 1 |
| Smoking in Pregnancy | 0.15 | 0.36 | 0 | 1 |
| Married | 0.63 | 0.48 | 0 | 1 |
| Maternal Education | 0.28 | 0.45 | 0 | 1 |
| Maternal Employment | 0.60 | 0.49 | 0 | 1 |

The authors showed that there has been a steady increase in the number of professional and managerial jobs (categories I & II in the NSSEC-5 classification) since 1981, with corresponding decreases in routine administration and manual jobs, being replaced by 'non-routine' service jobs (category V in the NSSEC-5 classification).

**Table 4.10- Comparison of parental occupational distributions in the NCDS, BCS and MCS**

| | NCDS | BCS | MCS |
|---|---|---|---|
| Managerial/Professional | 5.18% | 5.25% | 44.30% |
| Lower Managerial/Higher Technical | 14.67% | 12.34% | 13.68% |
| Intermediate Occupations | 56.26% | 61.21% | 6.76% |
| Small Employers/Own Account | 17.64% | 15.22% | 9.92% |
| Lower Supervisory/Technical | 6.24% | 5.98% | 25.33% |

These differences highlight the fact that although parental occupation may be used to estimate socioeconomic inequality within individual cohort studies, this specific measure should not be used to compare socioeconomic inequalities in child cognitive ability across the different cohort studies, due to the significant differences to this distribution of the variable across the different cohorts, and therefore lack of comparability. Although the income variables in the NCDS and MCS also have different scales due to the different manners in which they are collected, they are ranked when calculating the CI, and therefore are converted into an ordinal scale rather than a cardinal variable.

There are also several differences in the controlling characteristics across the cohort studies that the reader should be made aware of. For instance, there are significantly more non-white children in the MCS compared to both the NCDS and BCS, due to both increased levels of migration in the later part of the 20$^{th}$ century and the deliberate oversampling of ethnic minorities in the MCS. I accounted for this oversampling through the use of the MCS survey weights. Furthermore, average family sizes have decreased over time, with the average family in the MCS having around 2.4 children compared to around 3.1 children in the NCDS. The number of preterm births and children with low birth weights has remained relatively constant across the three cohort studies.

There have also been a number of changes in terms of maternal characteristics. For instance, there has been a slight increase in average maternal age over time, as well as increases in the number of mothers being in employment and staying in formal education beyond the minimum age. Furthermore, there has been a decrease in the number of mothers smoking during pregnancy from the NCDS and BCS to the MCS. The level of breastfeeding was around 70% in both the NCDS and the MCS, however this figure drops to around 37% in the BCS. Although this may reflect differences in the reporting of breastfeeding in the different surveys, it has also been argued that the 1970s reflected a historical nadir in breastfeeding rates in the UK, potentially due to obstetricians and midwives being more concerned with a safe childbirth from the mother's point of view during this period, and the increased use of formula milk (Crowther *et al* 2009).

### 4.6 Results and Discussion

#### 4.6.1 *Socioeconomic inequalities in child cognitive ability*

##### 4.6.1.1 *OLS models*

First, I analysed the relationship between SES and the child cognitive assessments in the NCDS, utilising OLS regression models and parental occupational classification as a broad measure of SES. Tables 4.11 and 4.12 show a summary of the results from OLS models for the cognitive assessments at ages 7 and 11 respectively. In the interests of space, full regression output is presented in Appendix 4D.

The results from Table 4.11 and 4.12 show that there were significant socioeconomic inequalities in child cognitive ability across all cognitive tests at both 7 and 11 in the NCDS, with those children whose fathers were in the lowest occupational classification having a disadvantage of between 0.4 to 0.9 SD compared to those cohort children whose fathers were in the highest occupational classification. Goodman *et al.,* (2015) have suggested that, in the context of child development, any effect size over 0.1 SD can be considered economically significant, and therefore these differences can be considered relatively substantial. In general, the magnitude of these inequalities was larger at age 11 compared to age 7, implying that socioeconomic inequalities in cognitive ability may have increased over childhood, with this in line with the findings of several prominent studies, including Feinstein (2003). The exception to this general trend was the measure of copying ability, which exhibited a remarkably similar level of socioeconomic inequality at both 7 and 11.

**Table 4.11- Relationship between SES measured by parental occupation and child cognitive ability (NCDS Age 7)**

| | (1) Reading | | (2) Maths | | (3) Drawing | | (4) Copying | |
|---|---|---|---|---|---|---|---|---|
| Parental Social Class | | | | | | | | |
| I | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| II | -0.116*** | (0.032) | -0.172*** | (0.045) | -0.094* | (0.049) | -0.088** | (0.044) |
| III | -0.316*** | (0.030) | -0.366*** | (0.041) | -0.218*** | (0.046) | -0.213*** | (0.040) |
| IV | -0.461*** | (0.037) | -0.465*** | (0.046) | -0.309*** | (0.050) | -0.277*** | (0.045) |
| V | -0.663*** | (0.050) | -0.545*** | (0.056) | -0.411*** | (0.059) | -0.405*** | (0.056) |
| Observations | 10921 | | 10921 | | 10921 | | 10921 | |
| R-squared | 0.149 | | 0.066 | | 0.054 | | 0.059 | |

*Notes:* Summary of empirical estimates. Full regression output available in Appendix 4D. Robust standard errors in parentheses. *** Significant at 1%, ** at 5%, * at 10%.

**Table 4.12- Relationship between SES measured by parental occupation and child cognitive ability (NCDS Age 11)**

| | (1) Verbal | | (2) Non-Verbal | | (3) Maths | | (4) Reading | | (5) Copying | |
|---|---|---|---|---|---|---|---|---|---|---|
| Parental Social Class | | | | | | | | | | |
| I | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| II | -0.186*** | (0.041) | -0.204*** | (0.042) | -0.214*** | (0.045) | -0.181*** | (0.044) | -0.096* | (0.051) |
| III | -0.452*** | (0.038) | -0.470*** | (0.039) | -0.562*** | (0.042) | -0.499*** | (0.041) | -0.203*** | (0.048) |
| IV | -0.590*** | (0.043) | -0.593*** | (0.044) | -0.730*** | (0.046) | -0.633*** | (0.045) | -0.275*** | (0.053) |
| V | -0.796*** | (0.054) | -0.839*** | (0.054) | -0.901*** | (0.054) | -0.805*** | (0.056) | -0.403*** | (0.064) |
| Observations | 9900 | | 9900 | | 9900 | | 9900 | | 9900 | |
| R-squared | 0.159 | | 0.155 | | 0.181 | | 0.191 | | 0.041 | |

*Notes:* Summary of empirical estimates. Full regression output available in Appendix 4D. Robust standard errors in parentheses. *** Significant at 1%, ** at 5%, * at 10%.

As shown in Appendix 4D, in general the other explanatory variables included in models had the signs and magnitude expected given the previous empirical and theoretical literature. For example, years of maternal education, maternal employment, maternal age, levels of breastfeeding and being white were positively associated with child cognitive ability, whilst smoking during pregnancy, an increased family size, being a preterm birth and having a low birth weight were all associated with decreased levels of cognitive ability. The effect of gender differed depending on the cognitive test in question, with boys having the advantage in maths and copying, while girls on average having higher levels of reading, drawing and verbal ability.

The additional results displayed in Table 4.13 show that these estimates were robust to the exclusion of the ethnicity variable, with very marginal differences in the magnitude of the coefficients and no difference in the level of statistical significance when the ethnicity variable was excluded from empirical analysis.

**Table 4.13- Relationship between SES measured by parental occupation and child cognitive ability with the ethnicity variable excluded (NCDS Age 7)**

| | (1) Reading | | (2) Maths | | (3) Drawing | | (4) Copying | |
|---|---|---|---|---|---|---|---|---|
| Parental Social Class | | | | | | | | |
| I | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| II | -0.110*** | (0.031) | -0.140*** | (0.043) | -0.077* | (0.046) | -0.089** | (0.041) |
| III | -0.316*** | (0.029) | -0.340*** | (0.039) | -0.201*** | (0.043) | -0.212*** | (0.038) |
| IV | -0.474*** | (0.035) | -0.456*** | (0.043) | -0.305*** | (0.047) | -0.282*** | (0.042) |
| V | -0.678*** | (0.047) | -0.553*** | (0.053) | -0.410*** | (0.055) | -0.413*** | (0.052) |
| Observations | 12545 | | 12545 | | 12545 | | 12545 | |
| R-squared | 0.151 | | 0.066 | | 0.054 | | 0.055 | |

*Notes:* Summary of empirical estimates. Robust standard errors in parentheses. *** Significant at 1%, ** at 5%, * at 10%.

The results displayed in Appendix 4E show that the inclusion of IPWs used to control for missing data in general marginally decreased the extent of socioeconomic inequality, therefore implying the associations presented in this section may be considered an upper bound of the true estimate.

Next, I estimated the relationship between SES and child cognitive ability in the BCS, using OLS regression models and parental occupational classification as the measure of SES. Tables 4.14 and 4.15 show the relationship between SES and child cognitive ability using OLS models at the ages of 5 and 10 respectively. In the interests of space, full regression output is presented in Appendix 4F.

Significant socioeconomic inequalities in child cognitive ability were shown for most of the cognitive tests across both age groups, with those children whose fathers are in the lowest occupational classification having a disadvantage of between 0.2 to 0.7 SD, compared to those whose fathers are in the highest occupational classification. The one exception to this pattern was the BAS Digits cognitive test, which showed smaller differences between socioeconomic groups, with these differences also not found to be statistically significant. In general there was less evidence of a widening of socioeconomic inequalities over time compared to the results from the NCDS. However, it was difficult to fully investigate any changes over time because of the lack of comparability between the measures of cognitive ability at the ages of 5 and 10 in this cohort study.

As shown in Appendix 4F, the other explanatory variables included in the model specifications had the sign and magnitude expected given the previous theoretical and empirical literature, with positive associations between cognitive ability and maternal factors such as education, age, employment and breastfeeding, and negative associations for factors such as family size and smoking during pregnancy. There were also significant gender disparities depending on the cognitive test, with males having advantages in cognitive tests such as vocabulary and the matrices subset of the BAS, and females having advantages in cognitive scores such as drawing ability and the digits subset of the BAS. The results from Appendix 4G show that these results were also robust to the inclusion of IPWs to control for missing data.

**Table 4.14- Relationship between SES measured by parental occupation and cognitive ability (BCS Age 5)**

| | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Drawing | | Copying | | Profile | | Vocabulary | |
| Parental Social Class | | | | | | | | |
| I | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| II | -0.055 | (0.040) | -0.125*** | (0.046) | -0.049 | (0.050) | -0.160*** | (0.051) |
| III | -0.147*** | (0.035) | -0.286*** | (0.041) | -0.132*** | (0.045) | -0.215*** | (0.045) |
| IV | -0.190*** | (0.041) | -0.400*** | (0.047) | -0.154*** | (0.051) | -0.349*** | (0.051) |
| V | -0.301*** | (0.049) | -0.541*** | (0.056) | -0.317*** | (0.059) | -0.582*** | (0.062) |
| Observations | 11167 | | 11167 | | 11167 | | 8616 | |
| R-squared | 0.042 | | 0.101 | | 0.018 | | 0.134 | |

*Notes:* Summary of empirical estimates Full output available in Appendix 4F. Robust standard errors in parentheses. *** Significant at 1%, ** at 5%, * at 10%.

**Table 4.15- Relationship between SES measured by parental occupation and cognitive ability (BCS Age 10)**

| | (1) | | (2) | | (3) | | (4) | | (5) | | (6) | | (7) | | (8) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Maths | | Reading | | Definitions | | Digits | | Similarities | | Matrices | | Spelling | | Vocabulary | |
| Social Class | | | | | | | | | | | | | | | | |
| I | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| II | -0.300*** | (0.047) | -0.233*** | (0.043) | -0.138** | (0.061) | 0.009 | (0.057) | 0.023 | (0.058) | -0.011 | (0.060) | -0.010 | (0.060) | 0.008 | (0.060) |
| III | -0.558*** | (0.042) | -0.455*** | (0.038) | -0.332*** | (0.056) | -0.022 | (0.052) | -0.051 | (0.053) | -0.112** | (0.055) | -0.073 | (0.054) | -0.078 | (0.055) |
| IV | -0.676*** | (0.048) | -0.601*** | (0.045) | -0.432*** | (0.059) | -0.028 | (0.056) | -0.087 | (0.057) | -0.155** | (0.060) | -0.123** | (0.060) | -0.144** | (0.059) |
| V | -0.854*** | (0.058) | -0.747*** | (0.057) | -0.549*** | (0.065) | -0.090 | (0.065) | -0.194*** | (0.065) | -0.298*** | (0.070) | -0.167** | (0.071) | -0.234** | (0.067) |
| Observations | 9181 | | 9187 | | 10790 | | 10790 | | 10790 | | 8573 | | 8255 | | 10790 | |
| R-squared | 0.151 | | 0.172 | | 0.091 | | 0.017 | | 0.025 | | 0.037 | | 0.048 | | 0.031 | |

*Notes:* Full regression output from OLS specifications. Full output available in Appendix 4F. Robust standard errors in parentheses. *** Significant at 1%, ** at 5%, * at 10%.

Next, I estimated the relationship between SES and child cognitive ability in the MCS, using the same techniques as for the NCDS and BCS. Tables 4.16 - 4.18 show the relationship between SES measured by parental occupation and child cognitive ability, estimated by OLS models at age 5, 7 and 11 respectively. Full regression output is presented in Appendix 4H.

**Table 4.16- Relationship between SES measured by parental occupation and cognitive ability (MCS Age 5)**

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | Verbal Similarities | | Vocabulary | | Pattern | |
| Parental Social Class | | | | | | |
| I | (Omitted) | | (Omitted) | | (Omitted) | |
| II | -0.094*** | (0.031) | -0.166*** | (0.029) | -0.154*** | (0.028) |
| III | -0.182*** | (0.044) | -0.258*** | (0.036) | -0.102*** | (0.036) |
| IV | -0.099*** | (0.037) | -0.278*** | (0.034) | -0.189*** | (0.039) |
| V | -0.154*** | (0.032) | -0.335*** | (0.026) | -0.250*** | (0.031) |
| Observations | 13592 | | 13592 | | 13592 | |
| R-Squared | 0.056 | | 0.185 | | 0.076 | |

*Notes:* Summary of empirical estimates. Full regression output displayed in Appendix 4H. Robust standard errors in parentheses. *** Significant at 1%, ** at 5%, * at 10%.

**Table 4.17- Relationship between SES measured by parental occupation and cognitive ability (MCS Age 7)**

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | Reading | | Maths | | Pattern | |
| Parental Social Class | | | | | | |
| I | (Omitted) | | (Omitted) | | (Omitted) | |
| II | -0.141*** | (0.032) | -0.191*** | (0.032) | -0.149*** | (0.033) |
| III | -0.271*** | (0.042) | -0.232*** | (0.041) | -0.109*** | (0.038) |
| IV | -0.323*** | (0.037) | -0.278*** | (0.043) | -0.198*** | (0.040) |
| V | -0.356*** | (0.031) | -0.347*** | (0.031) | -0.293*** | (0.033) |
| Observations | 12071 | | 12071 | | 12071 | |
| R-squared | 0.134 | | 0.094 | | 0.085 | |

*Notes:* Summary of empirical estimates. Full regression output displayed in Appendix 4H. Robust standard errors in parentheses. *** Significant at 1%, ** at 5%, * at 10%.

**Table 4.18- Relationship between SES measured by parental occupation and cognitive ability (MCS Age 11)**

| Parental Social Class | Verbal Ability | |
|---|---|---|
| I | (Omitted) | |
| II | -0.131*** | (0.035) |
| III | -0.233*** | (0.045) |
| IV | -0.214*** | (0.040) |
| V | -0.325*** | (0.033) |
| Observations | 11971 | |
| R-squared | 0.116 | |

*Notes:* Summary of empirical estimates. Full regression output displayed in Appendix 4H. Robust standard errors in parentheses. *** Significant at 1%, ** at 5%, * at 10%.

There was once more evidence of significant socioeconomic inequalities across all cognitive outcomes, with those children with parents in the lowest occupational classifications having a disadvantage of between 0.15 to 0.35 SD, compared to those children with parents in the highest occupational classification. Similar to the results from the BCS, there was little evidence of widening socioeconomic inequalities over time.

Examining the results presented in Appendix 4H, the other explanatory variables included in the empirical models had the sign and magnitude expected given the previous theoretical and empirical literature. For instance, there were positive associations between child cognitive ability and factors such as maternal education, age and breastfeeding, and negative associations for factors such as an increased family size, low birth weights and smoking during pregnancy. Although consistently correlated with cognitive ability in the NCDS and BCS, the correlation between maternal employment and cognitive ability was smaller in the MCS compared to the other cohort studies, with these differences also not always statistically significant. There were significant gender disparities depending on the cognitive test, with females having advantages in cognitive tests such as reading ability and pattern construction. There was no evidence of differences by gender for the measure of mathematical ability. The results from Appendix 4I show that these results were also robust to the inclusion of IPWs to control for missing data.

In general, the results from the various OLS models using parental occupation as a measure of SES imply a narrowing of the level of socioeconomic inequality across time, with the average disadvantage across all the cognitive tests between the highest and lowest parental occupational groups (as measured by the NSSEC-5) decreasing from just over 0.6 SD in the NCDS to around 0.4 SD in the BCS and 0.3 SD in the MCS respectively.

#### 4.6.1.2 *Concentration indices*

It is possible that different measures of SES and the different methodologies employed in the three cohort studies may lead to different estimates of the level of socioeconomic inequality. Therefore, I next estimated the relationship between SES and child cognitive ability in the NCDS and MCS using the CI and household income as the measure of SES. As discussed in sub-section 4.5.2, I did not calculate CIs for the BCS due to the lack of an applicable measure of household income.

Tables 4.19 and 4.20 show the results for income related socioeconomic inequalities in child cognitive ability from the NCDS.

**Table 4.19- Income related socioeconomic inequalities in child cognitive ability in the NCDS (Age 7)**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Inequality Measures | Maths | Reading | Draw A Man | Copying |
| CI | 0.044 | 0.035 | 0.024 | 0.022 |
| CCI | 0.091 | 0.113 | 0.043 | 0.051 |
| PCI | 0.044 | 0.035 | 0.021 | 0.020 |
| PCCI | 0.078 | 0.095 | 0.039 | 0.044 |
| Observations | 7375 | 7375 | 7375 | 7375 |

*Notes:* All indices are significant at the 1% level.

**Table 4.20- Income related socioeconomic inequalities in child cognitive ability in the NCDS (Age 11)**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Inequality Measures | Verbal | Non-Verbal | Reading | Maths | Copying |
| CI | 0.060 | 0.052 | 0.060 | 0.093 | 0.012 |
| CCI | 0.137 | 0.112 | 0.113 | 0.164 | 0.034 |
| PCI | 0.058 | 0.049 | 0.059 | 0.091 | 0.011 |
| PCCI | 0.120 | 0.100 | 0.107 | 0.144 | 0.030 |
| Observations | 7320 | 7320 | 7320 | 7320 | 7320 |

*Notes:* All indices are significant at the 1% level.

As expected, the results showed there to be statistically significant pro-rich income related socioeconomic inequalities in child cognitive ability in all child cognitive tests across both waves, with PCCIs ranging between 0.039 and 0.144 depending on the measure of cognitive ability. In the context of health, Koolman and van Doorslaer (2004) have argued that a CI of around 0.1 may have significant implications for policy, as a large redistribution of the dependent variable from the richest half to the poorest half would therefore be needed to achieve an index of 0. Using this interpretation as a guide, it appears that several of these CIs can be considered relatively large in magnitude. As with the empirical estimates from the OLS models shown in Tables 4.17 and 4.18, in general the level of these inequalities was larger in the age 11 survey than the age 7 survey, with the two measures of copying ability again the exception to this general rule.

Tables 4.21- 4.23 show the results for income related socioeconomic inequalities in child cognitive ability from the MCS. Once more, the results found there to be statistically significant pro-rich income related socioeconomic inequalities in all measures of child cognitive ability, with PCCIs ranging between 0.026 and 0.078, depending on the measure of cognitive ability[14]. Unlike the NCDS, none of the socioeconomic inequalities in the MCS were larger than the 0.1 'policy relevant' benchmark outlined by Koolman and van Doorslaer (2004). In general, the magnitude in the level of socioeconomic inequality appeared to be larger at age 7 and 11 than at age 5, however this was not the case for the pattern construction cognitive test.

**Table 4.21- Income related socioeconomic inequalities in child cognitive ability in the MCS (Age 5)**

| | (1) | (2) | (3) |
|---|---|---|---|
| Inequality Measures | Verbal Similarities | Vocabulary | Pattern |
| CI | 0.020 | 0.024 | 0.048 |
| CCI | 0.054 | 0.066 | 0.039 |
| PCI | 0.013 | 0.015 | 0.032 |
| PCCI | 0.035 | 0.038 | 0.026 |
| Observations | 13614 | 13614 | 13614 |

*Notes:* All indices are significant at the 1% level.

[14] It should be noted at this point that the results from models using the transitory measures of income (not displayed) showed almost identical empirical estimates to those using the permanent measure of income.

**Table 4.22- Income related socioeconomic inequalities in child cognitive ability in the MCS (Age 7)**

| | (1) | (2) | (3) |
|---|---|---|---|
| Inequality Measures | Reading | Maths | Pattern |
| CI | 0.025 | 0.044 | 0.018 |
| CCI | 0.124 | 0.117 | 0.040 |
| PCI | 0.019 | 0.033 | 0.012 |
| PCCI | 0.078 | 0.074 | 0.028 |
| Observations | 12071 | 12071 | 12071 |

*Notes:* All indices are significant at the 1% level.

**Table 4.23- Income Related Socioeconomic Inequalities in Child Cognitive Ability in the MCS (Age 11)**

| Inequality Measures | Verbal Ability |
|---|---|
| CI | 0.027 |
| CCI | 0.107 |
| PCI | 0.018 |
| PCCI | 0.062 |
| Observations | 11971 |

*Notes:* All indices are significant at the 1% level.

Similar to the results using parental occupation as the measure of SES, in general the results from the CI models using household income as the measure of SES imply a narrowing of the level of income related socioeconomic inequality over time, with the average PCCI across the various cognitive tests decreasing from just over 0.08 in the NCDS to just under 0.05 in the MCS.

### 4.6.2 *Changes in socioeconomic inequality over time*

Although results from both the OLS and CI models suggest that the level of income related socioeconomic inequality in child cognitive ability may have narrowed from the NCDS to the MCS, this observation is based on the use of different cognitive tests with different measurement scales. Bearing this in mind, to estimate the changes in the level of socioeconomic inequality over time from the NCDS to the MCS in a more robust manner, I restricted the empirical analysis to the two generally comparable sets of cognitive tests taken at the same age. The first of these comparisons was maths ability at age 7. Table 4.24 shows the CI, CCI, PCI and PCCI for both cognitive tests.

**Table 4.24- Income related socioeconomic inequalities in maths ability (Age 7) in the NCDS and MCS**

| | (1) | (2) |
|---|---|---|
| Inequality Measures | Maths NCDS | Maths MCS |
| CI | 0.044 | 0.044 |
| CCI | 0.091 | 0.117 |
| PCI | 0.044 | 0.033 |
| PCCI | 0.078 | 0.074 |
| Observations | 7375 | 12071 |

*Notes:* All indices are significant at the 1% level.

Although there was evidence of a marginal narrowing of socioeconomic inequality between the two cohorts once the CI had been corrected for standardising characteristics and the scale of each cognitive test, the magnitude of this difference can be considered very small. This can also be shown graphically by the CCs of Figure 4.6, with the MCS CC (in blue) lying marginally above the NCDS CC (in red) in the top half of the income distribution only.

Table 4.25 shows the output from the associated dominance analysis. These results suggest that while the MCS curve dominated the NCDS curve when using the less strict MCA decision rule at both the 5% and 1% significance levels, this result was not robust to the stricter IUP decision rule, which requires the MCS curve to dominate the NCDS curve at all 19 decision points. Overall, this implies that the level of income related socioeconomic inequality in maths ability at age 7 did not change significantly from the NCDS to the MCS.

**Table 4.25- Tests of dominance between the concentration curves for maths ability**

| Data 1 | Data 2 | Significance Level | # Points | Rule | Decision |
|---|---|---|---|---|---|
| NCDS | MCS | 5% | 19 | MCA | MCS Dominates |
| NCDS | MCS | 5% | 19 | IUP | Non-Dominance |
| NCDS | MCS | 1% | 19 | MCA | MCS Dominates |
| NCDS | MCS | 1% | 19 | IUP | Non-Dominance |

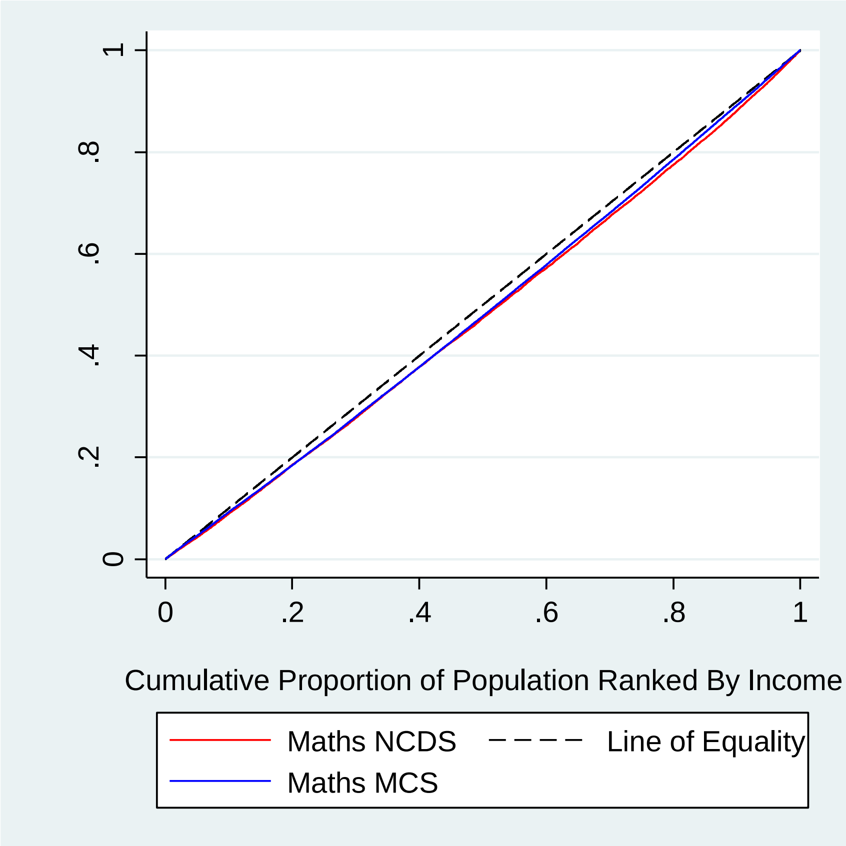


*Figure 4.6- Concentration curves for maths ability (Age 7)*

Secondly, I compared socioeconomic inequalities in verbal ability at age 11 in the NCDS and the MCS. Table 4.26 shows the CI, CCI, PCI and PCCI for both cognitive tests. Unlike the measures of maths ability at age 7 discussed previously, across the various measures of inequality there was found to be a significantly reduced level of socioeconomic inequality in the MCS (PCCI of 0.062) compared to the NCDS (PCCI of 0.120). This is illustrated graphically by the CCs in Figure 4.7, with the MCS CC (in blue) clearly lying above the NCDS CC across the whole income distribution.

**Table 4.26- Income related socioeconomic inequalities in verbal ability (Age 11) in the NCDS and MCS**

| | (1) | (2) |
|---|---|---|
| Inequality Measures | Verbal Ability NCDS | Verbal Ability MCS |
| CI | 0.060 | 0.027 |
| CCI | 0.137 | 0.107 |
| PCI | 0.058 | 0.018 |
| PCCI | 0.120 | 0.062 |
| Observations | 7320 | 11971 |

*Notes:* All indices are significant at the 1% level.

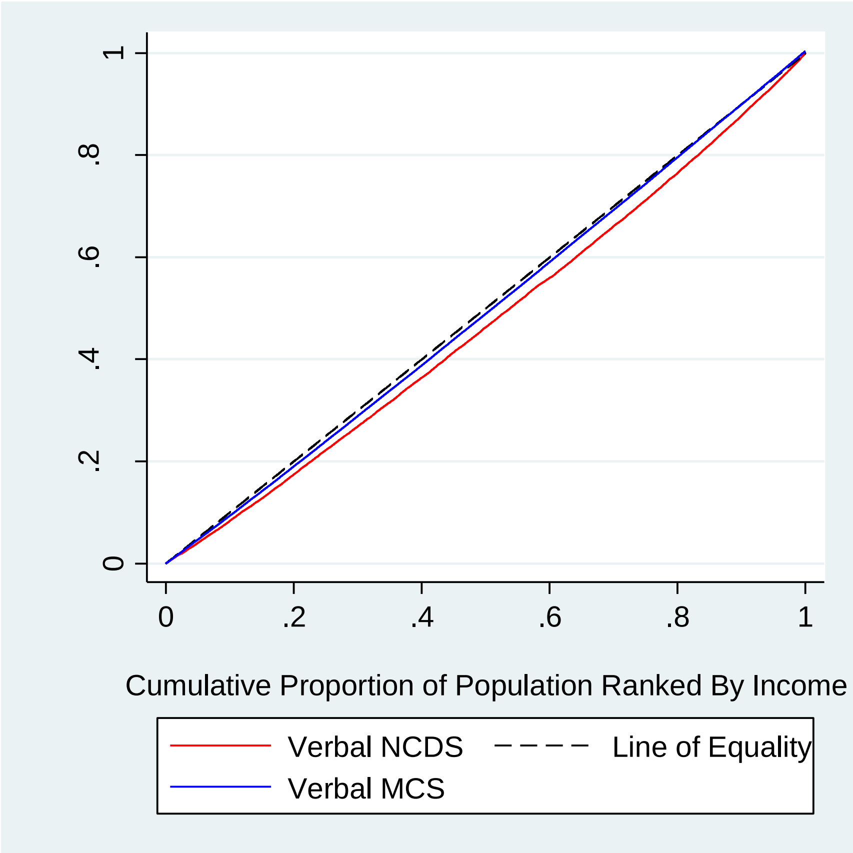


*Figure 4.7- Concentration curves for verbal ability (Age 11)*

Table 4.27 shows the output from the dominance analysis. This output implies that the MCS curve dominated the NCDS curve when using both the less strict MCA decision rule and the stricter IUP decision rule, which requires the MCS curve to dominate the NCDS curve at all 19 decision points. Therefore, unlike the measures of maths ability at age 7, this implies that the level of income related socioeconomic inequality in verbal ability at age 11 narrowed from the NCDS to the MCS, and that this change was also statistically significant at appropriate levels.

**Table 4.27- Tests of dominance between the concentration curves for verbal ability**

| Data 1 | Data 2 | Significance Level | # Points | Rule | Decision |
|---|---|---|---|---|---|
| NCDS | MCS | 5% | 19 | MCA | MCS Dominates |
| NCDS | MCS | 5% | 19 | IUP | MCS Dominates |
| NCDS | MCS | 1% | 19 | MCA | MCS Dominates |
| NCDS | MCS | 1% | 19 | IUP | MCS Dominates |

### 4.6.3 *Decomposition of the concentration index*

In the final stage of empirical analysis, I decomposed the CIs into their contributing factors, using the methods of Wagstaff *et al.,* (2003). Tables 4.28- 4.31 show the decompositions of the various CIs. Across both cohort studies and both measures of cognitive ability, it appears that the majority of the income related socioeconomic inequality in child cognitive ability was explained by household income or parental occupational classification. This combined proportion ranged from 74% in the NCDS at age 7 to 61% in the MCS aged 7. Although the correlation between certain parental occupational categories and child cognitive ability was found to be relatively modest in certain specifications, these measures were also found to be highly unequally distributed across the income distribution, therefore explaining the significant contribution they made to the overall level of socioeconomic inequality.

Besides household income and parental occupation, there were very few variables that consistently explained a significant proportion of the socioeconomic inequality. One exception to this rule was the measure of maternal education, which explained between 14% and 19% of the total level of socioeconomic inequality across the NCDS and the MCS. As well as having a significant correlation with child cognitive ability, the maternal education variables were also found to be highly unequally distributed across the socioeconomic distribution, with the CI for maternal education ranging between 0.3 and 0.4. There was also a small role for family size, which explained between 4-12% of the total level of income related socioeconomic inequality across the different cohort studies and cognitive tests.

There was very little evidence of consistent and significant changes to the contributing factors of income related socioeconomic inequality in cognitive ability over time. The one exception to this rule was the measure of family size, the contribution of which marginally decreased from 8% and 12% in the NCDS at ages 7 and 11 to 4% and 7% in the MCS at ages 7 and 11, with this potentially driven by the decreasing average family sizes over time, as shown in the descriptive statistics in Tables 4.7- 4.9.

## Table 4.28- Decomposition of CI for NCDS maths ability (Age 7)

| Covariates | Elasticity | CI | Contribution [a] | Aggregate Contribution [b] | Percentage Contribution | Aggregate % Contribution |
|---|---|---|---|---|---|---|
| Income | 1.124 | 0.021 | 0.023 | 0.023 | 53% | 53% |
| Managerial/Professional | 0.000 | 0.576 | 0.000 | | 0% | |
| Intermediate | -0.011 | 0.304 | -0.003 | | -7% | |
| Semi/Self Employed | -0.079 | -0.014 | 0.001 | | 2% | |
| Lower Supervisory | -0.029 | -0.236 | 0.007 | Parental Occupation | 15% | Parental Occupation |
| Semi-Routine | -0.012 | -0.383 | 0.005 | 0.010 | 11% | 21% |
| Boy | 0.022 | -0.008 | 0.000 | 0.000 | 0% | 0% |
| White | 0.189 | 0.000 | 0.000 | 0.000 | 0% | 0% |
| Low Birth Weight | -0.004 | -0.099 | 0.000 | 0.000 | 1% | 1% |
| Preterm Birth | -0.002 | -0.112 | 0.000 | 0.000 | 0% | 0% |
| Family Size | -0.058 | -0.063 | 0.004 | 0.004 | 8% | 8% |
| North | -0.002 | -0.139 | 0.000 | | 1% | |
| North West | -0.009 | -0.030 | 0.000 | | 1% | |
| East and West Riding | -0.007 | -0.033 | 0.000 | | 0% | |
| North Midlands | -0.007 | 0.019 | 0.000 | | 0% | |
| Midlands | -0.012 | -0.006 | 0.000 | | 0% | |
| East | -0.011 | 0.100 | -0.001 | | -3% | |
| South East | -0.014 | 0.099 | -0.001 | | -3% | |
| South | -0.009 | 0.153 | -0.001 | | -3% | |
| South West | -0.007 | 0.013 | 0.000 | | 0% | |
| Wales | 0.000 | -0.075 | 0.000 | Region | 0% | Region |
| Scotland | -0.015 | -0.095 | 0.001 | -0.002 | 3% | -4% |
| Maternal Age | 0.060 | -0.012 | -0.001 | -0.001 | -2% | -2% |
| Married | 0.113 | 0.005 | 0.001 | 0.001 | 1% | 1% |
| Smoking in Pregnancy | -0.009 | -0.086 | 0.001 | 0.001 | 2% | 2% |
| Child Breastfed | 0.016 | 0.044 | 0.001 | 0.001 | 2% | 2% |
| Mother Employed | -0.002 | 0.108 | 0.000 | 0.000 | -1% | -1% |
| Maternal Education | 0.027 | 0.314 | 0.008 | 0.008 | 19% | 19% |
| Sum | | | 0.044 | 0.044 | 100% | 100% |
| Residual | | | 0 | 0 | 0% | 0% |
| Total CI | | | 0.044 | 0.044 | 100% | 100% |

[a] Contribution of each individual covariate; [b] Aggregated contributions- sum of contributions for each set of categorical variables

| Table 4.29- Decomposition of CI for MCS maths ability (Age 7) | | | | | | |
|---|---|---|---|---|---|---|
| Covariates | Elasticity | CI | Contribution [a] | Aggregate Contribution [b] | Percentage Contribution | Aggregate % Contribution |
| Income | 0.048 | 0.315 | 0.015 | 0.015 | 34% | 34% |
| Managerial/Professional | 0.027 | 0.331 | 0.009 | | 20% | |
| Intermediate | 0.002 | -0.044 | 0.000 | | 0% | |
| Semi/Self Employed | 0.000 | -0.207 | 0.000 | | 0% | |
| Lower Supervisory | 0.000 | -0.226 | 0.000 | Parental Occupation | 0% | Parental Occupation |
| Semi-Routine | -0.007 | -0.430 | 0.003 | 0.012 | 7% | 27% |
| Boy | 0.005 | 0.004 | 0.000 | 0.000 | 0% | 0% |
| White | 0.057 | 0.047 | 0.003 | 0.003 | 6% | 6% |
| Low Birth Weight | -0.004 | -0.132 | 0.001 | 0.001 | 1% | 1% |
| Preterm Birth | 0.000 | -0.053 | 0.000 | 0.000 | 0% | 0% |
| Family Size | -0.028 | -0.066 | 0.002 | 0.002 | 4% | 4% |
| North East | 0.000 | -0.091 | 0.000 | | 0% | |
| North West | 0.000 | -0.080 | 0.000 | | 0% | |
| Yorkshire/Humberside | -0.002 | -0.140 | 0.000 | | 1% | |
| East Midlands | 0.001 | -0.001 | 0.000 | | 0% | |
| West Midlands | 0.001 | -0.097 | 0.000 | | 0% | |
| East of England | -0.003 | 0.025 | 0.000 | | 0% | |
| London | 0.004 | 0.074 | 0.000 | | 1% | |
| South East | -0.002 | 0.168 | 0.000 | | -1% | |
| South West | 0.000 | 0.076 | 0.000 | | 0% | |
| Wales | 0.002 | -0.070 | 0.000 | | 0% | |
| Scotland | -0.005 | 0.107 | -0.001 | Region | -1% | Region |
| Northern Ireland | 0.002 | -0.086 | 0.000 | -0.001 | 0% | 0% |
| Maternal Age | 0.002 | 0.037 | 0.000 | 0.000 | 0% | 0% |
| Married | 0.007 | 0.112 | 0.001 | 0.001 | 2% | 2% |
| Smoking in Pregnancy | 0.000 | -0.262 | 0.000 | 0.000 | 0% | 0% |
| Child Breastfed | 0.021 | 0.083 | 0.002 | 0.002 | 4% | 4% |
| Mother Employed | 0.009 | 0.176 | 0.002 | 0.002 | 4% | 4% |
| Maternal Education | 0.018 | 0.332 | 0.006 | 0.006 | 14% | 14% |
| Sum | | | 0.042 | 0.042 | 94% | 94% |
| Residual | | | 0.002 | 0.002 | 6% | 6% |
| Total CI | | | 0.044 | 0.044 | 100% | 100% |

[a] Contribution of each individual covariate; [b] Aggregated contributions- sum of contributions for each set of categorical variables

## Table 4.30- Decomposition of CI for NCDS verbal ability (Age 11)

| Covariates | Elasticity | CI | Contribution [a] | Aggregate Contribution [b] | Percentage Contribution | Aggregate % Contribution |
|---|---|---|---|---|---|---|
| Income | 1.320 | 0.021 | 0.027 | 0.027 | 45% | 45% |
| Managerial/Professional | 0.013 | 0.581 | 0.008 | | 12% | |
| Intermediate | 0.029 | 0.305 | 0.009 | | 15% | |
| Semi/Self Employed | 0.064 | -0.018 | -0.001 | | -2% | |
| Lower Supervisory | 0.012 | -0.230 | -0.003 | Parental Occupation | -4% | Parental Occupation |
| Semi-Routine | 0.000 | -0.391 | 0.000 | 0.013 | 0% | 21% |
| Boy | -0.042 | -0.006 | 0.000 | 0.000 | 0% | 0% |
| White | 0.117 | -0.001 | 0.000 | 0.000 | 0% | 0% |
| Low Birth Weight | -0.004 | -0.108 | 0.000 | 0.000 | 1% | 1% |
| Preterm Birth | -0.001 | -0.107 | 0.000 | 0.000 | 0% | 0% |
| Family Size | -0.118 | -0.059 | 0.007 | 0.007 | 12% | 12% |
| North | -0.002 | -0.150 | 0.000 | | 0% | |
| North West | 0.003 | -0.051 | 0.000 | | 0% | |
| East and West Riding | -0.005 | -0.046 | 0.000 | | 0% | |
| North Midlands | -0.001 | 0.007 | 0.000 | | 0% | |
| Midlands | -0.004 | -0.002 | 0.000 | | 0% | |
| East | -0.003 | 0.094 | 0.000 | | -1% | |
| South East | -0.002 | 0.110 | 0.000 | | 0% | |
| South | 0.000 | 0.180 | 0.000 | | 0% | |
| South West | 0.000 | 0.021 | 0.000 | | 0% | |
| Wales | 0.000 | -0.073 | 0.000 | Region | 0% | Region |
| Scotland | 0.000 | -0.108 | 0.000 | 0.000 | 0% | -1% |
| Maternal Age | 0.074 | -0.012 | -0.001 | -0.001 | -2% | -2% |
| Married | 0.075 | 0.005 | 0.000 | 0.000 | 1% | 1% |
| Smoking in Pregnancy | -0.017 | -0.086 | 0.001 | 0.001 | 2% | 2% |
| Child Breastfed | 0.023 | 0.045 | 0.001 | 0.001 | 2% | 2% |
| Mother Employed | 0.006 | 0.109 | 0.001 | 0.001 | 1% | 1% |
| Maternal Education | 0.029 | 0.311 | 0.009 | 0.009 | 15% | 15% |
| Sum | | | 0.059 | 0.059 | 97% | 97% |
| Residual | | | 0.001 | 0.001 | 3% | 3% |
| Total CI | | | 0.060 | 0.060 | 100% | 100% |

[a] Contribution of each individual covariate; [b] Aggregated contributions- sum of contributions for each set of categorical variables

**Table 4.31- Decomposition of CI for MCS verbal ability (Age 11)**

| Covariates | Elasticity | CI | Contribution [a] | Aggregate Contribution [b] | Percentage Contribution | Aggregate % Contribution |
|---|---|---|---|---|---|---|
| Income | 0.053 | 0.229 | 0.012 | 0.012 | 45% | 45% |
| Managerial/Professional | 0.013 | 0.346 | 0.004 | | 16% | |
| Intermediate | 0.001 | -0.022 | 0.000 | | 0% | |
| Semi/Self Employed | 0.000 | -0.162 | 0.000 | | 0% | |
| Lower Supervisory | 0.000 | -0.258 | 0.000 | Parental Occupation | 0% | Parental Occupation |
| Semi-Routine | -0.004 | -0.485 | 0.002 | 0.006 | 7% | 23% |
| Boy | 0.006 | 0.002 | 0.000 | 0.000 | 0% | 0% |
| White | 0.010 | 0.063 | 0.001 | 0.001 | 2% | 2% |
| Low Birth Weight | -0.001 | -0.201 | 0.000 | 0.000 | 0% | 0% |
| Preterm Birth | 0.000 | -0.105 | 0.000 | 0.000 | 0% | 0% |
| Family Size | -0.016 | -0.113 | 0.002 | 0.002 | 7% | 7% |
| North East | 0.000 | -0.170 | 0.000 | | 0% | |
| North West | 0.003 | -0.092 | 0.000 | | -1% | |
| Yorkshire/Humberside | -0.003 | -0.215 | 0.001 | | 2% | |
| East Midlands | 0.000 | 0.000 | 0.000 | | 0% | |
| West Midlands | -0.002 | -0.148 | 0.000 | | 1% | |
| East of England | -0.002 | 0.084 | 0.000 | | -1% | |
| London | 0.001 | 0.095 | 0.000 | | 1% | |
| South East | -0.002 | 0.262 | -0.001 | | -2% | |
| South West | -0.001 | 0.090 | 0.000 | | 0% | |
| Wales | 0.001 | -0.087 | 0.000 | | 0% | |
| Scotland | -0.002 | 0.168 | 0.000 | Region | -1% | Region |
| Northern Ireland | 0.003 | -0.164 | -0.001 | -0.001 | -2% | -3% |
| Maternal Age | -0.006 | 0.055 | 0.000 | 0.000 | -1% | -1% |
| Married | 0.001 | 0.127 | 0.000 | 0.000 | 1% | 1% |
| Smoking in Pregnancy | 0.000 | -0.298 | 0.000 | 0.000 | 0% | 0% |
| Child Breastfed | 0.017 | 0.104 | 0.002 | 0.002 | 6% | 6% |
| Mother Employed | 0.001 | 0.220 | 0.000 | 0.000 | 1% | 1% |
| Maternal Education | 0.011 | 0.415 | 0.004 | 0.004 | 17% | 17% |
| Sum | | | 0.026 | 0.026 | 98% | 98% |
| Residual | | | 0.001 | 0.001 | 2% | 2% |
| Total CI | | | 0.027 | 0.027 | 100% | 100% |

[a] Contribution of each individual covariate; [b] Aggregated contributions- sum of contributions for each set of categorical variables

### 4.6.4 Discussion

In line with the overwhelming majority of the previous theoretical and empirical literature, the results showed a significant level of socioeconomic inequality in child cognitive ability across the three cohort studies, with this result robust to the use of both parental occupation and household income as measures of SES. When using parental occupation classification as a measure of SES in OLS models, the difference in child cognitive between the highest and lowest occupational classifications ranged from 0.2 SD to 0.9 SD, depending on the cognitive test. These differences were higher than the 0.1 SD benchmark proposed by Goodman *et al.,* (2015) to indicate economically significant differences. When using household income as a measure of SES in CIs, PCCIs ranged from 0.026 to 0.144, depending on the cognitive test. Several of these differences were larger than the policy relevant 0.1 benchmark proposed by Koolman and van Doorslaer (2004), implying that a significant level of distribution would be needed to eliminate socioeconomic inequalities in these measures.

Although there was some evidence that the level of socioeconomic inequality increased from age 7 to age 11 in the NCDS, this general pattern was not found in either the BCS or MCS. One notable aspect of the results from the various model specifications is the substantial level of heterogeneity between the various cognitive tests, with the level of socioeconomic inequality critically dependent upon the cognitive test in question. This significant heterogeneity poses a potential problem for cross-cohort comparisons such as the empirical analysis from this chapter, as there is no guarantee that the changes found in one particular variable, for example maths ability, will be reflected in other measures, such as reading ability. These differences also emphasise the need to, where possible, use multiple outcome measures in empirical analysis, and also the need to be cautious when extrapolating changes in one measure of child cognitive ability to child cognitive ability in general, a practice found across the empirical literature, most recently in the studies of Goisis *et al,.* (2017a; 2017b).

Similar to the majority of the previous empirical literature, results for the two generally comparable measures of cognitive ability showed mixed evidence that the level of socioeconomic inequality in child cognitive ability had changed significantly over time, with the level of socioeconomic inequality in maths ability at age 7 found to be stable over time, and the level of socioeconomic inequality in verbal ability at age 11 decreasing from the NCDS to the MCS. There are several reasons why these mixed results may have been found.

Firstly, it may be the case that there genuinely has been very little change in the level of socioeconomic inequality in cognitive ability over time, due to the conflicting mechanisms outlined in section 4.3, such as increased investments in education and early life programmes such as Sure Start, yet increased levels of inequality in both income and parental education over time. Alternatively, it may be the case that there has indeed been a change in the level of socioeconomic inequality in child cognitive ability, and that the mixed evidence found in this empirical chapter instead reflects issues related to quality of the data, in terms of both the comparability of the measures of child cognitive ability and the measures of household income. This mixed evidence of changes in socioeconomic inequality over time also tentatively implies that child cognitive ability may not be a pathway through which socioeconomic health inequalities have increased over time in developed countries, as argued by Mackenbach (2012).

I also investigated the contributing factors to the socioeconomic inequality, as well as identifying if these factors had changed significantly from the NCDS to the MCS. Similar to the relatively limited previous literature, the majority of the socioeconomic inequality in child outcomes was explained by household income or parental occupational classification, with smaller roles found for maternal educational attainment and family size. Although these factors cannot strictly be seen as causal relationships, it gives an indication of the contributing factors that may be influential in shaping socioeconomic inequalities. A number of studies have emphasised other mediating factors that may also contribute to the overall level of socioeconomic inequality in child cognitive ability, such as the home environment (Guo and Harris 2000; Yeung *et al.,* 2002; Linver *et al.,* 2002; Davis-Kean 2005), attitudes and behaviours (Goodman and Gregg 2010; Goodman *et al.,* 2011, Hernandez-Alvara and Popli 2017), communication (Sohr-Preston *et al.,* 2013), maternal psychological functioning (Kiernan and Carmen Huerta 2008, Washbrook *et al.,* 2014) and self-regulation (Pearce *et al.,* 2016). Unfortunately, directly comparable variables for these factors were not available across the three cohort studies, and therefore investigating such mechanisms was beyond the scope of this chapter.

The findings from this chapter should be interpreted in the light of its limitations. Firstly, it is worth emphasising the fact that the cross-cohort nature of the study means there were a limited number of cognitive tests that could be compared across time. As shown by the considerable heterogeneity between the various cognitive tests, it may be the case that the small set of generally comparable cognitive tests did not give a full reflection of child cognitive ability. Furthermore, although every effort was made to ensure that the measures of household income were generally comparable, due to the different data collection strategies, it is possible that the different measures of income may have introduced bias into the empirical estimates, despite this variable being ranked when utilising the CI to estimate relative inequality.

Secondly, although there was mixed evidence of a significant change in the level of socioeconomic inequality in child cognitive ability over time, this may not be the case for other early life child outcome measures. Indeed, Heckman and Kautz (2012) have argued that alternative child outcomes, such as non-cognitive ability and health, should be incorporated into the empirical analysis of early life child outcomes in order to fully capture early life child circumstance. While the inclusion of such variables was beyond the scope of this chapter, I incorporated measures of child psychological well-being into the analysis of the next chapter (Chapter 5), and examined adolescent risky health behaviours in the final empirical chapter (Chapter 6).

Lastly, this analysis estimated the conditional association between SES and cognitive ability from cross sectional data, and therefore I did not estimate a true causal parameter. Finding a valid identification strategy (either through an IV strategy or natural experiment) is extremely difficult, let alone finding comparable identification strategies across three different datasets. Despite these relative weaknesses, this chapter is a valuable contribution to the empirical literature, in terms of being one of the first empirical studies to examine the change is socioeconomic inequalities in cognitive ability over time in the UK, and more generally for being one of the first empirical studies to apply more sophisticated inequality measures in the context of child cognitive ability.

The relationship between SES and early life child outcomes such as cognitive ability is also a significant policy issue, due to the potential impact that levels of child cognitive ability may have on health inequalities and intergenerational income persistence, as well as being a matter of social justice. The results which showed a decrease in the level of income related socioeconomic inequality in verbal ability at age 11 from the NCDS to the MCS can be considered an encouraging sign for social policy makers regarding previous policy if this aspect of cognitive ability is a particular focus of attention. However, this decrease in socioeconomic inequality was not shown for maths ability at age 7, and therefore I can make no firm policy recommendations for child cognitive ability in general from this empirical chapter. Furthermore, the persistent level of socioeconomic inequality across the various cognitive tests in the MCS (made up of children born in 2000 and 2001) implies that previous attempts to reduce this gap between the richest and the poorest members of society may not have had the desired effect, and that a substantial amount of further work is needed to reduce these differences to an acceptable level.

The results from the decomposition analysis showed that the distribution of the contributing factors to the overall level of income related socioeconomic inequality (such as maternal education levels) may be crucial in reducing socioeconomic inequalities. As argued by Shen *et al.,* (2013), this implies that policy makers not only need to change the socioeconomic distribution of the determinants, but also focus on 'proportionate universalism', which refers to the need to take universal actions with a scale and intensity proportionate to the level of disadvantage (Marmot *et al.,* 2010).

The limitations of this empirical chapter outlined above lead me to discuss avenues for future research. Firstly, a substantial amount of further research, with a broader range of comparable data regarding SES and child cognitive ability, is needed before one can truly establish whether there has been a significant increase in socioeconomic inequality in child cognitive ability over time. With a view to aiding research in this area, the ESRC and MRC funded Centre for Longitudinal Studies Enhancement Resources (CLOSER) data harmonisation project has recently been established (CLOSER 2017). The CLOSER project aims to use cross-cohort research to either test whether results are consistent across studies (as a form of sensitivity analysis), and to see how the results differ in the different time periods, social conditions and countries. In particular, the outputs from the *Harmonisation of Socioeconomic Status and Qualifications* work package may be used as a form of sensitivity analysis for the empirical estimates of this study, as the goal of this work package is to harmonise measures of family income, parental occupation, the physical surroundings of the family and the characteristics of geographical areas between a number of UK based cohort and longitudinal studies.

More generally, this chapter and studies such as Maika *et al.,* (2013) and Vallejo-Torres *et al.,* (2014) demonstrate that the CI can be a useful methodological tool outside the fields of health and health care utilisation. Historically, the overwhelming majority of empirical studies investigating the relationship between SES and non-health child outcomes (such as cognitive and non-cognitive ability) have used purely regression based methods to evaluate the effect at the mean level. In contrast, the CI allows for the estimation of the full distribution of income related socioeconomic inequality, and can be more easily compared across different groups and across time. Given these advantages, the CI methodology, along with other advanced measures of socioeconomic health inequality such as the relative distributions method (Handcock and Morris 1998), represent a compliment to the regression based methods usually used when analysing the relationship between SES and child cognitive ability.

A final area of potential further research could be to undertake a more detailed decomposition of the contributing factors to socioeconomic inequality in early life child outcomes such as cognitive and non-cognitive ability as measured by the CI. Specifically, the MCS could be an excellent dataset to use in order to investigate such a research question, given the extensive range of applicable covariates relating to the home environment, as well as parental attitudes and behaviours. This methodology can also be seen as a compliment to other decomposition methods commonly applied in the empirical literature, such as Oaxaca-Blinder decomposition (Oaxaca 1973), which portions the differences in a dependent variable between groups into 'explained' and 'unexplained' variation using regression methods.

**4.7 Conclusion**

Child cognitive ability is predicted to have a significant influence on later life outcomes including educational attainment, employment and risky health behaviours. Understanding both the level of inequality and the determinants of such outcomes is key in order to design effective and efficient policy interventions. In this chapter I investigated the degree of socioeconomic inequality in child cognitive ability in the UK, and in particular whether the level of socioeconomic inequality had changed over time.

Empirical estimates firstly showed a significant level of socioeconomic inequality in child cognitive ability across the overwhelming majority of child cognitive tests in the NCDS, BCS and MCS. The specific level of socioeconomic inequality depended significantly on the cognitive test in question, with a substantial amount of heterogeneity across the various cognitive tests. This finding was robust in both OLS regression models using parental occupational classification as a broad measure of SES, and CI analysis using household income as the measure of SES.

For the few cognitive tests that could be appropriately compared across time, I found there to be mixed evidence of a significant change over time. Although the level of socioeconomic inequality for maths ability at age 7 was almost identical across the NCDS and MCS, there was evidence of a statistically significant decrease in socioeconomic inequality in verbal ability at age 11. Using decomposition analysis, I found that household income and parental occupational classification accounted for between 60% and 70% of the total level of income related socioeconomic inequality across the cohort studies, with variables such as maternal educational attainment and family size explaining smaller proportions of the total level of socioeconomic inequality.

The findings of this chapter highlight several empirical issues in this research area, most prominently the difficulties in conducting cross-cohort comparisons, and the significant heterogeneity in the relationship between SES and child cognitive ability across different measures of cognitive ability, which draws into question empirical studies which rely on single measures of cognitive ability. As well as replicating the estimates of this empirical chapter using more comparable measures of SES currently being developed, future research should be directed at undertaking a more detailed decomposition of socioeconomic inequality, in order to identify potential mechanisms through which these undesirable inequalities may be reduced.

# Chapter 5. Family Size, Birth Order and Child Cognitive Ability and Psychological Well-Being

## 5.1 Introduction

Although a significant proportion of the empirical literature investigating the relationship between early life child characteristics and later life outcomes has specifically focused on the impact of child cognitive ability, another early life child characteristic that may have a significant impact is psychological well-being. Compared to child cognitive ability, child psychological well-being is a more difficult concept to accurately define. Also referred to in the economic and psychological literatures as social and emotional skills, character skills, non-cognitive skills, personality traits and emotional intelligence, child psychological well-being in this context refers to one's own beliefs, ability to deal with other people and the ability to master and motivate one's own behaviour (Goodman *et al.,* 2015).

Given the difficulty in accurately defining the measure, as well as a relative lack of datasets that include such measures in their battery of childhood assessments, this measure has historically received less attention than other early life child measures such as cognitive ability and health. However, Heckman and Kautz (2012) have argued that without a measure of child psychological traits alongside cognitive ability in life course models of well-being, the returns to child cognitive ability may be significantly overstated, and that the two measures jointly can account for more of the variance in adult outcomes than individually.

To illustrate this, Conti and Heckman (2012) have presented a theoretical framework that explicitly incorporates a dynamic, multidimensional measure of child capabilities into life course models of adult outcomes, rather than focussing on traditional child outcome measures such as cognitive ability. This model has two main implications. Firstly, due to its dynamic aspect, the model implies that interventions later in the life course may be inefficient, and that early life interventions should be preferred. More importantly in relation to this chapter, due to the treatment of child ability as a multidimensional measure, a deficiency in one aspect of child ability, such as cognitive skill, may be partially or fully counteracted by a higher level of another measure of child ability, such as psychological well-being.

Alongside this influential theoretical model, a number of recent empirical studies have investigated the association between child psychological well-being and later life outcomes utilising high quality UK cohort data. For instance, using the 1946 National Survey of Health and Development (NSHD), both Colman *et al.,* (2007) and Colman *et al.,* (2009) have shown that having severe levels of teacher reported internalising and externalising behaviour significantly increased the probability of reporting mental health problems in later life. Furthermore, using the Rutter teacher questionnaire (Rutter 1967) as a marker of child psychological well-being, both Richards and Huppert (2011) and Gaysina *et al.,* (2011) have shown child psychological well-being to be significantly related to mean levels of adult life satisfaction and body mass index across the life course respectively.

Using the NCDS, Carnerio *et al.,* (2007) have shown that an overall measure of psychological well-being (as measured by the Bristol Social Adjustment Scale) has a significant association with a range of later life outcomes, including educational attainment, employment status, involvement with crime and health. This finding was also robust to sub group analysis across different socioeconomic groups. Furthermore, Goodman *et al.,* (2011) have shown that poor emotional health in childhood (measured by both self-reported visits to a psychologist or psychiatrist and an independent measure of emotional maladjustment) casts a 'long shadow' on adult outcomes such as physical and psychological health, labour supply and relationship status, with this association significantly larger than the impact of child physical health.

Most recently, Macmillan (2013) and Layard *et al.,* (2014) have used the BCS to estimate the association between psychological well-being (measured by the Rutter Scale) on a variety of later life outcomes, including employment rates, income and life-satisfaction. Both studies found a significant association, with the magnitude of this association shown to be larger than measures of both child cognitive ability and family SES.

Alongside this growing evidence base on the impact of child psychological well-being on adult outcomes, child psychological well-being has recently been placed higher on the political agenda in the UK. For instance, former shadow education secretary Tristam Hunt MP has noted that building such skills are "as essential as academic achievement when it came to succeeding in life"[15], while a 2013 National Institute for Health and Clinical Excellence (NICE) local government briefing recommended a broad, multi-agency strategy to promote and support social, emotional and psychological well-being in children and young

[15] Speech to Demos conference on Character, 8th December 2014

people, in order to create a strong foundation for healthy behaviours and educational attainment (NICE 2013).

As both the theoretical and empirical literature have emphasised the significant potential impact of both child psychological well-being and cognitive ability across the life course, it is key that the root causes of such measures are fully understood, in order to design effective and efficient policy interventions. This may be especially important in relation to psychological well-being, given that a number of studies have reported that the prevalence of emotional and psychological issues in children and adolescents has significantly increased over time in the UK (Collishaw *et al.,* 2004; Maughan *et al.,* 2005; Green *et al.,* 2005; Hagell *et al.,* 2013). Whilst there are certain factors that have consistently been shown to be correlated with child outcomes, such as gender, ethnicity, household structure and various measures of SES (Green *et al.,* 2005; Currie and Lin 2007), other factors frequently included in the child production function have a less sound evidence base. Two factors that fall firmly into this second category are family size and birth order.

Historically, a large number of studies from a variety of fields have investigated the relationship between family size, birth order and various measures of child achievement, with the majority showing a strong negative correlation between family size and child outcomes, with little evidence of negative correlation between a higher birth order and child outcomes. However, in the past 15 years, a number of studies have argued that two methodological issues may have been biasing empirical estimates in this historical literature. For family size, critics have argued that using linear regression methods to analyse the relationship may be significantly hampered by endogeneity, as child bearing decisions are not made in isolation, and may depend on a set of unobserved parental characteristics which are also correlated with child outcomes. For birth order, critics have argued that the majority of the existing empirical evidence may also be significantly biased, due to problems disentangling the substantial relationship between birth order and family size.

Using the 4$^{th}$ wave of the MCS, this chapter had two main aims. Firstly, I aimed to estimate the causal effect of family size on measures of both psychological well-being and child cognitive ability, measured at age 7. Secondly, I aimed to estimate the conditional association between birth order and the same outcome measures. For family size, I initially estimated OLS models to identify a conditional association, whilst controlling for birth order and number of other child and household characteristics. In an attempt to correct for the probable endogeneity of family size and estimate a causal effect, I then estimated 2SLS models, using the sibling sex composition of the first two children in the family and the incidence of twin births in the family as two plausible sources of exogenous variation in family size. For birth order, I used both OLS and non-parametric Nearest Neighbour Matching (NNM) models to estimate birth order differences in child psychological well-being and cognitive ability within specific family sizes, in order to reduce levels of bias stemming from the significant correlation between birth order and family size.

### 5.2 Previous Work

#### 5.2.1 *Early empirical literature*

The previous empirical literature examining the relationship between family size, birth order and child outcomes can be split into two broad periods. The early empirical literature (mostly published in the 1980's using data from the USA) mainly relied on linear regression methods to analyse models of child achievement, with the majority showing a significant negative correlation between a larger family size and child outcomes, and little evidence of a relationship between birth order and these outcomes. Whilst in the interests of space I do not evaluate each of these studies in detail, a selection of the more notable early studies are discussed below.

One notable early study is that of Olneck and Bills (1979), who investigated the influence of family size and birth order differences in cognitive skill, educational attainment and other socioeconomic success in later life using a small sample of brothers collected from Kalamazoo, Michigan. Using linear regression models, empirical results showed that having a larger family size was negatively associated with child achievement, both in terms of child cognitive ability and longer term economic success. Results also showed no statistically significant within family birth order effects, with the authors instead emphasising the importance of unmeasured preferences and economic resources that vary across, but not within, different families. However, similar to several other early studies in this field (for instance Oberlander *et al.,* 1970; Lindart 1977; Stafford 1987; Rodgers 2000) this analysis was based on a relatively small, unrepresentative sample of individuals (N=690), and therefore the empirical estimates were likely subject to various selection biases.

Using a larger estimation sample pooled from a number of surveys, Blake (1981) analysed the relationship between family size, birth order and child educational attainment (measured by college attendance) using path analysis methods and controlling for a range of measures, including those related to the home environment. Across the various surveys, empirical estimates once more showed that while holding birth order constant, family size was significantly negatively correlated with the educational outcomes of the child, with the magnitude of this correlation around the same as that of household SES. Empirical estimates looking specifically at birth order showed no systematic differences within specified family sizes, with the authors arguing that feedback effects from older siblings may counteract the predicted negative effect of being a later born child. However, similar to several other studies in this early literature (Hauser *et al.,* 1985; Hauser *et al.,* 1986; Behrman and Taubman 1986; Kessler 1991), the use of later life educational attainment may not be considered the most appropriate measure of child achievement, given the variety of other household factors that may impact this outcome.

Using both a large sample (*N*=3000) and objective measures of child achievement, the influential study of Hanushak (1992) used data collected over a four year period by the Gary Income Maintenance Experiment (a social experiment on the effect of different levels of benefits and tax rates), merged with achievement information concerning the children from the experimental families. Empirical estimates showed that family size directly affected child achievement in both preschool and school, with this relationship more apparent amongst smaller family sizes. For birth order, empirical estimates showed that although there was no favouritism directed at earlier born children, these earlier born children may be at a distinct advantage due to the increased probability of being in a smaller family size. Other notable contributions to this early literature which used large datasets and objective measures of child achievement include Zajonc (1976), Steelmen and Mercy (1980), Page and Grandon (1979), Retherford and Sewell (1991), and Iacovou (2008), with the results from these studies mostly in line with those of Hanushak (1992).

However, despite this large evidence base relating family size to child outcomes, there are several methodological problems associated with these early studies, which may render their empirical estimates biased. Firstly, it is unlikely that the family size coefficient estimated from a linear regression model will identify a causal effect, due to the strong possibility that parental investments into children and the number of children are the result of the same jointly determined unobserved optimisation process. Secondly, Heiland (2009) has argued that it is likely that the general findings of no significant birth order effects may also be inaccurate, due to the significant difficulties disentangling the clearly strong relationship between birth order and family size.

### 5.2.2 *Later empirical literature*

As a response to these perceived methodological problems, a more recent strand of empirical literature has focussed on identifying the causal effect of family size on child outcomes using IV methods, and has also attempted to generate more precise estimates of birth order effects by utilising large-level, nationally representative datasets and empirical methods specifically designed to disentangle family size and birth order. Compared to the early empirical literature, the results of these later studies in general have pointed to a severely reduced or absent causal effect of family size, yet a larger significant negative birth order effect once the relationship with family size has been accounted for. In the interests of space, I do not discuss each of these studies in detail, and instead present a selection of the most prominent studies.

In a series of influential and highly cited studies, Black *et al.,* (2005, 2010, 2011) exploited an extremely large and rich administrative dataset containing information on nearly the entire population of Norway to analyse the effects of both family size and birth order on a wide variety of child outcomes. In the first of their studies (2005), the authors analysed the effect of family size and birth order on later life educational attainment (measured by the number of years spent in formal education), as well as measures of employment and wages. Although OLS models indicated a significant negative correlation between family size and a variety of economic outcomes such as years of education completed, adult income and employment levels, once birth order was controlled for and the family size variable was instrumented by the incidence of twin births (a methodology first introduced by Rosenzweig and Wolpin 1980), the family size effects were reduced and rendered statistically insignificant. Alongside this, the study also investigated the impact of birth order within distinct family sizes. Using family fixed effects models to account for clustering within households, empirical estimates showed that across all family sizes, there was a significant negative effect of higher birth orders on educational attainment.

In their subsequent studies (Black *et al.,* 2010; 2011), the authors concentrated on the effect of both family size and birth order on cognitive skill (measured by an IQ test) rather than later life educational attainment. The authors also complemented their empirical analysis with the use of the gender composition instrument (a methodology first introduced by Angrist and Evans (1998) in the context of maternal labour supply) alongside the previously used twin births instrument. Unlike their previous analysis, analysis from linear regression models with extensive controls for family background factors showed no significant relationship between family size and child outcomes, with 2SLS estimates using the gender composition instrument also yielding no significant causal effects. However, 2SLS estimates implementing the twin births instrument implied that increased family size had a small, negative effect on IQ levels. The authors partially attributed this small effect to the fact that family size increases from twin births are assumed to be unplanned, whereas family size increases from sibling gender composition are assumed to be the choice of the parents. For birth order, empirical analysis once more showed significant birth order effects both in cross sectional and within family analysis, with these effects not mediated by differences in birth characteristics or endowments.

In another influential study, Angrist *et al.,* (2010) used large samples from Israeli census data to assess the causal effect of family size on a wide range of human capital and economic well-being. Similar to Black *et al.,* (2010), the authors employed multiple econometric strategies to capture a wide variety of exogenous fertility variation, including the use of the sibling sex composition and twin birth IV strategies, and different preferences within ethnic groups. Using an extensive range of econometric models across different subpopulations and birth orders, the empirical analysis showed the linear regression estimates of family size on economic well-being to be substantial and negative. However the 2SLS estimates from the various model specifications generated little evidence that there was a significant causal relationship. The authors also noted a number of possible explanations for the lack of significant effect, including the notion that parents may negate exogenous increases in family size by working longer hours or consuming less leisure, or the fact that an increase in family size may decrease maternal supply, which in turn may increase at home child care for older children.

Using data from the large Wisconsin Longitudinal Study, De Haan (2010) applied multiple IV strategies to explicitly investigate the effect of both family size and birth order on a range of educational outcomes. Similar to Angrist *et al.,* (2010), empirical estimates showed a significant reduction in the correlation between family size and child outcomes once birth order and parental schooling were controlled for, and no significant family size effects once potential endogeneity was controlled for. The author estimated birth order effects separately for each family size, taking into account clustering within households by estimating family fixed effects models. Empirical estimates for birth order showed significant negative birth order effects for educational outcomes, with the authors arguing that this may potentially be due to increased financial transfers made by parents to first-born children. Similar to Black *et al.,* (2011), the author also noted that family fixed effects models made little impact on the interpretation of the empirical estimates, implying that the within family birth order variation in child outcomes is likely to be relatively minor. Additionally, the author analysed two potential mechanisms through which a family size effect may manifest itself: birth spacing and parental allocation of resources. Although empirical estimates showed no birth spacing effects, the parental allocation of resources differed significantly by birth order, indicating that this may be a potential pathway through which birth order impacts child outcomes.

A number of other studies have also contributed to this more recent empirical literature, including those focussing on the impact of family size and/or birth order on measures of child cognitive ability (Jaeger 2009; Heilend 2009; Mogstad and Wiswall 2016; Pavan 2016), educational attainment (Caceres-Delphino 2006; Conley and Glauber 2006; Booth and Kee 2009; Rosenzweig and Zhang 2009; Aslund and Gronqvist 2010; Kristensen and Bjerkedal 2010; Fruhwirth-Schnatter *et al.,* 2014; Fitzsimmons and Malde 2014), health (Argys *et al,.* 2006; Henderson *et al.,* 2008; Millimet and Wang 2011; Avrett *et al,.* 2011; Lundborg *et al.,* 2013), and crime (Breining *et al,.* 2017). Similar to the four studies discussed in more detail above, the vast majority of these studies have shown little evidence of a substantial causal effect of family size on child outcomes, with more evidence of significant birth order differences.

Despite the significant body of work described above relating both family size and birth order to various child outcomes, there are two relevant areas of interest that remain underexplored. Firstly, for those studies analysing the relationship between family size, birth order and child outcomes using UK data, few have attempted to account for either of the methodological challenges encountered by the earlier empirical literature. Secondly, the previous empirical literature has almost exclusively investigated the relationship between family size and birth order on measures of cognitive ability and educational outcomes, with very few studies having considered the impact that such factors may have on measures of psychological well-being. This is despite the fact that such psychological traits are predicted to have a similar, if not larger, impact on later life adult outcomes than cognitive ability (Heckman and Kautz 2012).

The only study that has taken account of the methodological challenges and investigated the relationship between both family size and birth order on a measure of psychological well-being in a UK setting is that of Silles (2010). Using the NCDS, this study implemented two separate IV strategies in order to identify a causal effect of family size. The first identification strategy used was parental reproductive capacity (specifically the number of siblings of the individual's mother and the length of time between marriage and the birth of the first child), with the second identification strategy used being the sibling sex composition of the first two children. Unlike the majority of the literature, empirical estimates showed that family size in fact had a substantial negative causal effect on child behavioural development (as measured by the British Social Adjustment Guide) in both OLS and 2SLS models. The 2SLS estimates were significantly larger than the OLS estimates, with the authors counterintuitively suggesting that the adverse effect of an increased family size may in fact be underestimated in the potentially biased OLS estimates. For birth order, estimates from OLS models showed that for any given family size, there was a distinct first-born advantage for cognitive ability and behavioural development, with last-born children also appearing to have advantages over middle born children in terms of behaviour.

However, there are three potential problems with this study. Firstly, as noted by the authors, the data used is now around 50 years old. Given that the average number of children per mother has decreased from around 2.4 in 1960 to 1.8 in 2010, and the average age at which a woman has a child has increased from 27 to around 32 over the same time period (ONS 2012), it is likely that the empirical estimates in this study cannot be generalised to more recent cohorts in the UK. Secondly, there was very little justification given regarding the validity of the parental reproductive capacity IV strategy, despite the extensive controls for socioeconomic and human capital attainment that are included in order to 'free' the strategy from potential bias. Thirdly, the sibling sex composition IV strategy was shown to be weak, with a Cragg-Donald statistic (Cragg and Donald 1993) below the 'rule of thumb' value of 10 (Stock *et al.,* 2002).

The only other study that has explicitly analysed the relationship between birth order and a measure of child psychological well-being in the UK is that of Lawson and Mace (2010), who used the Avon Longitudinal Study of Parents and Children (ALSPAC) dataset and measured psychological well-being through the Strength and Difficulties Questionnaire (SDQ). Using multi-level modelling techniques, the authors showed a significant later born *advantage* in child psychological well-being, with this counterintuitive result being attributed by the authors to the increased social interactions later born children may have with older siblings. However, similar to the earlier empirical literature in this area, this study made no attempt to disentangle the effects of family size from those of birth order, making the observed birth order effects potentially spurious given the strong correlation between family size and birth order.

Given the previous literature, in this chapter I contribute to the applied empirical literature in two main ways. The first contribution is that this is the first study to attempt to estimate the causal effect of family size on child outcomes in a modern UK cohort using multiple sources of exogenous variation in family size. The second contribution is that it is one of the first studies to investigate the impact of birth order on child psychological well-being whilst taking into account the methodological challenge of separating the effects of family size and birth order.

Although one unpublished study (Hanna 2011) has analysed the effect of family size and birth order on child cognitive ability using the MCS, this chapter differs from that study in a variety of important ways. Firstly, the Hanna (2011) study used waves 2 and 3 of the MCS (when the children are aged 3 and 5 respectively), whereas in this chapter I used wave 4 (when the children are aged 7). Secondly, the study only considered one measure of child cognitive ability (vocabulary), whereas in this chapter I considered two different subscales of child psychological well-being (internalising and externalising ability), as well as three different measures of child cognitive ability (reading ability, maths ability and pattern construction).

Thirdly, the Hanna (2011) study used 'the presence of twins at the last birth' to instrument family size, which implies that the author used own twin birth status as the indicator of twin birth (it is not entirely clear from the manuscript what the specific empirical strategy was). Using own twin status as an instrument for family size in the context of child outcomes will almost certainly generate biased empirical estimates, as own twin birth status is likely be related to child outcomes through other pathways, such as a low birth weight. In contrast, in this chapter I used the household grid of the MCS in order to construct two plausibly exogenous forms of variation in family size: the sibling sex composition of the first two siblings and twin births within the family. Finally, the Hanna (2011) study also applied several important sample restrictions, such as excluding those children whose parents are from an ethnic minority (a relatively high proportion in the MCS compared to other datasets due to the oversampling of ethnic minorities). Overall, it is clear that, despite some similarities, this chapter is sufficiently different to the study of Hanna (2011), and therefore warrants investigation.

## 5.3 Theoretical Considerations

There are two main hypotheses that I test in the empirical analysis:

a) Is there a causal effect of family size on child psychological well-being and cognitive ability?
b) Is there an association between a higher birth order and child psychological well-being and cognitive ability?

In sections 5.3.1-5.3.3 below, I outline the theoretical reasoning behind both hypotheses.

### 5.3.1 *Family size*

A number of theoretical models from the economic, psychological and sociological literatures have considered the relationship between family size and child outcomes. The most prominent of these frameworks in the economic literature is the Quantity vs Quality model (QQ model) of fertility, presented by Becker and Lewis (1974). This model treats children as analogous to consumer goods, with parents deriving utility from both the quantity and 'quality' of children, as well as the consumption of other commodities. Given that there are fixed time and budget constraints and parents are utility maximising, this model showed that there may be a trade-off between the quantity and perceived 'quality' of a child, as additional children increase demands for both financial resources and time inputs of the parents. Therefore, the QQ model predicts that children born in larger families may be hindered, as they have to share resources and time with their parents and their siblings.

Becker and Tomes (1976) extended the Becker and Lewis (1974) model to integrate social interactions, in order to analyse the robustness of the QQ model to several external factors. For instance, given that an increase in parental income will lead to a large increase in parental expenditures on children, the authors showed that the increase in the quality of children would have to come from an increase in these expenditures, due to the fact that child endowments are assumed to be fixed. This in turn will cause the demand for children to be reduced. This implies, for example, that the QQ trade-off may be more pronounced amongst lower socioeconomic groups than higher socioeconomic groups.

Alongside this influential economic model, the Confluence Model (Zajonc 1976) and Resource Dilution Model (RD model) (Blake 1981) stem from the psychological and sociological literatures respectively. Rather than economic resources, the Confluence Model argues that the ability of a child is dependent on the average intelligence of the household. Given that the arrival of a new child (initially with no intellectual skill) will decrease the average intellectual level in the family, large families will provide a more immature environment, which may negatively influence the child's level of intelligence. Rather than average family intelligence, the RD model relates child ability to the home environment created by the parents, whether this being the quality of the learning environment, outside activities or personal attention. Given that additional siblings will reduce (or dilute) the proportion of resources received by any one child, this may impact the perceived 'quality' of the child.

Although the three theories discussed above dominate the theoretical literature regarding the impact of family size on child outcomes, a number of authors have instead argued that the relationship between family size and child outcomes may not be so clear cut. For instance, Velandia *et al.,* (1978) and Page and Grandon (1979) have argued that the empirical implications of the above theories may be better explained by a set of observable and unobservable household level 'admixtures' potentially relating to both family size and child outcomes, for example social class and ethnicity. Similarly, Rodgers *et al.,* (2000) has theorised that family size has little causal effect on child outcomes, instead arguing that the observed family size differences may be in fact working through a non-behavioural component of the model, this being the homogeneity of the intelligence within a family compared to between families. The authors point to the fact that most of evidence supporting the QQ, confluence and RD models come from cross sectional data, which may include a number of biases, and advocate the use of within family data to investigate a within family problem.

### 5.3.2 *Birth order*

As well as family size, a number of theoretical models have also been presented to explain potential birth order differences in child outcomes. Ejrnaes and Portner (2004) have argued that these models can be divided into a number of categories, including financial and time constraints, household environment and biological effects.

From an economic perspective, a number of studies have argued that birth order effects may be explained by a variation of the human capital model, in which parents are faced with various financial and time constraints over the life course. For instance, Birdsall (1979) argued that given there is only a limited amount of time a parent can spend with their children, an eldest child will spend more time with the parents compared to later born children, particularly in the crucial early years of life. Building on this framework, Behrman *et al.,* (1982) and Behrman and Taubman (1986) have argued that the extent of these predicted birth order effects may specifically depend on the preferences of the parents. If the parents are non-discriminatory between their different children, they will allocate the same amount of time to each of their children. However, as argued by Hertwig *et al.,* (2002), dividing up resources equally amongst different children at each distinct time point may itself create inter-temporal inequities between different birth orders. If parents instead attempt to maximise overall achievement, and therefore their utility, they will put a higher level of resources on the more productive children. In this case, the addition of a higher quality child will exacerbate the problem of an extra child. Alternatively, if parents seek to ensure that all of their children have equal outcomes, they may divert a higher level of resources to less productive children to compensate for their lack of productivity.

The household environment explanation of birth order effects relates back to the confluence model (Zajonc 1976). Given that the model predicts that child ability may be determined by the intellectual environment the child grows up in, this implies that children further down the birth order are at a distinct disadvantage, as they will grow up in a lower intellectual environment compared to their older siblings. These effects may be particularly large for the last born child, as they do not have any younger siblings to help teach. However, this model also implies that such effects can be heavily mediated by larger spacing between births, and the relative intellectual ability of the child's siblings.

The biological explanation of negative birth order effects relates to the impact of maternal depletion on birth endowments (Behrman and Taubman 1986). Given that later born children will by definition have older mothers, it is argued that this may advantage older children, as older mothers tend to have children of lower birth weight, are more likely to have children with birth defects and are more likely to have dizygotic multiple births, all of which are associated with a number of adverse child outcomes.

However, although the majority of the theoretical models have pointed to a negative relationship between later birth order and levels of child ability, parts of this theoretical literature have instead argued that there may be advantages of having a higher birth order. For instance, using a model relating to the intra-household allocation of resources in conjunction with endogenous fertility, Ejrnaes and Portner (2004) have argued that parents may decide to stop having children when the genetic endowment of the last born child is higher than expected, and that therefore parents may in fact favour the last-born children. The authors also note that the expected compensatory behaviour between heterogeneous children may not be observed due to inequality-averse parents only having one child.

Furthermore, a number of authors (Behrman *et al.,* 1982; Behrman and Taubman 1986; Hertwig *et al.,* 2002) have argued that in economic terms, having older parents may in fact be considered an advantage, as older parents may be more responsible and mature, and therefore may also be closer to reaching the peak of their earnings profile. Consequently, siblings further down the birth order may benefit from the increase in family income over time, as parents may be able to dedicate proportionally more financial resources on children lower down the birth order compared to their older siblings (Parish and Wills 1993).

Finally, although several authors have argued that in biological terms, having higher maternal age at birth may be considered a hindrance to child development, other studies have argued that this increased maternal age may in fact be an advantage, mediated either through the mother's womb becoming more effective at nurturing a foetus (Khong *et al.,* 2003) or successive children being hypo-masculinized by maternal immunization to the H-Y antigen (Beer and Horn 2000).

### 5.3.3 *Empirical implications*

From the various theories considered in subsections 5.3.1 and 5.3.2, one can relate how both family size and birth order may be related to child outcomes such as psychological well-being and cognitive ability. For family size, the majority of the theoretical frameworks, including the influential QQ model, predict that having a larger family size will have a significant negative effect on child outcomes, due to the dilution of parental resources between the increased numbers of siblings. For birth order, the majority of the theoretical frameworks presented argue that being a later born child will also have a significant negative effect on child outcomes, through the differing time spent with parents relative to other siblings, the household environment and biological effects. However, the theoretical literature is not universally in favour of negative effects of both family size and birth order, and the various models imply that that there are a number of other factors that may impact the strength and direction of the predicted relationships, such as socioeconomic factors and the home environment. Therefore, in the empirical analysis, it is important to account for these potentially confounding observable factors, in an attempt to isolate the specific effects of both family size and birth order on child outcomes[16].

Given the arguments of Becker and Tomes (1976) regarding the robustness of the QQ model to external factors such as household income, it is clear that it is important to control for a wide range of socioeconomic factors that may influence the level of resources invested in the child, such as levels of household income and parental occupation, as it is likely that the trade-off will significantly differ across socioeconomic groups. Similarly, the confluence model (Zajonc 1976) implies that the average level of household intelligence may influence child ability. Although data limitations meant that I was unable to control for the intelligence of the other siblings present in the household or paternal education, I was able to control for the highest educational attainment of the mother. The inclusion of this education variable may also be able to help control for intergenerational transfer of ability, given the strong predicted relationship between maternal education and child outcomes noted by studies such as Carnerio *et al.,* (2013).

The confluence model also implies that the spacing between siblings may impact the intellectual environment children grow up in, and therefore may influence child outcomes.

[16] It should be noted that an additional requirement in the 2SLS models is that controlling variables should be strictly exogenous. This issue is discussed further in the results (sub-section 5.6).

To help control for this, I included a measure of the average birth spacing between siblings for those children with siblings. As predicted by the RD model, another factor that may influence levels of child ability is the home learning environment. In order to control for the differing home environments that children may encounter, I included three variables related to the home learning environment from the MCS: the amount of time parents take reading to their children, how often the child draws and paints at home and the number of trips to the library.

Parish and Wills (1993) have argued that there may also be significant life-cycle effects which could impact the outcomes of children of different birth orders in a variety of ways. Therefore, I included a number of factors which are expected to vary with maternal age, such as employment status, the birth weight of the child and how long the child was breastfed.

Although controlling for a wide variety of socioeconomic and household characteristics may be able to account for a significant amount of the potential confounding and mediating characteristics predicted by the theoretical models, the 'admixture' model favoured by Velandia and Page (1978) and Rodgers *et al.,* (2000) still predicts that the effect of family size from such models will be biased, due to the importance of both unobservable between-family processes which may be related to child outcomes, and the confounding effects of birth order. In empirical analysis, I attempted to account for this possibility through the use of 2SLS models, which seek to isolate a causal effect of the endogenous family size variable by utilising plausibly exogenous variation in family size.

For birth order, several studies have argued that differences in child outcomes according to birth order may be driven by the inequitable distribution of resources within families (Rodgers *et al.,* 2000) and that between household surveys may not be appropriate. Due to the nature of the dataset used, I was unable to account for birth order differences within individual households[17]. Therefore, my specific empirical strategy involved both estimating birth order differences within specified family sizes, and controlling for a wide range of potentially confounding characteristics. As a further step, my empirical strategy also involved the use of non-parametric NNM models, which do not impose a strict functional form and by

[17] I am however comforted by the fact that the few studies in the literature that have used family fixed effects models to control for within family variation have noted very little difference in the empirical estimates (Black *et al.,* 2005, De Haan *et al.,* 2010)

definition only consider pairwise comparisons within a region of common support, meaning that there is at least one match for each included observation (Cerulli 2015).

**5.4 Estimation Strategy**

Informed by both the past theoretical and empirical literature, I used a number of econometric techniques to: 1) estimate the causal effect of family size on child cognitive ability and psychological well-being; and 2) estimate the conditional association between birth order and the same outcomes. In order to estimate the relationship between family size and the child outcomes, I first estimated OLS models, whilst controlling for a wide range of child and household factors which can be seen as confounders. Then, in order to control for endogeneity and estimate a causal effect, I estimated 2SLS models, utilising the sibling sex composition and the incidence of twin births as two plausibly exogenous forms of variation in family size. I tested the strength and exogeneity of the IV strategies in order to determine if the instruments were indeed valid for the research question.

In order to estimate the association between birth order and child outcomes, I would have ideally liked a longitudinal household survey with a set of comparable child outcomes at each age. If such a dataset was available, I would have been able to compare a particular child outcome for a first born child at a certain age to the same child outcome for a later born child within the same household at the same age, controlling for a small number of time-varying factors. Given that such a dataset was not available, I instead followed the methodology of Price (2008), and attempted to compare each cohort child with a child from a similar family in terms of observable characteristics, but a different birth order. Two model specifications were used to estimate this relationship. Firstly, I estimated an OLS model within distinct family sizes in an attempt to reduce potential endogeneity related to factors common to certain family sizes. To complement these OLS models, I estimated non-parametric NNM estimators within the same distinct family sizes. I checked the balancing of the covariates in NNM models using variance ratios, to ensure the validity of these estimates (Austin 2009).

### 5.4.1 *Family size*

#### 5.4.1.1 *Ordinary least squares model*

The starting point of this analysis was the OLS model. The OLS specification used in this chapter to investigate the relationship between family size and child outcomes can be given by:

$$CO_i = \beta_0 + \beta_1 FS_i + \beta_2 \boldsymbol{x}_{ji} + \varepsilon_i , \qquad (5.1)$$

where *i = 1,2,…n*

Let $CO_i$ represent a standardised child outcome such as psychological well-being or cognitive ability for cohort child $i$. $FS_i$ is a measure of the number of siblings in the family of cohort child *i*, with its associated parameter coefficient $\beta_1$. $\boldsymbol{x}_{ji}$ is a large vector of individual and household characteristics assumed to be confounders, with their parameter coefficients $\beta_2$. $\varepsilon_i$ represents the random error term. I estimated standard errors using the Taylor-Linearization method, the default setting when implementing survey weights in a stratified sample such as the MCS.

If the vector of individual and family characteristics was to capture all of the observable and unobservable factors related to both family size and child outcomes, and the error term was therefore assumed to be strictly exogenous, then the estimates of family size on child outcomes from this model can be seen as the true causal effect. However, it is likely that there are a number of unobservable household characteristics related to both family size and child outcomes that may bias this relationship, and therefore an OLS model of this form may generate inconsistent estimates, due to endogeneity caused by omitted variables.

This endogeneity issue can be shown more intuitively using a DAG. When endogeneity is not an issue, an estimate of family size on a child outcome from an OLS model can be assumed to be the true causal estimate, as shown in Figure 5.1. However, it is likely that there are a vector of unobserved characteristics ($\boldsymbol{x}_1$) (made up of various aspects of the parental optimisation process, such as discount rates, network effects, teaching ability and preferences for family size) that affect the number of children a family has, and also determinant child outcomes, as shown in Figure 5.2.

Given that such variables are unobserved, these variables will therefore constitute part of the error term (the composite family size fixed effect), leading the family size variable to be rendered endogenous due to omitted variable bias. The estimates from OLS models are therefore likely to be over-exaggerated in this context, with the true negative effect of family size smaller in magnitude than the parameter estimated from an OLS model. This implies that there is a need to implement econometric methods which sufficiently account for this endogeneity to capture a true causal relationship, such as 2SLS models, which use a variable exogenous to the main equation yet significantly correlated with the endogenous variable to estimate a causal relationship.

$$Family\ Size \longrightarrow Child\ Outcome$$

*Figure 5.1- DAG showing the effect of family size on child outcomes without the presence of unobserved confounders*

$$\begin{tikzcd}
Family\ Size \arrow[rr] & & Child\ Outcome \\
& \boldsymbol{x}_1 \arrow[ul] \arrow[ur] &
\end{tikzcd}$$

*Figure 5.2- DAG showing the effect of family size on child outcomes in the presence of unobserved confounders*

#### 5.4.1.2 *Sibling sex composition instrument*

The first IV strategy I used in this chapter was the sex composition of the first two children in a family. Originally introduced by Angrist and Evans (1998) in order to assess the causal impact of family size on parental labour supply, this instrument draws exogenous variation in family size from the phenomena that some parents may prefer to have a mixed sex sibship group rather than a same sex sibship group, a pattern first reported by Westoff and Potter (1963). Assuming that gender is allocated randomly, it follows that a family who have either two boys or two girls as their first two children may be more inclined to have more children than a family with a mixed sex sibship group.

To construct the sibling sex composition instrument, I created dummy variables for cohort children who are born into families where the first two children (which may or not include the cohort child) are both males from the household grid, before doing the same for females. Then, I combined these variables to create a dummy variable *SAMESEX,* which was equal to 1 if the first two siblings in a family are of the same gender and 0 if the first two siblings are of the opposite gender. Sibling sex composition acting as an instrument for family size is shown graphically in Figure 5.3.

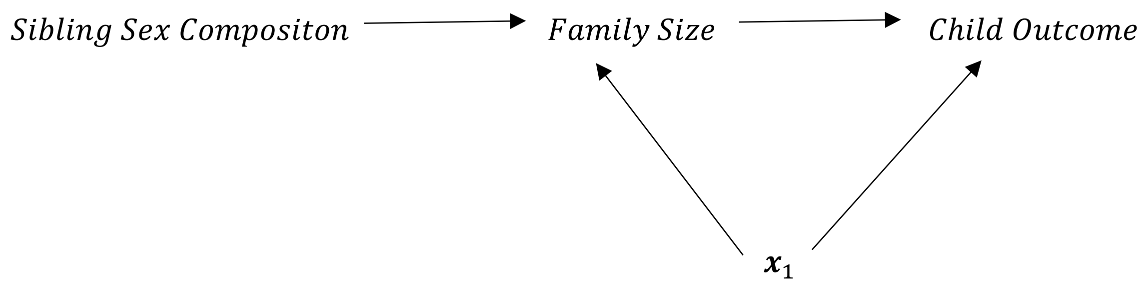


*Figure 5.3- DAG showing sibling sex composition acting as an instrument for family size in relation to child outcomes*

2SLS models are made up of two consecutive OLS regressions. In the first stage, the potentially endogenous family size variable was regressed on the sibling sex composition of the first two siblings and a vector of other explanatory variables:

$$FS_i = \beta_0 + \beta_1 SS_i + \beta_2 \boldsymbol{x}_{ij} + \varepsilon_i \,, \tag{5.2}$$

where *i = 1,2,…n*

Let $FS_i$ represent a measure of the number of siblings in the family of cohort child $i$. $SS_i$ represents a measure of the sibling sex composition with its associated parameter coefficient $\beta_1$. $\boldsymbol{x}_{ji}$ is a large vector of individual and household characteristics assumed to be confounders, with their associated parameter coefficients $\beta_2$. $\varepsilon_i$ represents the random error term.

In the second stage, the standardized measures of psychological well-being or cognitive ability were regressed on the prediction of family size from the first stage equation, as well as the same vector of explanatory variables:

$$CO_i = \psi_0 + \psi_1 \widehat{FS}_i + \psi_2 \boldsymbol{x}_{ji} + \eta_{\mathrm{i}}\,, \tag{5.3}$$

where *i = 1,2,…n*

Let $CO_i$ represent a standardised child outcome such as psychological well-being or cognitive ability for individual $i$. $\widehat{FS}_i$ is a prediction of the family size variable from the first stage for child *i*, with its parameter coefficient $\psi_1$. $\boldsymbol{x}_{ji}$ is a large vector of individual and household characteristics assumed to be confounders, with their associated parameter coefficients $\psi_2$. $\eta_{\mathrm{i}}$ represents the idiosyncratic error term, which is once more assumed to be randomly distributed.

Some studies have argued that there are mechanisms through which the gender composition of children may impact child outcomes through other avenues, such as economies of scale for same sex children (for instance the sharing of clothes) (Rosenzweig and Wolpin 2000). However, while some studies have shown small associations with child outcomes (Butcher and Case 1994; Dahl and Moretti 2008), others have shown no statistically significant effects (Kaestner 1997; Hauser and Kuo 1998). As the sibling sex composition instrument is essentially an interaction between the genders of the first two children, it may be correlated with the gender of either, and may therefore violate the exogeneity condition. In order to reduce the likelihood of any omitted variable bias stemming from any of these sources, I followed the method of Angrist and Evans (1998) and

Angrist *et al.,* (2010) by including dummy variables for a male first born and male second born as extra regressors in the 2SLS models using sibling sex composition as an instrument.

#### 5.4.1.3 ***Twin births instrument***

To complement the sibling sex composition instrument, I also used the incidence of twin births in the family as a second IV strategy. First introduced by Rosenzweig and Wolpin (1980), and popularised in recent studies such as Black *et al.,* (2005, 2010) and Angrist *et al.,* (2010), identification from this instrument relies on the fact that twin births are a conditionally random occurrence which exogenously increases family size beyond the expected level.

The constructed instrument captured the effect of sibling twin births on family size, rather than own twin birth status. Studies that have investigated the causal effect of family size on maternal labour market outcomes using cohort data, such as Braakmann and Wildman (2016), have previously used the cohort member's own twin status as an instrument. This instrument is perfectly valid in this context, as there is no conceivable way that own twin status could affect maternal labour supply aside from through increased family size. However, there are conceivable mechanisms through which own twin status may directly affect child outcomes, for example through a lower birth weight, and therefore using own twin birth status as an instrument for family size in the context of child outcomes will likely lead to biased empirical estimates. Twin births acting as an instrument for family size is shown graphically in Figure 5.4.

As with the sex composition of the siblings, I identified twin births in the family from the household grid of the MCS, which details the age, gender and relation of the cohort child to all members of the family currently living in the child's household. Twin siblings were defined as siblings of the cohort child who had the same age (given in years) and month of birth. This variable, *TWINS*, was equal to 1 if there is a set of twins in the family, and 0 otherwise.

As twin births are a relatively rare occurrence, the majority of the previous studies which implement the twin births IV strategy have used large scale administrative datasets, with extremely large sample sizes. Due to the nature of their samples, the authors of such studies have been able to isolate the marginal effect of a twin birth at each specific birth order. As the sample size of the MCS does not allow for the measurement of the effect at each different parity, the twin instrument I used instead pooled the effects of an extra child across first and second born children, in effect calculating a weighted average of the effects of an extra child on family size.

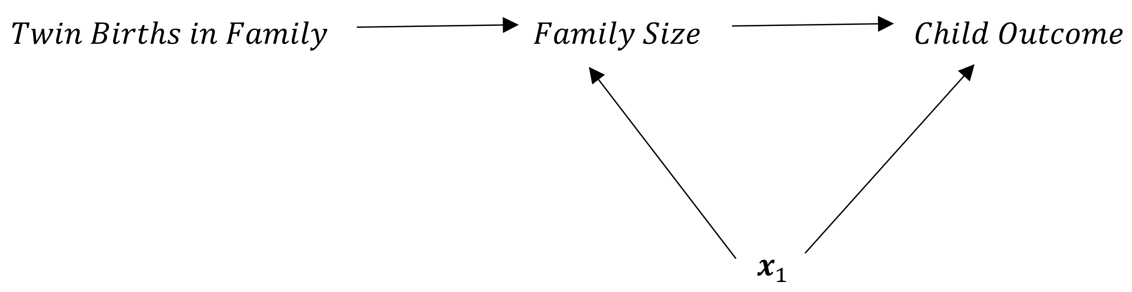


*Figure 5.4- DAG showing twin births acting as an instrument for family size in relation to child outcomes*

In the first stage of the 2SLS model, the potentially endogenous family size was regressed on twin births in the family and a vector of other explanatory variables:

$$FS_i = \beta_0 + \beta_1 TW_i + \beta_2 \boldsymbol{x}_{ij} + \varepsilon_i \,, \tag{5.4}$$

where *i = 1,2,…n*

Let $FS_i$ represent a measure of the number of siblings in the family of cohort child *i*. $TW_i$ represents the occurrence of twin births in the family, with its parameter coefficient $\beta_1$. $\boldsymbol{x}_{ij}$ is a large vector of individual and household characteristics assumed to be confounders, with their associated parameter coefficients $\beta_2$. $\varepsilon_i$ represents the idiosyncratic error term, which is assumed to be randomly distributed.

In the second stage, the standardized measure of psychological well-being or cognitive ability was regressed on the prediction of family size from the first stage equation, as well as the same vector of explanatory variables:

$$CO_i = \psi_0 + \psi_1 \widehat{FS}_i + \psi_2 \boldsymbol{x}_{ji} + \eta_i \tag{5.5}$$

where *i = 1,2,…n*

Let $CO_i$ represent a standardised child outcome such as psychological well-being or cognitive ability for individual $i$. $\widehat{FS}_i$ is a prediction of the family size variable from the first stage for child *i*, with its parameter coefficient $\psi_1$. $\boldsymbol{x}_{ji}$ is a large vector of individual and household characteristics assumed to be confounders, with their associated parameter coefficients $\psi_2$. $\eta_i$ represents the idiosyncratic error term, which is once more assumed to be randomly distributed.

There are several other issues that have been raised in relation to the twin births IV strategy. Firstly, research has shown that maternal age and ethnicity may significantly increase the probability of having a twin birth. To account for this potential bias, I included maternal age in the regression model in both linear and quadratic form, while dummy variables for ethnic origin were also included.

Secondly, as discussed in length by Braakmann and Wildman (2016), the increased use of fertility treatments in modern society may potentially bias 2SLS estimates, as fertility treatments have been shown to significantly increase the probability of a mother having twin births. Although this would not be an issue if fertility treatments were randomly assigned, the authors showed that mothers who receive fertility treatments are likely to be fundamentally different in terms of education levels, age and ethnicity from those who do not. Despite the fact that the resulting bias was shown to be comparatively small, to account for this potential bias I excluded those children who have mothers with a history of receiving fertility treatments from analysis.

Thirdly, Rosenzweig and Zhang (2009) have argued that the birth of twins reduces the space between the births of siblings, which may in turn be correlated with child outcomes. Although the literature regarding the effects of birth spacing on child outcomes is somewhat mixed, to reduce the likelihood of any bias stemming from this source, I included a birth-spacing variable as an additional regressor in the estimating equation. Specifically, this variable measured the average age difference (to the nearest quarter of year) between the cohort child and all of their siblings currently living in the household.

A final issue regarding the use of the twin births instrument is the fact that the twin birth induced variation in family size depends crucially on the time that has passed since the occurrence of the twin births. The effect of a twin birth on family size (the first stage) will vary significantly over time, as parents may adjust their fertility. For instance, say a woman's preferred number of children is three. If she has a singleton child as her first birth and an unplanned twin birth as her second birth, she will still have her desired number of children, but in a shorter than expected time frame. Therefore, in the short term she will have more children than she expected, but over time this effect will diminish.

As a result of the time-varying effects of the twin births instrument, comparing results across different cross sectional samples without accounting for the time passed since the multiple birth might be problematic. This is due to the fact that the distribution of twins has changed over time, with the number of UK multiple births increasing from around 8000 in 1990 to 11000 in 2010 (ONS 2014). However, as noted by Braakmann and Wildman (2016), although this issue adds a further source of heterogeneity to the empirical results, this does not point to 'bias' in the traditional sense, and simply hinders the direct comparison of results across different samples.

I implemented and verified the 2SLS estimators using the *ivreg2* and *ivregress* commands. Like the OLS estimator, standard errors were calculated using the Taylor-Linearization method, the default setting when implementing survey weights in a stratified sample such as the MCS. However, despite accounting for the stratified sampling structure, these error terms are no longer seen to be independent and identically distributed. Due to this, the traditional statistical tests for under-identification (Anderson Lagrange Multiplier Test Statistic (Anderson 1951)) and weak identification of the IV strategy (Cragg-Donald Wald statistic (Cragg and Donald 1993)) are seen to be invalid (Baum *et al.,* 2015). Therefore, alongside the first stage F-statistics (which although widely used rely heavily on the assumption of conditional homoscedasticity of the error term), alternative statistical tests must be implemented in order to test for the under-identification and weak identification of the IV strategies. To test whether the endogenous regressor alone is identified, I reported the LM and Wald versions of the Kleibergen-Papp rk statistic (Kleibergen and Papp 2006). To test for weak identification, I reported the correspondingly robust Kleibergen-Paap Wald rk statistic. In all cases, the critical values used were those suggested by Stock *et al.,* (2002).

Due to the fact that 2SLS models calculate the LATE rather than the ATE, the two IV strategies used in this chapter captured two different and distinct LATEs. The sibling sex composition instrument estimated the ATE of an increased family size due to the sex composition of the first two siblings, in a sub-sample of first or second born children who have at least one other sibling. In contrast, the twin births instrument estimated the ATE of an increased family size due to the conditionally random occurrence of twin births in the family, in a sub-sample of first or second born children who have at least two other siblings. Differences in estimates from different IVs need not necessarily signal a failure of the exclusion restriction, and instead may be attributable to differences in the types of people who are affected by the underlying experiments implicit in any IV identification strategy. This distinction is particularly relevant in this context, as the increase in family size caused by the sibling sex composition is assumed to be planned (based on parental preferences for variety in the sex composition of their children), while the increase in family size caused by the incidence of twin births is assumed to be unplanned.

### 5.4.2 *Birth Order*

#### 5.4.2.1 *Ordinary Least Squares*

When analysing the impact of birth order on child outcomes, the starting point of the analysis was an OLS model. The OLS specification I used in this chapter to investigate the relationship between birth order and child outcomes can be given by:

$$CO_{ik} = \beta_0 + \beta_1 BO_{ik} + \beta_2 \boldsymbol{x}_{ijk} + \varepsilon_{ik} \qquad for\ k = 2, 3, 4\ , \tag{5.6}$$

where *i = 1,2,…n*

In each equation, let $CO_{ik}$ represent the child outcome for individual $i$ with family size $k$. $BO_{ik}$ is a variable indicating the birth order of individual $i$ with its associated parameter coefficient $\beta_1$. $\boldsymbol{x}_{ijk}$ is a vector of individual and family characteristics with their associated parameter coefficients $\beta_2$. $\varepsilon_{i_j}$ represents the idiosyncratic error term, which is assumed to be randomly distributed.

Black *et al.,* (2017) have argued that it is conceptually difficult to contemplate true causal effects of birth order, since the birth order of siblings by definition cannot be manipulated.

Although family fixed effects could in theory be used to differentiate any time-invariant characteristics within a family, this was unfortunately not feasible in this dataset. Therefore, following the methodology of Price (2008), I compared similar children from the MCS in terms of observable characteristics and from the same distinct family size, but with different birth orders. This strategy can be shown more intuitively using Figure 5.5.

| | Two Children | Three Children | Four Children |
|---|---|---|---|
| First Born | A | C | F |
| Middle Born | x | D | G |
| Last Born | B | E | H |

*Figure 5.5- Potential birth order comparisons*

For example, in order to estimate the effect of being a last born child in a two child family, I estimated an OLS model in two child families with a dummy variable equal to 1 if the child is a last born (child 'B' in Figure 5.5) and 0 if the child is first born (child 'A'). In order to estimate the effect of being a middle born child in a three of four child family, I estimated an OLS model with a dummy variable equal to 1 if the child is middle born children ('D' or 'G') and 0 if the child is a first born child ('C' or 'F'). Finally, in order to estimate the effect of being a last born child in a three or four child family, I estimated an OLS model with a dummy variable equal to 1 if the child is a last born (child 'E' or 'H') and 0 if the child is a first born ('C' or 'F').

There were three sample restrictions I imposed when estimating birth order effects in this manner. Firstly, I did not estimate birth order effects for children with no siblings. Secondly, due to the small number of observations, I did not run analysis on families with more than four siblings[18]. Lastly, due to a lack of observations for certain family size-birth order combinations, I converted the birth order variable into a categorical variable with categories for first-born, middle-born and last-born children for analysis.

[18] This still allowed me to run analysis on roughly 95% of the applicable MCS sample

In order to calculate a true causal effect of birth order on child outcomes using this specific methodology, I would have had to assume that the unobserved factors associated with family size (which bias the estimates of the effects of both family size and birth order in OLS models) were completely swept from the model by holding family size constant and controlling for a range of observable characteristics, and therefore could not confound the birth order estimates. In reality this is an unfeasible assumption, and instead I assumed that the inclusion of a wide variety of controlling variables ensured that any potential biases were minimised, and that the estimated parameters represented conditional associations rather than true causal effects.

#### 5.4.2.2 *Nearest neighbour matching*

The second method I used to estimate birth order effects was matching. Matching methods have their roots in the extensive, multidisciplinary literature regarding the 'treatment effect' (Neyman 1934; Rubin 1974), defined as the effect of a specific binary treatment variable on an outcome variable, once the effects of any potential confounders affecting this link have been ruled out (Cerulli 2015). Matching methods provide a nonparametric approach to identifying the ATE, defined as the expected effect of the treatment on a random unit from the whole sample. Although such methods were originally developed in statistics and epidemiology, such methods have become increasingly used in microeconometric studies (Caliendo and Kopeining 2008).

The matching method attempts to mimic an experiment by choosing a comparison group from among the non-treated individuals such that the selected group is as similar as possible to the treatment group in terms of the observable characteristics (Blundell *et al.,* 2005). Whereas the potential bias of OLS regression models depends on the richness of the control variables that may be included in regressions to capture omitted factors, matching methods extend this by attempting to control directly and flexibly the variables at the root of the selection bias.

The matching method I used in this chapter was NNM[19]. NNM methods estimate treatment effects by imputing the missing potential outcome for each subject using an average of the

[19] As argued by Huber (2015), NNM can be considered the most appropriate matching method to use in this context, as I have an idea of the determinants of the outcome measure (psychological well-being and cognitive ability), but do not know the determinants of the treatment status (a higher birth order). If I instead knew the observable determinants of the treatment status, Propensity Score Matching (PSM), Inverse Probability Weighting (IPW) or doubly robust methods would most likely be more appropriate methods.

outcomes of similar subjects that receive the other treatment level. The similarity between subjects is based on a weighted function of the covariates for each observation (Abadie and Imbens 2006, 2011). The most common weighting function used is the Mahalanobis distance (Mahalanobis 1936), in which weights are derived from the inverse of the variance-covariance matrix of the covariates. The average treatment effect on the treated (ATET) can then be calculated by taking the average of the difference between the observed and imputed potential outcomes for each subject. The ATET can be calculated by taking the ATE for the treated subjects only. As with all matching estimators, NNM methods may be seen as preferable to regression based methods such as OLS, as they reduce the number of non-treated individuals to a sub-sample with characteristics more homogenous to the treated units, and only consider units in a region of common support (Cerulli 2015).

In exactly the same manner as the OLS models, in this chapter I used NNM to compare cohort children from the MCS who had similar observable characteristics, were from the same family size, but who had different birth orders. In the context of matching and the treatment effect, the 'untreated' individuals were regarded as the earlier born children, while the 'treated' individuals were those children who have higher birth orders.

I used the NNM algorithm with a single match per observation and replacement of the comparison individuals, as it has been argued that although matching with replacement increases the variance of the estimate, it does reduce the relative bias (Abadie and Imbens 2006). I found exact matches for child gender, ethnicity, low birth weight and a measure of birth spacing[20], with as close of a match as possible found for the other potentially confounding covariates included in the matching models. Abadie and Imbens (2011) have shown that NNM estimators are not consistent in large samples when matching on more than two continuous covariates, and propose a bias corrected estimator, which is more consistent. Due to this potential bias, I converted the continuous variables into appropriate binary measures.

I implemented the NNM models using the *teffects nnmatch* command. The specific treatment effect I used was the ATET, as the focus of the study was the effect on the treated individuals (those children with a higher birth order) rather than the average effect at the population level. In order to ensure that the distributions of the observable characteristics

[20] I chose these variables through an iterative process aimed at minimising the differences between the 'treated' and 'untreated' groups, while ensuring that the common support condition was met.

were sufficiently balanced over the treatment levels, I calculated variance ratios of the observed covariates using the *tebalance* command. Rubin (2001) states that the variance ratio is defined as the ratio of treated and control variances, where balance is defined by values close to 1.0 and variables are out of balance if the variance ratio is greater than 2.0 or less than 0.5.

To date, the matching estimators provided by Stata (*teffects*) and Stata users (*psmatch2*) (Leuven and Sianesi 2003) do not incorporate the full use of sampling weights in analysis. Indeed, Leuven and Sianesi (2003) argue that the accommodation of sampling weights in the context of matching estimators is not clear in the theoretical literature. Therefore, I was not able to weight the NNM estimates of the conditional association between birth order and child outcomes, and therefore these estimates cannot be seen to be fully representative of the UK population.

**5.5 Data and Variables**

The data from this chapter was taken from the MCS, which I described in detail in Chapter 2. Specifically related to the research question in this empirical chapter, the MCS contains a range of child outcome measures at age 7, including a multidimensional measure of psychological well-being and three different measures of cognitive ability, and a range of child and household characteristics. Furthermore, the MCS also crucially includes the household grid, which contains information regarding the age, month of birth and gender of every member of the cohort child's household. This grid allowed me to construct the two IVs used in empirical analysis. Similar to Chapter 4, I used the survey weights provided by the CLS to account for the stratified cluster sample design.

**5.5.1 *Dependent variables***

The two measures of psychological well-being I used in this chapter were measures taken from the Strength and Difficulties Questionnaire (SDQ). Based on the Rutter Questionnaires (Rutter 1967) and developed by Goodman (1997), the SDQ is a brief behaviour screening questionnaire designed to examine children's behaviours and emotions in a number of settings, including screening, clinical assessment, and as a treatment-outcome measure or research tool. The SDQ has several desirable properties compared to similar instruments, including its conciseness, versatility and ability to cover a number of different dimensions. Between the ages of 4-10, the questionnaire (which takes roughly 5 minutes to complete) is completed by a parent or teacher on behalf of the child, whereas between the ages of 11-17 the questionnaire is self-reported by the adolescent themselves.

The questionnaire consists of 25 items in five different domains: conduct problems, emotional symptoms, hyperactivity-inattention, peer problems and prosocial behaviour. For each attribute, the respondent is asked whether in the past six months, a given statement is ‘not true’, ‘somewhat true’ or ‘certainly true’, with each attribute being scored 0, 1 or 2 depending if the attribute is positive or negative. The complete SDQ questionnaire is shown in Appendix 5A.

A common way of scoring the SDQ is to analyse the 5 different dimensions individually. With each dimension consisting of 5 items, the maximum score for each dimension is 10. Higher scores indicate increased levels of behavioural problems, aside from the prosocial behaviour subscale, where higher scores indicate decreased levels of behavioural problems. However, Goodman and Goodman (2009) have argued that rather than using the five scales separately, it may be preferable to amalgamate four of the scales into two subscales representing externalising ability and internalising behaviour respectively. The externalising score is the sum of the conduct and hyperactivity scales, whereas the internalising score is the sum of emotional and peer problems. The maximum score for each measure is therefore 20. It is these internalising and externalising behaviour scores that I used as the measures of psychological well-being in this chapter. These broad subscales have been used extensively in the applied literature, and have also been shown to be valid in a UK setting (Borra *et al.,* 2012; Del Bono *et al.,* 2016). In order to qualitatively compare the empirical estimates from the psychological well-being measures to those from the cognitive assessments, I reverse coded the SDQ measures (meaning that a higher scores indicated a higher level of psychological well-being) and standardised the measures to mean 0, SD 1, similar to the study of Moroni (2016).

As noted by Stone *et al.,* (2010) in a wide ranging review, despite its brevity compared to longer scales, the SDQ has shown strong psychometric properties, with satisfactory levels of internal consistency, test-retest reliability and inter-rater agreement. Research has also been undertaken regarding how the questionnaire compares to other well-known measures that attempt to quantify the same aspects of child behavioural development. The vast majority of the published literature has indicated that the questionnaire performs well when compared to its counterparts, whether the questionnaire is self-reported, parent reported or teacher reported. Examples of this good comparative performance include comparisons of the SDQ to Rutter Questionnaires (Goodman 1997), the Child Behaviour Checklist (Goodman and Scott 1999) and the Health of the Nation Outcome Scales for Children and Adolescents (HoNOSACA) (Mathai *et al.,* 2003).

The three measures of child cognitive ability I used in this chapter were the British Ability Scales (BAS) Word Reading test[21], the BAS Pattern Construction test and an adapted version of the National Foundation for Educational Research (NFER) Progress in Maths Test. I also used these measures of cognitive ability in the empirical analysis of the previous chapter, and therefore in the interests of space, the reader is directed to Appendix 4B for a full description of these cognitive assessments, which were each standardised to mean 0, SD 1 for analysis.

### 5.5.2 *Key explanatory variables*

The measure of family size I used in this chapter was calculated using the derived variable DDTOTS00, which contains all children living within the household in the fourth wave of the MCS, including the cohort child themselves. When estimating OLS models, I converted this variable into a categorical variable, with categories for having no siblings, one sibling, two siblings, three siblings and more than three siblings. The omitted category was having no siblings. In accordance with several other studies, for example Angrist *et al.,* (2010), when implementing the sibling sex composition IV strategy, I converted the family size variable into a binary variable, in order to capture the specific marginal effect of moving from a household with two children to a household with more than two siblings. I therefore converted this variable to equal to 1 if total number of children in the family was three or over, and 0 otherwise. Along the same grounds, I converted the family size variable when using the twin births IV strategy into a binary variable, in this case a variable equal to 1 if the total number of siblings was four or over, and 0 otherwise.

The measure of birth order I used was calculated from the derived variable ADOTHS00, which calculates the number of siblings in the household of the cohort child at the time of birth. In the OLS and 2SLS models specifically focussing on the impact of family size on child outcomes, I included birth order as a control, coded as a categorical variable with categories

[21] In Wales, 139 cohort children undertook a different reading test called 'Our Adventure', which cannot be directly compared the BAS Word Reading Test as they are completely different tests. I therefore excluded cohort children who completed this test from empirical analysis.

for first born, second born, third born and fourth born and above, with first born being the omitted category. Due to sample size restrictions, in the OLS and NNM models specifically focussing on the association between birth order and child outcomes within specified family sizes, I converted the categorical birth order variable into three dummy variables: first born, middle born and last born, which acted as 'treatments' in the various model specifications.

### 5.5.3 *Other explanatory variables*

Informed by the previous theoretical and empirical literature, I also included a variety of child, mother and family characteristics in the model specifications, in order to reduce potential levels of endogeneity created by omitting variables that may confound the relationship between family size, birth order and child outcomes. Table 5.1 presents a complete list of variables and definitions used in the various models.

The first of the child characteristics I included was that of birth spacing. A number of studies, for instance Zajonc (1976), Behrman and Taubman (1986) and Price (2008), have argued that the space between births may be an important factor in relation to child outcomes, as larger spacing may impact the intellectual environment the child grows up in, and may exacerbate difference in the financial resources available by birth order. Ideally, I would have wanted to control for the spacing between the cohort child and all of their siblings. However, as the cohort children all have different numbers of siblings, this becomes difficult to account for in empirical models. Therefore, in order to account for birth spacing, I included a measure of average birth spacing in the empirical models. This measure divided the birth spacing of all births in a family by the number of children in the family. I also included a quadratic term in the empirical models to account for any non-linear effects of average birth spacing.

I included a dummy variable indicating the gender of the child, as gender differences in the cognitive ability of children have been widely reported in the psychological literature, for instance by Hedges and Nowell (1995) and Weiss *et al.,* (2003). Ardila and Rosselli (2011) assert that there are three major differences in cognitive abilities by sex that have been reported: females having higher levels of verbal ability, males having higher levels of spatial ability, and males having higher levels of arithmetical ability. Furthermore, gender differences have also been reported in relation to non-cognitive development. Specifically regarding the SDQ, Murris *et al.,* (2003) amongst others have reported gender differences in some of the SDQ subscales.

**Table 5.1- Variable labels and definitions for regression models**

| Variable Name | Description | MCS Variable(s) used |
|---|---|---|
| ***Dependent Variables*** | | |
| READING_STD | Measure of Reading Ability, standardised to mean 0, standard deviation 1 | DCWRSD00 |
| MATHS_STD | Measure of Maths Ability, standardised to mean 0, standard deviation 1 | MATHS7SA |
| PATTERN_STD | Measure of Pattern Construction, standardised to mean 0, standard deviation 1 | DCWRSD00 |
| INTERNALISING_STD | Sum of the conduct and hyperactivity sub scales of the SDQ, standardised to mean 0, standard deviation 1 | DDCONDA0<br>DDHYPEA0 |
| EXTERNALISING_STD | Sum of the peer relationship and emotional sub scales of the SDQ, standardised to mean 0, standard deviation 1 | DDEMOTA0<br>DDPEERA0 |
| ***Key Explanatory Variables*** | | |
| *FAMILY_SIZE* | Categorical measure of the number of siblings the cohort child has. 0 = non siblings, 1 = one sibling, 2 = two siblings, 3 = three siblings, 4 = more than 3 siblings | DDTOTS00 |
| *FAMILY_SIZE_3* | Binary measure of the number of siblings used when implementing the sibling sex composition IV strategy. | DDTOTS00 |
| *FAMILY_SIZE_4* | Binary measure of the number of siblings used when implementing the twin births IV strategy. | DDTOTS00 |
| *BIRTH_ORDER* | Measure of birth order used as a controlling variable in the OLS and 2SLS models investigating the effect of family size. 0 = First Born, 1 = Second Born, 2 = Third Born, 3 = Fourth Born or Higher | ADOTHS00 |
| *FIRST_BORN* | Binary measure of birth order used in OLS/NNM models investigating the effect of birth order. 0 = Second born or Higher, 1 = First Born | ADOTHS00 |
| *MIDDLE_BORN* | Binary measure of birth order used in OLS/NNM models investigating the effect of birth order. 0 = First Born or Last Born, 1 = Middle Born | ADOTHS00 |
| *LAST_BORN* | Binary measure of birth order used in OLS/NNM models investigating the effect of birth order. 0 = First Born or Middle Born, 1 = Last Born | ADOTHS00 |
| ***Instrumental Variables*** | | |
| *SAMESEX* | Binary measure of the sex composition of the first two siblings in a family. 0 = First two siblings are different genders, 1 = First two siblings are the same gender | DHCSEX00<br>DHPSEX00 |
| *TWINS* | Binary measure of incidence of twin births in the family. 0 = No twin births in the family, 1 = Twin births in the family | DHCAGE00<br>DHCREL00<br>DHCREL00 |
| ***Child Characteristics*** | | |
| *BIRTH_SPACING* | Space in years between the cohort child and siblings/number of siblings. In matching models this variable is dichotomised to 0 if the average spacing is under 3 years, and 1 if over 3 years. | DHCAGE00<br>DHCREL00<br>DHCREL00 |
| *(BIRTH_SPACING)$^2$* | As above, but squared | |
| *GENDER* | 0 = Child is female, 1 = Child is male | DHCSEX00 |
| *WHITE* | 0 = Child is non-White, 1 = Child is White | BETHUCL7 |
| *INDIAN* | 0 = Child is non-Indian, 1 = Child is Indian | BETHUCL7 |
| *PAKISATANI* | 0 = Child is non-Pakistani, 1 = Child is Pakistani | BETHUCL7 |
| *BANGLADESHI* | 0 = Child is non-Bangladeshi, 1 = Child is Bangladeshi | BETHUCL7 |
| *BLACK AFRICAN* | 0 = Child is non-Black African, 1 = Child is Black African | BETHUCL7 |
| *BLACK CARRIBEAN* | 0 = Child is non- Black Caribbean, 1 = Child is Black Caribbean | BETHUCL7 |
| *OTHER* | 0 = Child is non-'other', 1 = Child is another ethnicity | BETHUCL7 |
| *LONDON* | 0 = Child does not live in London, 1 = Child lives in London | ADREGN00 |
| *NORTH_EAST* | 0 = Child does not live in the North East, 1 = Child lives in the North East | ADREGN00 |
| *NORTH_WEST* | 0 = Child does not live in the North West, 1 = Child lives in the North Wester | ADREGN00 |
| *YORSHIRE_HUMBER* | 0 = Child does not live in Yorkshire/Humber, 1 = Child lives in Yorkshire/Humber | ADREGN00 |

**Table 5.1- Variable labels and definitions for regression models (continued)**

| | | |
|---|---|---|
| *EAST_MIDLANDS* | 0 = Child does not live in East Midlands, 1 = Child lives in East Midlands | ADREGN00 |
| *WEST_MIDLANDS* | 0 = Child does not live in West Midlands, 1 = Child lives in West Midlands | ADREGN00 |
| *EAST_ENGLAND* | 0 = Child does not live in East England, 1 = Child lives in East England | ADREGN00 |
| *SOUTH_EAST* | 0 = Child does not live in the South East, 1 = Child lives in the South East | ADREGN00 |
| *SOUTH_WEST* | 0 = Child does not live in the South West, 1 = Child lives in the South West | ADREGN00 |
| *SCOTLAND* | 0 = Child does not live in Scotland, 1 = Child lives in Scotland | ADREGN00 |
| *NORTHERN_IRELAND* | 0 = Child does not live in Northern Ireland, 1 = Child lives in Northern Ireland | ADREGN00 |
| *LOW_BIRTH_ WEIGHT* | 0 = Child weighed over 2500 grams at birth, 1 = Child weighed under 2500 | ADBWGTA0 |
| *PRETERM_BIRTH* | 0 = Gestational age lower than 37 weeks, 1 = Gestational age higher than 37 | ADGESTC0 |
| ***Maternal Characteristics*** | | |
| *MATERNAL AGE* | Mother's age at birth in years. In matching models this variable is dichotomised to 0 if the mother was under 30 at birth, and 1 if over 30. | AMDAGB00 |
| *(MATERNAL AGE)$^2$* | As above, but squared. | AMDAGB00 |
| *BREASTFEEDING* | Categorical measure of length of breastfeeding. 0 = Never breastfed, 1 = breastfed for under 3 months, 2 = breastfed for between 3 months and 6 months, 3 = breastfed for over 6 months. In matching models this variable is dichotomised to 0 if the mother did not breastfeed, and 1 if she did | AMBFEV0<br>AMBFED0<br>AMBFEW0<br>AMBFEM0 |
| *SMOKING_PREG* | Binary measure of smoking in pregnancy. 0 = Did not Smoke, 1 = Smoked | AMCICH00 |
| *MATERNAL_HEALTH* | Self-reported maternal health. 1 = Excellent, 2 = Very good, 3 = Good, 4 = Fair, 5 = Poor. In matching models this variable is dichotomised to 0 if the mother reports fair or poor health, and 1 otherwise. | DMGENA00 |
| *MATERNAL_DEPRESSION* | Self-reported measure of maternal mental health. 0 = Kessler Score <6, 1 = Kessler Score > 6 | DMKESS00 |
| ***Socioeconomic Characteristics*** | | |
| *INCOME_QUINTILE* | Total equivalised household income split into quintiles. 1 = lowest income quintile, 5 = highest income quintile. In matching models this variable is dichotomised to 0 if the household is in the bottom 3 income quintiles and 1 if the household is in the top 2 income quintiles | DOECDUK0 |
| *MATERNAL_EDUCATION* | Mother's highest educational qualification. 0 = no formal qualifications, 1 = GCSE level qualifications, 2 = A-Level/Diploma qualifications, 3 = Degree level qualifications. In matching models this variable is dichotomised to 1 if the mother does has a degree, and 0 otherwise. | AMACQU00 |
| *MATERNAL_EMPLOYMENT* | Dummy variable for maternal employment during pregnancy. 0 = No job during pregnancy, 1 = Job during pregnancy | AMWKPR00 |
| *NSSEC_5* | Highest occupation in the family. 1 = Managerial/Professional, 2 = Intermediate, 3 = Semi/Self-Employed, 4 = Lower Supervisory and Technical, 5 = Semi-routine/routine. In matching models this variable is dichotomised to 1 if one member of the household has a managerial/professional occupation, and 0 otherwise | DMDO5C00<br>DPD05C00 |
| ***Home Environment Characteristics*** | | |
| *PAINTING* | Frequency parent draws and paints with child. 1 = almost every day, 2 = several times a week, 3 = once or twice a week, 4 = once or twice a month, 5 = less often than once a month, 6 = every day. In matching models, this variables is dichotomised to 1 if the parent paints and draws with the child several times a week or more, and 0 otherwise | DMPAMAA0<br>DMPAMAB0<br>DMPAMAC0 |
| *HELP_READING* | Frequency parent helps with reading. 1 = every day, 2 = several time a week, 3 = once or twice a week, 4 = once or twice a month, 5 = less often and 6= never. In matching models, this variable is dichotomised to 1 if the parent reads with the child several times a week or more, and 0 otherwise | DMALWHA0<br>DMALWHB0<br>DMALWHC0 |
| *LIBRARY* | Frequency child visits library. 0 = Never, 1 = At least once a year, 2= every few months, 3= at least once a month, 4= once or twice a week, 5= several times a week and 6= almost every day. In matching models, this variable is dichotomised to 1 if the parent reads with the child attends the library more than once a month, and 0 otherwise | DMLIBRA0<br>DMLIBRB0<br>DMLIBRC0 |

The author's study on a Finnish population of children showed that while males had significantly higher levels of conduct problems, females had significantly higher levels of emotional problems and prosocial behaviour.

As well as the gender of the child, a further child characteristic I included in the econometric models was ethnicity. The MCS was designed to over sample families from minority ethnic populations, and therefore around 13% of the estimation sample identify themselves as being a member of an ethnic minority. Todd and Wolpin (2007) have shown that there may be significant disparities in child outcomes between different ethnicities in the UK. Due to the relatively high number of ethnic minority children in the sample, it was particularly imperative to control for ethnicity in a flexible way. Historically, empirical studies have controlled for ethnicity using a dummy variable for being white. However, due to the fact that the main ethnic minority groups differ from each other in ways that are not picked up by using a combined group of non-whites, it is argued that a more appropriate method may be to control for each individual ethnic minority group (Modood 1992; Senior and Bhopal 1994; Bhopal 2002). In this chapter I controlled for ethnicity with a series of dummy variables for the Indian, Pakistani, Bangladeshi, Black African, Black Caribbean and 'other' populations, with the omitted variable the most populous race, White.

Whilst controlling for gender and ethnicity is common in educational research, considering the impact of within country spatial variation on such outcomes is a surprisingly recent development. Taylor *et al.,* (2013) have shown that educational outcomes "exhibit distinctive spatial distributions", partially due to the fact that certain educational policies are targeted at local levels in order to focus provisions on areas with high levels of social disadvantage and national level policies are significantly mediated at the local level. This issue is particularly relevant in the UK setting, as together with local level inequalities within countries, there are also disparities between the four nations of the UK (England, Northern Ireland, Scotland and Wales), since the government devolved power over education to these countries in the late 1990s. In this chapter I included dummy variables for the various regional areas, with the reference category the most populous region, London.

Two further variables that I controlled for were being a preterm birth and having a low birth weight, with these factors in a sense acting as proxies for genetic endowments (Del Bono *et al.,* 2016), which as Behrman and Taubman (1986) have argued, may provide a potential explanation for differences by birth order. A number of empirical studies have also shown that early life characteristics are significantly related to a variety of child outcomes (Sommerfelt *et al.,* 2000; Behrman and Rosenzweig 2004; Del Bono and Ermisch 2009).

The two early life variables are highly correlated due to the fact that one of the distinctive determinants of a low birth weight is being a preterm birth. However, it is important to control for both factors, as there are other issues that may contribute to a low birth weight, for instance genetics and maternal behaviours such as smoking cigarettes and drinking alcohol. I included preterm birth as a dummy variable for having a gestational age lower than 259 days (37 weeks), and low birth weight as a dummy variable for having a birth weight lower than 2500 grams.

As well as child characteristics, I also included a number of maternal characteristics in the econometric models. For example, a number of authors (Behrman *et al.,* 1982; Behrman and Taubman 1986; Parish and Willis 1993; Fergusson 1993; Hertwig *et al.,* 2002) have argued that life-cycle effects may be significantly related to child outcomes, due to younger parents being poorer than they will be later in the life-cycle. To control for this possibility, I included linear and quadratic measures of maternal age as an explanatory variable in empirical models. Although studies such as Geronimus (1994) have argued that this relationship may be fully or partially mediated by various measures of SES, I included this measure to capture any independent effect. Although some studies (for instance Saha *et al.,* 2009) have also shown that paternal age may have an effect on child outcomes, I could not control for paternal age in this chapter due to significant levels of missing data.

A further maternal characteristic I included was breastfeeding. Several empirical studies have shown that levels of breastfeeding by the mother in the early years may have significant effects on child outcomes. For instance, Horwood *et al.,* (1998, 2001), using a sub-sample from a New Zealand cohort survey, found that increasing the duration of breastfeeding is significantly linked to IQ, reading ability and mathematical ability from the ages of 8-13. Although the authors also argued that a large portion of this difference can be explained by the fact that mothers who breastfeed tend to be older, more educated and from a higher social class, a small portion of the difference was seemingly driven by higher levels of breastfeeding. I entered breastfeeding into the model as a categorical variable, with categories for never being breastfed, being breastfed for under 3 months, being breastfed between 3 and 6 months and being breastfed for over 6 months.

Maternal smoking during pregnancy has also been linked to deficits in child outcomes. For instance, Julvez *et al.,* (2007) used a Spanish cohort study to show that there is a significant association between maternal smoking and child cognitive and behavioural development, even whilst controlling for several confounding variables such as household income, maternal education and maternal age. Potential pathways through which maternal smoking may affect child outcomes include the impact that smoking has on the birth weight of the child and the impact on in utero brain growth. I entered maternal smoking into the empirical models as a dummy variable, with a value of 1 if the mother smoked at all during the pregnancy, and 0 otherwise.

I also controlled for measures of maternal physical and mental health. Propper *et al.,* (2007) have argued that poor maternal health is likely to impact the effectiveness of any other inputs which may affect child outcomes (such as maternal employment and family income), and also may affect the quantity and quality of time that a mother has available to her children. I entered maternal physical health into the empirical model as a self-reported categorical variable, with categories for: Excellent, Good, Fair, Poor and Very Poor. I entered poor maternal mental health into the model specification as a binary version of the Kessler scale, with values of seven or above coded as 1, and 0 otherwise.

The final maternal characteristics I controlled for were two measures of SES, maternal education and maternal employment. A number of empirical studies (for instance Carneiro *et al.,* 2013) have shown that maternal education levels are significantly associated with child outcomes, with this association potentially mediated though maternal achievement beliefs or the ability to provide a stimulating home environment for their children (Davis-Kean 2005). I entered maternal education into the model as a categorical variable, with categories for no formal qualifications, GCSE level qualifications, A-Level or diploma level qualifications and degree level qualifications. As with paternal age, I was unable to include paternal education attainment in empirical models due to significant levels of missing data.

As well as maternal education, it is also argued that maternal employment may be significantly associated with child outcomes. For instance, in the context of cognitive development, Waldfogel *et al.,* (2002) have argued that maternal employment in the early years of a child's life may affect child outcomes through the home environment, breastfeeding, levels of nonmaternal child care in the early years of life and unobserved factors related to both maternal employment in the early years and child outcomes. I entered maternal employment into the model as a binary variable, with a value of 1 if the mother had a job in the first wave of the MCS, and 0 otherwise.

I also included a number of family socioeconomic variables in the various empirical models, as such variables may help control for the high probability that family size and birth order trade-offs may be more pronounced in families with less economic resources. One important socioeconomic variable is household income. A multitude of empirical evidence from the economic and psychological fields has shown that household income is significantly associated with levels of cognitive ability, psychological well-being and other outcomes such as health in childhood (Blau 1999; Guo and Harris 2000; Yeung *et al.,* 2002; Case *et al.,* 2002; Dooley and Stewart 2007; Violato *et al.,* 2011). The household income variable I used in this chapter was a derived measured of equivalised household income, split into quintiles.

The final socioeconomic variable I included in the model was a standardised measure of parental occupation, the NSSEC-5. This measure places occupations into five distinct categories: managerial and professional occupations, intermediate occupations, small employers and own account workers, lower supervisory and technical occupations and semi-routine and routine occupations. To include information from both the mother and father, this was calculated as the highest occupational classification in the family. I included this measure as a categorical variable, with managerial and professional occupations being the omitted category.

In empirical models I also controlled for a number of measures relating to the home learning environment (HLE), which refer to parenting practices that can be seen as being helpful to a child's development. Bradley (2002) has argued that parenting practices such as reading to children and 'warm' interactions are associated with better child development and may in fact mediate the relationship between SES and a range of child development outcome measures. Furthermore, the resource dilution model (Blake 1981) has explicitly related the relationship between family size child outcomes to the HLE, and argues that the introduction of additional siblings will dilute the proportion of resource received by any one child.

As detailed by De La Rochebrochard (2012), the MCS has various measures of the HLE collected over the different waves of the MCS, which correspond to the 'home learning environment index' put forward by Melhuish *et al.,* (2008). The HLE measures in the 4$^{th}$ wave of the MCS include variables related to trips to the library, parental help with child reading and how often the parent draws or paints with the child. I entered each of these variables into the econometric models as categorical variables, with various categories relating to the frequency of these activities taking place.

### 5.5.4 *Missing data*

The estimation sample in this chapter was restricted by levels of missing data. As shown in Table 5.2, the mean and standard deviations of the variables in the full estimation sample were slightly different to those in the full sample, indicating that not accounting for missing data may have led to biased empirical estimates and conclusions. The vast majority of this missing data stemmed from three main sources: the measures of cognitive ability (n=429), the NSSEC-5 measure of parental occupation (n=391) and the Kessler measure of maternal depression (n=630).

In order to minimise any potential bias from missing data, in this chapter I followed the recommendations made by the CLS (who manage the MCS). Plewis (2007) and Hansen (2014) have argued that, where possible, data analysts should use the full battery of survey weights provided by the CLS in order account for levels of non-response. As an illustrative example, a comparison of the weighted and unweighted OLS models (shown in Appendix 5B) imply that ignoring the issue of missing data and not taking into account the survey sampling structure of the MCS may overestimate the impact of family size on child outcomes.

As further robustness checks, I weighted the various regression models by the inverse probability of the cohort child being in the estimation sample, using the methods presented by Bartlett (2012). Models were also estimated without the inclusion of the measures of parental occupation and maternal depression, which together generated a significant proportion of the missing data.

### 5.5.5 *Exclusion criteria*

There were a number of exclusion criteria. Firstly, when estimating the causal effect of family size in 2SLS models using the sibling sex composition instrument, I excluded cohort children with no siblings, as the minimum number of children in a family with any of sibling sex compositions (boy-boy, girl-girl, girl-boy) is two. When estimating the causal effect of family size using the twins in the family instrument, I excluded both cohort children with no siblings and cohort children with one sibling, as the minimum number of children in a family with a cohort child and twin siblings is three.

**Table 5.2- Comparison of characteristics in the MCS sample and the full estimation sample**

| | Full MCS Sample | | | Full Estimation Sample | | |
|---|---|---|---|---|---|---|
| Variable | Mean | Std Dev | N | Mean | Std Dev | N |
| Internalising | 0.008 | 0.994 | 13261 | 0 | 1 | 11796 |
| Externalising | 0.004 | 0.998 | 13261 | 0 | 1 | 11796 |
| Reading | 0.008 | 0.997 | 12832 | 0 | 1 | 11796 |
| Maths | 0.008 | 0.999 | 12998 | 0 | 1 | 11796 |
| Pattern | 0.005 | 0.999 | 12954 | 0 | 1 | 11796 |
| Family Size | 2.555 | 1.104 | 13260 | 2.477 | 0.967 | 11796 |
| Birth Order | 0.883 | 0.918 | 13261 | 0.856 | 0.896 | 11796 |
| Average Birth Spacing | 3.030 | 2.371 | 13261 | 2.982 | 2.314 | 11796 |
| (Average Birth Spacing)$^2$ | 14.800 | 23.014 | 13261 | 14.244 | 21.742 | 11796 |
| Boy | 0.505 | 0.500 | 13261 | 0.503 | 0.500 | 11796 |
| London | 0.118 | 0.323 | 13261 | 0.111 | 0.314 | 11796 |
| North East | 0.028 | 0.165 | 13261 | 0.028 | 0.164 | 11796 |
| North West | 0.077 | 0.266 | 13261 | 0.075 | 0.264 | 11796 |
| Yorkshire/Humber | 0.071 | 0.257 | 13261 | 0.069 | 0.254 | 11796 |
| East Midlands | 0.049 | 0.217 | 13261 | 0.052 | 0.222 | 11796 |
| West Midlands | 0.070 | 0.255 | 13261 | 0.067 | 0.250 | 11796 |
| East England | 0.069 | 0.254 | 13261 | 0.072 | 0.258 | 11796 |
| South East | 0.092 | 0.290 | 13261 | 0.097 | 0.297 | 11796 |
| South West | 0.050 | 0.218 | 13261 | 0.054 | 0.226 | 11796 |
| Wales | 0.150 | 0.357 | 13261 | 0.142 | 0.349 | 11796 |
| Scotland | 0.122 | 0.327 | 13261 | 0.127 | 0.333 | 11796 |
| Northern Ireland | 0.103 | 0.304 | 13261 | 0.105 | 0.306 | 11796 |
| White | 0.838 | 0.368 | 13261 | 0.867 | 0.340 | 11796 |
| Indian | 0.027 | 0.162 | 13261 | 0.026 | 0.159 | 11796 |
| Pakistani | 0.047 | 0.211 | 13261 | 0.036 | 0.186 | 11796 |
| Bangladeshi | 0.018 | 0.131 | 13261 | 0.011 | 0.106 | 11796 |
| Black Caribbean | 0.022 | 0.147 | 13261 | 0.021 | 0.145 | 11796 |
| Black African | 0.022 | 0.148 | 13261 | 0.016 | 0.127 | 11796 |
| Other | 0.024 | 0.153 | 13261 | 0.021 | 0.142 | 11796 |
| Preterm Birth | 0.077 | 0.266 | 13261 | 0.075 | 0.263 | 11796 |
| Low Birth Weight | 0.074 | 0.261 | 13261 | 0.070 | 0.256 | 11796 |
| Poor Maternal Health | 2.327 | 1.011 | 13184 | 2.305 | 1.002 | 11796 |
| Breastfeeding | 0.967 | 0.834 | 13235 | 0.984 | 0.836 | 11796 |
| Pregnant Smoking | 0.146 | 0.353 | 13261 | 0.147 | 0.354 | 11796 |
| Maternal Age | 28.685 | 5.837 | 13260 | 28.870 | 5.739 | 11796 |
| (Maternal Age)$^2$ | 856.911 | 334.473 | 13260 | 866.399 | 330.468 | 11796 |
| Income Quintile | 2.991 | 1.405 | 13243 | 3.103 | 1.385 | 11796 |
| Maternal Education | 1.394 | 0.963 | 13231 | 1.463 | 0.945 | 11796 |
| Maternal Depression | 0.143 | 0.350 | 12631 | 0.137 | 0.344 | 11796 |
| Parental Occupation | 2.437 | 1.629 | 12870 | 2.372 | 1.609 | 11796 |
| Maternal Employment | 0.662 | 0.473 | 13228 | 0.701 | 0.458 | 11796 |
| Painting/Drawing | 4.233 | 1.213 | 13208 | 4.248 | 1.179 | 11796 |
| Help with Reading | 3.310 | 2.020 | 13168 | 3.330 | 2.028 | 11796 |
| Trips to Library | 1.677 | 1.400 | 13190 | 1.692 | 1.388 | 11796 |

This difference in the estimation sample for the two IV strategies also meant that I was unable to estimate both instruments simultaneously, which would have allowed me to formally compare the two identification strategies and also conduct overidentification tests. Furthermore, in all 2SLS models, I only undertook analysis on first or second born children, as it has been argued that the outcomes of later born children may come from an endogenously selected sample (Angrist *et al.,* 2010). Although this significantly reduced the respective estimation samples, it was a necessary condition for the quasi-experimental identification strategies to be internally valid.

There were also two exclusion criteria when estimating the association between birth order and child outcomes. Firstly, I could not conduct analysis on cohort children with no siblings. Secondly, due to small sample sizes, I could not conduct analysis on cohort children with more than four siblings. However, this still allowed me to estimate the relationship between birth order and child outcomes for over 95% of the applicable estimation sample.

### 5.5.6 *Descriptive relationships*

Descriptive statistics for the full estimation sample are displayed in Table 5.3. Around 12% of the full estimation sample were only children, with 47%, 27% and 10% of the cohort children having one, two and three siblings respectively. Only 4% of the cohort children had more than three siblings. Around 42% of the sample were first born children, with 37%, 15% and 5% of the cohort children second, third and fourth born respectively. Only 1% of the cohort children were fifth born or higher.

Appendix 5C shows the descriptive relationships between the average level of the psychological well-being and cognitive ability across the various family sizes and birth orders in bar chart form. For family size, there was a similar pattern across the three child cognitive ability measures, with children from smaller family sizes (either only children or children with one sibling) generally having higher levels of cognitive ability compared to those from larger families. For the pattern construction cognitive test, there was also evidence of a marginal only child disadvantage compared to children with one sibling, implying that in this case, the relationship between family size and child cognitive ability may be non-linear.

| Table 5.3- Descriptive statistics of the full estimation sample (N=11796) | | | | |
|---|---|---|---|---|
| Variable | Mean | Std Dev | Minimum | Maximum |
| Internalising | 0 | 1 | -6.041 | 0.976 |
| Externalising | 0 | 1 | -4.347 | 1.313 |
| Reading | 0 | 1 | -3.220 | 1.861 |
| Maths | 0 | 1 | -1.912 | 2.413 |
| Pattern | 0 | 1 | -3.081 | 2.430 |
| Family Size | 2.477 | 0.967 | 1 | 5 |
| Birth Order | 0.856 | 0.896 | 0 | 3 |
| Average Birth Spacing | 2.982 | 2.314 | 0 | 26 |
| (Average Birth Spacing)$^2$ | 14.244 | 21.742 | 0 | 676 |
| Boy | 0.503 | 0.500 | 0 | 1 |
| London | 0.111 | 0.314 | 0 | 1 |
| North East | 0.028 | 0.164 | 0 | 1 |
| North West | 0.075 | 0.264 | 0 | 1 |
| Yorkshire/Humber | 0.069 | 0.254 | 0 | 1 |
| East Midlands | 0.052 | 0.222 | 0 | 1 |
| West Midlands | 0.067 | 0.250 | 0 | 1 |
| East England | 0.072 | 0.258 | 0 | 1 |
| South East | 0.097 | 0.297 | 0 | 1 |
| South West | 0.054 | 0.226 | 0 | 1 |
| Wales | 0.142 | 0.349 | 0 | 1 |
| Scotland | 0.127 | 0.333 | 0 | 1 |
| Northern Ireland | 0.105 | 0.306 | 0 | 1 |
| White | 0.867 | 0.340 | 0 | 1 |
| Indian | 0.026 | 0.159 | 0 | 1 |
| Pakistani | 0.036 | 0.186 | 0 | 1 |
| Bangladeshi | 0.011 | 0.106 | 0 | 1 |
| Black Caribbean | 0.021 | 0.145 | 0 | 1 |
| Black African | 0.016 | 0.127 | 0 | 1 |
| Other | 0.021 | 0.142 | 0 | 1 |
| Preterm Birth | 0.075 | 0.263 | 0 | 1 |
| Low Birth Weight | 0.070 | 0.256 | 0 | 1 |
| Poor Maternal Health | 2.305 | 1.002 | 1 | 5 |
| Breastfeeding | 0.984 | 0.836 | 0 | 3 |
| Pregnant Smoking | 0.147 | 0.354 | 0 | 1 |
| Maternal Age | 28.870 | 5.739 | 14 | 51 |
| (Maternal Age)$^2$ | 866.399 | 330.468 | 196 | 2601 |
| Income Quintile | 3.103 | 1.385 | 1 | 5 |
| Maternal Education | 1.463 | 0.945 | 0 | 3 |
| Maternal Depression | 0.137 | 0.344 | 0 | 1 |
| Parental Occupation | 2.372 | 1.609 | 1 | 5 |
| Maternal Employment | 0.701 | 0.458 | 0 | 1 |
| Painting/Drawing | 4.248 | 1.179 | 1 | 6 |
| Help with Reading | 3.330 | 2.028 | 1 | 6 |
| Trips to Library | 1.692 | 1.388 | 0 | 6 |

This non-linear descriptive relationship was more clearly shown in the relationship between family size and the two measures of child psychological well-being, which showed an only child disadvantage compared to those children with both one sibling and those children with two siblings.

For birth order, the descriptive relationships showed a negative association between birth order and child cognitive ability, with earlier born children at a significant advantage compared to later born children. This approximately linear relationship was not shown for psychological well-being however, which instead showed first born disadvantages compared to second and third born, with this disadvantage particularly large for levels of internalising behaviour.

## 5.6 Results and Discussion

### 5.6.1 *Family size*

#### 5.6.1.1 *Ordinary least squares*

I first estimated the relationship between family size and the various child outcome measures using OLS regression models. Table 5.4 shows a summary of the empirical estimates from the OLS models for the full estimation sample. In the interests of space, the full regression output for the various OLS models is presented in Appendix 5D.

**Table 5.4- Conditional association between family size and child outcomes in OLS models**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Internalising | Externalising | Reading | Maths | Pattern |
| No Siblings | (Omitted) | (Omitted) | (Omitted) | (Omitted) | (Omitted) |
| One Sibling | -0.001 | -0.077* | -0.022 | -0.031 | 0.032 |
| | (0.046) | (0.043) | (0.041) | (0.042) | (0.044) |
| Two Siblings | -0.128** | -0.126** | -0.059 | -0.062 | 0.007 |
| | (0.053) | (0.054) | (0.052) | (0.050) | (0.048) |
| Three Siblings | -0.222*** | -0.144* | -0.118** | -0.072 | -0.060 |
| | (0.070) | (0.078) | (0.060) | (0.063) | (0.063) |
| More than Three Siblings | -0.238** | -0.180** | -0.084 | -0.107 | -0.136 |
| | (0.093) | (0.088) | (0.083) | (0.086) | (0.092) |
| Observations | 11796 | 11796 | 11796 | 11796 | 11796 |
| R-Squared | 0.141 | 0.165 | 0.203 | 0.118 | 0.111 |

*Notes:* Results from OLS regression models. Omitted category is only children (Family Size = 1).Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%. Each column represents a separate regression, with all models controlling for a range of child, maternal, socioeconomic and household characteristics. Full regression output is displayed in Appendix 5D.

As shown in columns 1 and 2, for the vast majority of family sizes, there was evidence of a significant conditional association between an increased family size and a decreased level of child psychological well-being, once the variety of potentially confounding characteristics were included the model specification. This association was larger for the internalising sub scale than the externalising sub scale, with those cohort children with three or more siblings on average having a 0.24 and 0.18 of a SD disadvantage compared to first born children in terms of internalising and externalising ability respectively. As noted by Goodman *et al.,* (2015), in the context of child development any effect size over 0.1 SD can be considered economically significant, and therefore these differences can be considered substantial.

As shown in columns 3 to 5, for the three measures of cognitive ability, there was little evidence of statistically significant differences by family size. Although there was evidence of a significant negative association between being from a four child family and reading ability (0.118 SD), this significant association was not found for other family sizes, and also was not found for either maths ability or pattern construction in any family size.

As shown by the full regression output in Appendix 5D, the other explanatory variables I included in the model specifications mostly followed the pattern one would expect given the previous theoretical and empirical literature. For example, early life characteristics, such as having a low birth weight and lower levels of breastfeeding, were consistently negatively associated with all child outcome measures. Although being a preterm birth was not statistically significant, this was most probably due to the large correlation with low birth weight. Having an older mother was also shown to be positively associated with child outcomes, although this association was not always statistically significant and was found to be non-linear in certain specifications.

As expected, there was also evidence of a significant socioeconomic gradient in child outcomes across a number of measures, including household income, parental occupation and maternal education. Both maternal physical and mental health were also shown to be significantly negative associated with all child outcomes, with a large and statistically significant association between maternal depression and the two measures of psychological well-being being particularly noteworthy.

**Table 5.5 - OLS regression models with and without the inclusion of the maternal depression and parental occupation variables**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | Internalising | | Externalising | | Reading | | Maths | | Pattern | |
| | Full Estimation Sample | No Maternal Depression or Parental Occupation | Full Estimation Sample | No Maternal Depression or Parental Occupation | Full Estimation Sample | No Maternal Depression or Parental Occupation | Full Estimation Sample | No Maternal Depression or Parental Occupation | Full Estimation Sample | No Maternal Depression or Parental Occupation |
| Family Size = 2 | -0.001 | 0.004 | -0.077* | -0.078* | -0.022 | -0.009 | -0.031 | -0.021 | 0.032 | 0.022 |
| | (0.046) | (0.045) | (0.043) | (0.041) | (0.041) | (0.036) | (0.042) | (0.043) | (0.044) | (0.041) |
| Family Size = 3 | -0.128** | -0.120** | -0.126** | -0.111** | -0.059 | -0.055 | -0.062 | -0.042 | 0.007 | 0.002 |
| | (0.053) | (0.054) | (0.054) | (0.052) | (0.052) | (0.049) | (0.050) | (0.051) | (0.048) | (0.045) |
| Family Size = 4 | -0.222*** | -0.198*** | -0.144* | -0.135* | -0.118** | -0.090 | -0.072 | -0.030 | -0.060 | -0.033 |
| | (0.070) | (0.069) | (0.078) | (0.072) | (0.060) | (0.059) | (0.063) | (0.067) | (0.063) | (0.062) |
| Family Size = >4 | -0.238** | -0.239*** | -0.180** | -0.161** | -0.084 | -0.081 | -0.107 | -0.076 | -0.136 | -0.089 |
| | (0.093) | (0.085) | (0.088) | (0.078) | (0.083) | (0.073) | (0.086) | (0.077) | (0.092) | (0.078) |
| Observations | 11796 | 12575 | 11796 | 12575 | 11796 | 12575 | 11796 | 12575 | 11796 | 12575 |
| R-Squared | 0.141 | 0.095 | 0.165 | 0.140 | 0.203 | 0.202 | 0.118 | 0.124 | 0.111 | 0.120 |

*Notes:* Results from OLS regression models. Omitted category is only children (Family Size = 1).Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%. Each column represents a separate regression, with all models controlling for a range of child, maternal, socioeconomic and household characteristics. Columns 1, 3, 5, 7 & 9 are estimates from the full regression sample. Columns 2, 4, 6, 8 & 10 are the same regressions, with the maternal depression and parental occupation variables excluded.

Finally, evidence showed that a better HLE was positively associated with increased child cognitive ability. However, these associations were not shown for the two measures of psychological well-being, and were also not always statistically significant. As shown in Table 5.5, the results were robust to the exclusion of both the maternal mental health and parental occupational variables (which together generated a significant amount of missing data). Furthermore, as shown in Appendix 5E, the results were also robust to the implementation of IPWs to control for missing data.

#### 5.6.1.2 *Two stage least squares*

The estimates from OLS models will be biased if the error term is not exogenous to the main equation, which was very likely in this case. Therefore, I next estimated the relationship between family size and the various child outcome measures using 2SLS models, which explicitly attempted to control for the endogeneity almost certainly present in the OLS models. Unlike the OLS models, I was unable to account for the potential non-linear relationship between family size and child outcomes, as this would have required a separate instrument for each specified family size[22] and therefore a considerably larger dataset. Consequently, similar to the study of Angrist *et al.,* (2010), the family size variables I included in the empirical specifications were binary variables. When using the sibling sex composition IV strategy, the family size variable took the value of 1 if the family size was three or over, and 0 otherwise, in order to capture the marginal effect of moving from a two child household to a three child household. When using the twin births IV strategy, the family size variable took the value of 1 if the family size was four or over, and 0 otherwise, in order to capture the marginal effect of moving from a three child household to a four child household.

Before presenting the empirical estimates of family size on child psychological well-being and cognitive ability, I estimated the first stage validity of the IV strategies to ensure that the strategies were internally valid. In order to be a valid instrument, the sibling sex composition and twin births IV strategies must satisfy two main conditions. Firstly, the IV must be

[22] Using a significantly larger dataset, Mogstad and Wiswall (2016) have examined the non-linear causal relationship between family size and child outcomes using 'unrestricted' family size models. This was beyond the scope of this empirical chapter.

significantly related to family size. Tables 5.6 and 5.7 exhibit the first stage validity of the two IV strategies.

Table 5.6 shows that the having a same sex sibship pairing increased the probability of having a third child by 0.066 once a full set of characteristics were controlled for, with the magnitude of this coefficient in line with the majority of the past empirical literature utilising this instrument, including Conley and Glauber (2006), Angrist *et al.,* (2010) and Black *et al.,* (2011). Table 5.7 shows that having a twin in the family increased the probability of having a fourth child by 0.403 once a full set of characteristics were controlled for. If the incidence of twin births was indeed random, one would expect the effect of a twin birth on family size immediately after birth to be very close to 1, as the mother would have one more child than originally expected. However, as argued by Braakmann and Wildman (2016), the time that has passed since the twin birth occurred will help to explain this reduced effect, as families will have had time to adjust their future fertility in response to the incidence of twin births, with some being able to return to their planned family size. Despite this, the instrument remained strong, implying that a significant number of mothers end up with a larger family size than originally intended[23].

**Table 5.6- First stage estimates: effect of sibling sex composition on the probability of family size=>3**

| | (1) | (2) |
|---|---|---|
| | No Controls | Full Set of Controls |
| Samesex=1 | 0.070*** | 0.066*** |
| | (0.012) | (0.010) |
| Kleibergen-Paap LM | 33.038*** | 33.151*** |
| | (0.000) | (0.000) |
| Cragg-Donald Wald | 45.927 | 45.707 |
| Kleibergen-Paap Wald | 33.255 | 33.099 |
| R-Squared | 0.006 | 0.133 |
| Observations | 7885 | 7885 |

*Notes:* Taylor-Linearized Standard Errors in Parentheses. ***, ** & * indicate statistical significance at the 1%, 5% & 10% levels

For both instruments, the null hypothesis of underidentifcation in the Kleibergen-Paap LM test was also rejected at all significance levels, implying that the excluded instruments were sufficiently correlated to the assumed endogenous regressor, family size. Furthermore, the

[23] Ideally, I would have wanted to examine the impact of twin births at last birth on completed family size, however the sample size and nature of the MCS make this unfeasible.

null hypothesis of weak identification in the Cragg-Donald and Kleibergen-Paap Wald Tests was also rejected at all significance levels, implying that the excluded instruments were not only sufficiently correlated to the endogenous regressor, but did not suffer from the weak instrument problem that can cause IV models to perform poorly.

**Table 5.7- First stage estimates: effect of twin births on the probability of family Size=>4**

| | (1) | (2) |
|---|---|---|
| | No Controls | Full Set of Controls |
| Twin Births in Family =1 | 0.429*** | 0.403*** |
| | (0.058) | (0.056) |
| Kleibergen-Paap LM | 31.946 | 26.819 |
| | (0.000) | (0.000) |
| Cragg-Donald Wald | 118.243 | 102.753 |
| Kleibergen-Paap Wald | 52.830 | 42.676 |
| R-Squared | 0.041 | 0.146 |
| Observations | 2379 | 2379 |

*Notes:* Taylor-Linearized Standard Errors in Parentheses. *, ** & *** indicates statistical significance at the 10%, 5% & 1% levels

The second condition for the IV to be valid is that the instrument cannot be correlated with the unobserved error term. Although this condition is formally untestable in a just-identified setting such as this, if the IVs are indeed exogenous, one would expect the covariates to be evenly balanced between the samples in which the sibling sex composition or twin births instruments are equal to 1 and the samples in which the instruments are equal to 0. If there are systematic and significant differences between the observable characteristics, this would imply that the instrument may not be randomly assigned, and that there also may be significant differences in unobservable characteristics between the two samples that invalidate the exclusion criteria. As a specification test for such exogeneity, I checked whether the observed covariates were balanced between the different group using simple two sample t-tests, weighted to take into account the sampling structure of the MCS.

Table 5.8 shows a comparison of observable characteristics for those cohort children from families where the first two siblings are the same gender and those cohort children from families where the first two siblings are different gender. As shown, aside from family size, in general the observed covariates were well balanced. However, there were some statistically significant differences that should be taken into account.

**Table 5.8- Comparison of characteristics with and without the sibling sex composition instrument**

| | Samesex=0 | | Samesex=1 | | |
|---|---|---|---|---|---|
| Variable | Mean | Standard Deviation | Mean | Standard Deviation | P-Value Means Diff |
| Family Size>=3 | 0.273 | 0.445 | 0.331 | 0.470 | 0.000*** |
| Birth Order | 0.551 | 0.497 | 0.547 | 0.498 | 0.963 |
| Average Birth Spacing | 3.073 | 1.897 | 3.208 | 1.917 | 0.018** |
| $(\text{Average Birth Spacing})^2$ | 13.042 | 19.681 | 13.968 | 17.159 | 0.091* |
| Boy | 0.487 | 0.500 | 0.519 | 0.500 | 0.120 |
| London | 0.112 | 0.005 | 0.112 | 0.005 | 0.561 |
| North East | 0.024 | 0.152 | 0.028 | 0.164 | 0.389 |
| North West | 0.076 | 0.265 | 0.070 | 0.255 | 0.752 |
| Yorkshire | 0.071 | 0.258 | 0.068 | 0.251 | 0.762 |
| East Midlands | 0.049 | 0.216 | 0.058 | 0.235 | 0.068* |
| West Midlands | 0.071 | 0.256 | 0.060 | 0.237 | 0.124 |
| East England | 0.073 | 0.260 | 0.074 | 0.262 | 0.853 |
| South East | 0.101 | 0.301 | 0.107 | 0.309 | 0.639 |
| South West | 0.053 | 0.225 | 0.061 | 0.239 | 0.428 |
| Wales | 0.135 | 0.342 | 0.144 | 0.351 | 0.216 |
| Scotland | 0.135 | 0.342 | 0.122 | 0.327 | 0.119 |
| Northern Ireland | 0.099 | 0.299 | 0.098 | 0.297 | 0.980 |
| White | 0.878 | 0.005 | 0.879 | 0.005 | 0.349 |
| Indian | 0.025 | 0.156 | 0.030 | 0.171 | 0.178 |
| Pakistani | 0.030 | 0.170 | 0.031 | 0.172 | 0.073* |
| Bangladeshi | 0.009 | 0.093 | 0.009 | 0.096 | 0.712 |
| Black Caribbean | 0.021 | 0.144 | 0.017 | 0.130 | 0.925 |
| Black African | 0.016 | 0.125 | 0.011 | 0.106 | 0.107 |
| Other | 0.020 | 0.139 | 0.020 | 0.139 | 0.683 |
| Preterm Birth | 0.069 | 0.254 | 0.073 | 0.261 | 0.306 |
| Low Birth Weight | 0.067 | 0.244 | 0.068 | 0.258 | 0.304 |
| Maternal Health | 2.255 | 0.990 | 2.257 | 0.986 | 0.669 |
| Breastfeeding | 1.033 | 0.842 | 1.022 | 0.837 | 0.966 |
| Smoking in Pregnancy | 0.135 | 0.341 | 0.136 | 0.343 | 0.724 |
| Maternal Age | 28.315 | 5.601 | 28.339 | 5.561 | 0.440 |
| $(\text{Maternal Age})^2$ | 833.084 | 318.230 | 833.995 | 315.218 | 0.527 |
| Income Quintile | 3.256 | 1.362 | 3.226 | 1.342 | 0.405 |
| Maternal Education | 1.561 | 0.952 | 1.548 | 0.953 | 0.667 |
| Maternal Depression | 0.124 | 0.330 | 0.128 | 0.334 | 0.452 |
| Parental Occupation | 2.210 | 1.554 | 2.278 | 1.575 | 0.104 |
| Maternal Employment | 0.750 | 0.433 | 0.742 | 0.437 | 0.986 |
| Painting/Drawing | 4.240 | 1.142 | 4.242 | 1.133 | 0.824 |
| Help with Reading | 3.370 | 2.050 | 3.335 | 2.034 | 0.324 |
| Trips to the Library | 1.735 | 1.364 | 1.730 | 1.375 | 0.613 |
| *N* | *3931* | | *3954* | | |

*Notes:* Differences based on a two-sample t-test with unequal variances, weighted to take account of the sampling structure. *, ** & *** indicates statistical significance at the 10%, 5% & 1% levels

| **Table 5.9- Comparison of characteristics with and without the twin births instrument** | | | | | |
|---|---|---|---|---|---|
| | Twin Births=0 | | Twin Births=1 | | |
| Variable | Mean | Standard Deviation | Mean | Standard Deviation | P-Value Means Diff |
| Family Size>=4 | 0.148 | 0.355 | 0.529 | 0.502 | 0.000*** |
| Birth Order | 0.524 | 0.484 | 0.359 | 0.441 | 0.000*** |
| Average Birth Spacing | 3.392 | 1.443 | 3.238 | 1.672 | 0.235 |
| (Average Birth Spacing)$^2$ | 13.585 | 9.975 | 13.250 | 10.994 | 0.320 |
| Boy | 0.501 | 0.500 | 0.529 | 0.502 | 0.936 |
| London | 0.128 | 0.006 | 0.206 | 0.041 | 0.052* |
| North East | 0.021 | 0.145 | 0.024 | 0.152 | 0.821 |
| North West | 0.079 | 0.270 | 0.035 | 0.186 | 0.066* |
| Yorkshire | 0.070 | 0.256 | 0.024 | 0.152 | 0.681 |
| East Midlands | 0.044 | 0.205 | 0.024 | 0.152 | 0.222 |
| West Midlands | 0.073 | 0.260 | 0.106 | 0.310 | 0.595 |
| East England | 0.077 | 0.267 | 0.071 | 0.258 | 0.612 |
| South East | 0.095 | 0.293 | 0.059 | 0.237 | 0.021** |
| South West | 0.051 | 0.220 | 0.047 | 0.213 | 0.630 |
| Wales | 0.130 | 0.337 | 0.129 | 0.338 | 0.717 |
| Scotland | 0.109 | 0.312 | 0.176 | 0.383 | 0.053* |
| Northern Ireland | 0.128 | 0.334 | 0.094 | 0.294 | 0.378 |
| White | 0.078 | 0.008 | 0.804 | 0.041 | 0.961 |
| Indian | 0.024 | 0.153 | 0.047 | 0.213 | 0.719 |
| Pakistani | 0.065 | 0.247 | 0.035 | 0.186 | 0.803 |
| Bangladeshi | 0.018 | 0.134 | 0.012 | 0.108 | 0.114 |
| Black Caribbean | 0.021 | 0.143 | 0.000 | 0.000 | 0.000*** |
| Black African | 0.019 | 0.137 | 0.047 | 0.213 | 0.255 |
| Other | 0.021 | 0.143 | 0.024 | 0.152 | 0.947 |
| Preterm Birth | 0.075 | 0.263 | 0.141 | 0.350 | 0.183 |
| Low Birth Weight | 0.072 | 0.258 | 0.129 | 0.338 | 0.303 |
| Maternal Health | 2.259 | 0.998 | 2.365 | 1.153 | 0.920 |
| Breastfeeding | 1.011 | 0.846 | 1.094 | 0.750 | 0.178 |
| Smoking in Pregnancy | 0.141 | 0.348 | 0.153 | 0.362 | 0.820 |
| Maternal Age | 26.848 | 5.293 | 26.482 | 6.033 | 0.765 |
| (Maternal Age)$^2$ | 748.807 | 288.694 | 737.282 | 335.765 | 0.920 |
| Income Quintile | 2.909 | 1.344 | 2.824 | 1.236 | 0.787 |
| Maternal Education | 1.505 | 0.994 | 1.494 | 0.881 | 0.556 |
| Maternal Depression | 0.139 | 0.346 | 0.176 | 0.383 | 0.685 |
| Parental Occupation | 2.425 | 1.623 | 2.494 | 1.659 | 0.201 |
| Maternal Employment | 0.652 | 0.476 | 0.741 | 0.441 | 0.153 |
| Painting/Drawing | 4.331 | 1.163 | 4.400 | 1.104 | 0.852 |
| Help with Reading | 3.395 | 2.034 | 3.600 | 2.013 | 0.298 |
| Trips to the Library | 1.683 | 1.407 | 1.600 | 1.329 | 0.440 |
| $N$ | 2294 | | 85 | | |

*Notes:* Differences based on a two-sample t-test with unequal variances, weighted to take account of the sampling structure. *, ** & *** indicates statistical significance at the 10%, 5% & 1% levels

Firstly, in the sample of cohort children from families where the first two siblings were of the same gender, there were marginally more cohort children from Pakistani origin and more cohort children residing in the East Midlands. Minor differences such as these were controlled for through the inclusion of a full set of dummy variables for ethnicity and geographical area.

Secondly, in the sample of cohort children from families where the first two siblings were of the same gender, there were marginally higher average spacings between the births within the family, with this potentially being driven by the difference in family size between the two groups. This difference was also relatively small in magnitude, and was controlled for through the inclusion of birth spacing variables in the various econometric models. Overall, the conditional randomness of the sibling sex composition instrument was supported.

Table 5.9 shows a comparison of the observed characteristics for those cohort children from families who have experienced a twin birth, and those who have not. As shown, in general the observed characteristics were well-balanced. However, there were again some differences that should be taken into account. Firstly, in the sample of cohort children from families with a twin birth, there were more children from London and Scotland, and less cohort children from the North West, South East and of Black Caribbean ethnicity. These significant differences were almost certainly driven by the small sample of those with a twin birth in the family, and were controlled through the inclusion of a full set of region and ethnicity dummy variables. The only other variable that showed significant change was that of birth order, with this difference once more probably driven by the significant correlation between family size and birth order. Once more, these differences were relatively small in magnitude and were controlled for through the inclusion of the applicable variables, meaning that overall, the conditional randomness of the twin births instrument was also supported.

Given that the two IV strategies both appear to be valid, Tables 5.10- 5.13 show a summary of the empirical estimates from the 2SLS models using the respective instruments. In the interests of space, the full regression output is shown in Appendix 5F. I first estimated the causal effect of family size on child outcomes using the sibling sex composition instrument. At this point it is worth reminding the reader that in order for the identification strategy using this IV to be valid, this estimation sample was made up of first and second born children who had at least one sibling, which explained the significant reduction in the estimation sample size (around 67% of the full estimation sample was retained for these models).

As shown in both Table 5.10 and 5.11, both the Wald estimators and 2SLS models using the sibling sex composition instrument had very large point estimates (with effect sizes in the fully controlled models ranging from 0.328 SD for maths ability to 0.531 SD for pattern construction), counterintuitively implying that not accounting for the endogeneity of family size in OLS models may severely underestimate the negative impact that an increased family size can have on both child psychological well-being and cognitive ability. This magnitude of coefficient was also similar to that of Silles (2010), who implemented the sibling sex composition instrument in the context of child outcomes using the NCDS. However, given that the associated standard errors of these IV estimators were also significantly larger than those in the OLS models, the estimates were rendered statistically insignificant at all appropriate levels[24]. These large standard errors almost certainly reflected the introduction of an additional source of uncertainty (in the form of the instrument, which by definition is imperfectly correlated with the explanatory variable) (Wooldridge 2010).

**Table 5.10- Family size and child psychological well-being in 2SLS models using the sibling sex composition instrument**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Internalising | Internalising | Externalising | Externalising |
| Three or More Siblings | -0.534<br>(0.393) | -0.348<br>(0.384) | -0.571<br>(0.390) | -0.376<br>(0.403) |
| Covariates | × | ✓ | × | ✓ |
| Observations | 7885 | 7885 | 7885 | 7885 |
| R-Squared | 0.014 | 0.139 | 0.037 | 0.150 |

*Notes:* Results from 2SLS regression models using the sex composition of the first two siblings as an instrument for family size. This sample is restricted to first and second born children who have at least one sibling. Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%. Each column represents a separate regression, with all models controlling for a range of child, maternal, socioeconomic and household characteristics. Full regression output is found in Appendix 5F.

[24] It must be noted that the estimates using a linear measure of family size were almost identical to those using a binary measure of family size presented above. In the interests of space the estimates using the linear measure of family size are not presented in the main text or the appendices.

| **Table 5.11- Family size and child cognitive ability in 2SLS models using the sibling sex composition instrument** | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Reading | Reading | Maths | Maths | Pattern | Pattern |
| Three or More Siblings | -0.607<br>(0.371) | -0.492<br>(0.327) | -0.432<br>(0.377) | -0.328<br>(0.353) | -0.643<br>(0.484) | -0.531<br>(0.444) |
| Covariates | ✗ | ✓ | ✗ | ✓ | ✗ | ✓ |
| Observations | 7885 | 7885 | 7885 | 7885 | 7885 | 7885 |
| R-Squared | 0.040 | 0.154 | 0.019 | 0.109 | 0.054 | 0.072 |

*Notes:* Results from 2SLS regression models using the sex composition of the first two siblings as an instrument for family size. This sample is restricted to first and second born children who have at least one sibling. Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%. Each column represents a separate regression, with all models controlling for a range of child, maternal, socioeconomic and household characteristics. Full regression output is found in Appendix 5F.

As shown in the full regression output found in Appendix 5F, the other covariates included in the various 2SLS regression models followed the pattern that one would expect given the past theoretical and empirical literature, and were extremely similar to those from the full OLS model specifications.

Next, I estimated the causal effect of family size on child outcomes using the twin births instrument. It worth reminding the reader that in order for the identification strategy using this instrument to be internally valid, the estimation sample was made up of first and second born children who had at least two siblings, and was therefore significantly smaller than the full estimation sample or the estimation sample when using the sibling sex composition instrument (just over 20% of the full estimation sample were included in these models).

As shown in Table 5.12, there was little evidence of a significant causal effect of family size on child psychological well-being, either in the Wald estimators or the full 2SLS models. Unlike the 2SLS estimates using the sibling sex composition instrument, these estimates were both qualitatively and quantitatively in line with those from the OLS models. However, the inflated standard errors associated with IV methods rendered the coefficients statistically insignificant.

As shown in Table 5.13, the lack of a statistically significant causal effect was also found for the three measures of child cognitive ability, with the reading ability coefficient in fact turning positive. For the majority of the child outcome measures, the introduction of the variety of controlling variables strengthened the negative relationship between the assumed endogenous family size variable and the various child outcomes. Although these results may have been explained by the relatively small sample size for studies in this area, it is also possible that these results were explained by unobserved confounding rendering the controlling covariates endogenous, despite Table 5.8 showing the covariates to be relatively evenly balanced across the treatment groups. This issue will be examined further in the discussion. As shown by the full regression output in Appendix 5G, the controlling explanatory variables in models of both sets of child outcomes mostly followed the pattern one would expect given the previous theoretical and empirical literature, and in general were similar to those from the OLS models and 2SLS models using the sibling sex composition instrument.

**Table 5.12- Family size and child psychological well-being in 2SLS models using the twin births instrument**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Internalising | Internalising | Externalising | Externalising |
| Four or More Siblings | -0.097<br>(0.271) | -0.150<br>(0.280) | -0.144<br>(0.243) | -0.181<br>(0.329) |
| Covariates | × | ✓ | × | ✓ |
| Observations | 2379 | 2379 | 2379 | 2379 |
| R-Squared | 0.022 | 0.155 | 0.016 | 0.195 |

*Notes:* Results from 2SLS regression models using twin births as an instrument for family size. This sample is restricted to first and second born children who have at least two siblings. Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%. Each column represents a separate regression, with all models controlling for a range of child, maternal, socioeconomic and household characteristics. Full regression output is displayed in Appendix 5G.

**Table 5.13- Family size and child cognitive ability in 2SLS models using the twin births instrument**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Reading | Reading | Maths | Maths | Pattern | Pattern |
| Four or More Siblings | 0.300<br>(0.341) | 0.204<br>(0.260) | -0.170<br>(0.247) | -0.186<br>(0.232) | -0.210<br>(0.297) | -0.079<br>(0.291) |
| Covariates | × | ✓ | × | ✓ | × | ✓ |
| Observations | 2379 | 2379 | 2379 | 2379 | 2379 | 2379 |
| R-Squared | 0.034 | 0.258 | 0.008 | 0.186 | 0.010 | 0.166 |

*Notes:* Results from 2SLS regression models using twin births as an instrument for family size. This sample is restricted to first and second born children who have at least two siblings. Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%. Each column represents a separate regression, with all models controlling for a range of child, maternal, socioeconomic and household characteristics. Full regression output is found in Appendix 5G.

### 5.6.2 *Birth order*

#### 5.6.2.1 *Ordinary least squares*

Next, I estimated the relationship between birth order and the various child outcomes. As shown in the full regression output of Appendices 5D, 5F and 5G, when included as a controlling variable in the OLS and 2SLS models investigating the impact of family size on child outcomes, birth order was significantly correlated with the various child outcome measures in a number of empirical specifications. However, birth order estimates from such models are likely to be biased, due to difficulties disentangling the extremely strong correlation between birth order and family size.

Tables 5.14 and 5.15 show a summary of the empirical estimates from the OLS models. In the interests of space, the full regression output from these models is shown in Appendix 5H. It is worth reminding the reader at this point that due to the need to estimate birth order effects within specific family sizes to reduce levels of endogeneity, each regression coefficient in Tables 5.14 and 5.15 was estimated from a different regression model.

I first estimated the association between birth order and child psychological well-being. For the measure of Internalising Ability (comprised of the conduct and hyperactivity subscales of the SDQ), there was a clear pattern of last born *advantage*, with this relationship present in all three distinct family sizes. This association can be considered large in magnitude (ranging from 0.17 SD in two child families to 0.32 in four children families) and was shown to be statistically significant. There was also evidence of a middle born advantage compared to first born children in four child families, with the magnitude of this relationship large (0.25 SD) and statistically significant.

However, the evidence for an association between birth order and the measure of Externalising Ability (comprised of the emotional and peer subscales of the SDQ) was more mixed. Although there was shown to be a large and statistically significant last born advantage is four child families, there was also shown to be a significant middle born disadvantage in three child families, and little evidence of significant differences for other birth order-family size combinations.

**Table 5.14- Conditional association between birth order and child psychological well-being in OLS models**

| | Internalising Ability | | | Externalising Ability | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Two Child Family | Three Child Family | Four Child Family | Two Child Family | Three Child Family | Four Child Family |
| Middle Born | - | 0.053 | 0.251* | - | -0.153*** | 0.250 |
| | | (0.058) | (0.151) | | (0.056) | (0.162) |
| Observations | - | 1994 | 759 | - | 1994 | 759 |
| R-Squared | | 0.157 | 0.246 | | 0.196 | 0.270 |
| Last Born | 0.168*** | 0.186*** | 0.319*** | 0.004 | 0.056 | 0.167** |
| | (0.034) | (0.046) | (0.085) | (0.035) | (0.045) | (0.080) |
| Observations | 5506 | 3229 | 1167 | 5506 | 3229 | 1167 |
| R-Squared | 0.151 | 0.151 | 0.191 | 0.168 | 0.191 | 0.225 |

*Notes:* Results from OLS regression models. This sample is restricted to children who have at least one sibling. Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%. Each column represents a separate regression, with all models controlling for a range of child, maternal, socioeconomic and household characteristics. Full regression output in found in Appendix 5H.

**Table 5.15- Relationship between birth order and child cognitive ability in OLS models**

| | Reading Ability | | | Maths Ability | | | Pattern Construction | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | Two Child Family | Three Child Family | Four Child Family | Two Child Family | Three Child Family | Four Child Family | Two Child Family | Three Child Family | Four Child Family |
| Middle Born | - | - 0.088 | 0.017 | - | -0.022 | 0.118 | - | 0.081 | -0.024 |
| | | (0.058) | (0.097) | | (0.062) | (0.107) | | (0.059) | (0.137) |
| Observations | - | 1994 | 759 | - | 1994 | 759 | - | 1994 | 759 |
| R-Squared | | 0.257 | 0.362 | | 0.195 | 0.248 | | 0.163 | 0.189 |
| Last Born | -0.119*** | -0.168*** | -0.040 | -0.047 | -0.025 | 0.113 | -0.055 | -0.025 | 0.088 |
| | (0.031) | (0.048) | (0.075) | (0.032) | (0.043) | (0.069) | (0.039) | (0.043) | (0.079) |
| Observations | 5506 | 3229 | 1167 | 5506 | 3229 | 1167 | 5506 | 3229 | 1167 |
| R-Squared | 0.176 | 0.230 | 0.319 | 0.107 | 0.150 | 0.181 | 0.108 | 0.135 | 0.148 |

*Notes:* Results from OLS regression models. This sample is restricted to children who have at least one sibling. For Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%. Each column represents a separate regression, with all models controlling for a range of child, maternal, socioeconomic and household characteristics. Full regression output in found in Appendix 5H.

Secondly, I estimated the conditional association between birth order and the various measures of child cognitive ability. As with the estimates of the effect of family size, across the various outcomes measures there was little consistent evidence of an association between birth order and child cognitive ability. Although there was evidence of a large and statistically significant last born disadvantage for reading ability in two child and three child families, this relationship was not present for either the maths ability or pattern construction cognitive tests.

#### 5.6.2.2 *Nearest neighbour matching*

Next, I estimated the association between birth order and child outcomes using NNM models, with the results shown in Tables 5.16 and 5.17. For the empirical estimates from NNM models to be internally valid, it is important that the observed covariates are reasonably well balanced between the untreated and treated groups.

Ideally, I would have wanted to use the method of Imai and Ratkonic (2014), which formally examines the balance of the covariates over the different treatment levels through an overidentification test. However, due to the NNM model being the specification of choice in this chapter rather than PSM or IPW, this was not possible.

Therefore, as a form of robustness check I examined the balancing of the covariates across the various treatment groups. At this point it is once more worth noting that due to problems incorporating continuous variables into NNM models (Abidie and Imbens 2011) and the risks of over-parameterisation (Caliendo and Kopeining 2005), a number of continuous and categorical variables were converted into binary variables for the matching procedure. Details of these variable changes for the NNM models are explained in detail in Table 5.1.

As shown in Table 5.18, in the vast majority of cases, the matching procedure significantly reduced the variance ratios to values relatively close to 1 (a value of 1 in this context implies perfect balance between the covariates across the treatment groups). However, there were some larger imbalances across the treatment groups that must be taken into account. As asserted by Rubin (2001), variables can be considered significantly unbalanced if the variance ratios are greater than 2.0 or lower than 0.5.

**Table 5.16- Association between birth order and child psychological well-being in NNM models**

| | Internalising Ability | | | Externalising Ability | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Two Child Family | Three Child Family | Four Child Family | Two Child Family | Three Child Family | Four Child Family |
| Middle Born | - | -0.051 | 0.080 | | -0.146*** | -0.051 |
| | | (0.056) | (0.156) | | (0.055) | (0.136) |
| Observations | - | 1994 | 729 | | 1994 | 729 |
| Last Born | 0.161*** | 0.120*** | 0.257*** | 0.018 | 0.037 | 0.175** |
| | (0.032) | (0.044) | (0.087) | (0.032) | (0.046) | (0.087) |
| Observations | 5506 | 3229 | 1159 | 5506 | 3229 | 1159 |

*Notes:* Results from OLS regression models. This sample is restricted to children who have at least one sibling. Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%. Each column represents a separate regression, with all models controlling for a range of child, maternal, socioeconomic and household characteristics

**Table 5.17- Relationship between birth order and child cognitive ability in NNM models**

| | Reading Ability | | | Maths Ability | | | Pattern Construction | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | Two Child Family | Three Child Family | Four Child Family | Two Child Family | Three Child Family | Four Child Family | Two Child Family | Three Child Family | Four Child Family |
| Middle Born | | -0.073 | -0.044 | | 0.013 | 0.221 | | 0.017 | -0.116 |
| | | (0.052) | (0.132) | | (0.058) | (0.151) | | (0.054) | (0.164) |
| Observations | | 1994 | 729 | | 1994 | 729 | | 1994 | 729 |
| Last Born | -0.049 | -0.141*** | 0.010 | -0.016 | -0.062 | 0.62 | -0.029 | -0.067 | 0.98 |
| | (0.031) | (0.044) | (0.078) | (0.034) | (0.047) | (0.082) | (0.035) | (0.048) | (0.084) |
| Observations | 5506 | 3229 | 1159 | 5506 | 3229 | 1159 | 5506 | 3229 | 1159 |

*Notes:* Results from OLS regression models. This sample is restricted to children who have at least one sibling. For Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%. Each column represents a separate regression, with all models controlling for a range of child, maternal, socioeconomic and household characteristics

**Table 5.18- Comparison of variance ratios for balancing covariates in NNM estimators**

| Variable | Family Size=2 Raw | Family Size=2 Matched | Family Size=3 Raw | Family Size=3 Matched | Family Size=3, No last born Raw | Family Size=3, No last born Matched | Family Size=4 Raw | Family Size=4 Matched | Family Size=4, No last born Raw | Family Size=4, No last born Matched |
|---|---|---|---|---|---|---|---|---|---|---|
| Birth Spacing | 0.896 | 1.000 | 0.977 | 1.000 | 1.445 | 1.000 | 0.888 | 1.000 | 1.636 | 1.000 |
| Boy | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.006 | 1.000 | 1.018 | 1.000 |
| North East | 1.127 | 1.012 | 1.188 | 1.094 | 1.179 | 1.035 | 0.624 | 1.000 | 1.956 | 1.978 |
| North West | 0.952 | 0.991 | 0.956 | 0.960 | 0.880 | 0.948 | 0.991 | 0.946 | 1.162 | 1.357 |
| Yorkshire | 1.085 | 0.987 | 0.884 | 1.028 | 0.885 | 1.070 | 0.726 | 1.000 | 1.527 | 1.070 |
| East Midlands | 1.237 | 1.015 | 1.384 | 0.976 | 1.029 | 1.286 | 1.167 | 1.053 | 1.868 | 1.888 |
| West Midlands | 1.137 | 1.010 | 0.867 | 1.092 | 0.955 | 1.011 | 1.040 | 0.976 | 0.909 | 0.934 |
| East England | 1.080 | 0.996 | 1.011 | 0.963 | 1.431 | 0.991 | 0.869 | 1.032 | 1.577 | 1.287 |
| South East | 0.898 | 0.997 | 0.996 | 1.015 | 1.237 | 1.066 | 1.195 | 1.000 | 0.858 | 1.699 |
| South West | 1.049 | 1.000 | 0.945 | 1.031 | 0.787 | 1.017 | 1.030 | 1.000 | 0.855 | 1.033 |
| Wales | 1.102 | 1.000 | 1.045 | 0.990 | 0.936 | 1.018 | 0.991 | 1.015 | 1.593 | 0.917 |
| Scotland | 0.973 | 1.004 | 1.126 | 0.989 | 1.193 | 0.988 | 0.995 | 0.977 | 0.704 | 0.927 |
| N Ireland | 0.814 | 1.004 | 0.960 | 1.038 | 1.063 | 0.961 | 1.167 | 1.035 | 0.896 | 0.837 |
| White | 0.875 | 1.000 | 0.935 | 1.000 | 0.944 | 1.000 | 1.064 | 1.000 | 0.916 | 1.000 |
| Low Gest Age | 0.827 | 1.152 | 0.955 | 1.057 | 0.969 | 1.123 | 1.239 | 1.183 | 1.147 | 1.661 |
| Low Birth Weight | 0.694 | 1.000 | 0.873 | 1.000 | 0.948 | 1.000 | 1.052 | 1.000 | 0.635 | 1.000 |
| Maternal Health | 1.016 | 1.059 | 1.049 | 1.043 | 1.044 | 1.069 | 1.002 | 1.022 | 0.989 | 0.999 |
| Breastfeeding | 1.252 | 1.162 | 1.156 | 1.115 | 1.274 | 1.224 | 1.056 | 1.062 | 1.419 | 1.163 |
| Preg Smoke | 0.988 | 1.244 | 1.047 | 1.190 | 1.607 | 1.226 | 0.888 | 1.254 | 4.164 | 1.862 |
| Maternal Age | 1.224 | 1.031 | 1.165 | 0.983 | 1.464 | 1.270 | 1.058 | 0.924 | 1.260 | 1.175 |
| Income Quintile | 0.999 | 1.004 | 0.996 | 0.984 | 0.957 | 0.963 | 1.063 | 1.176 | 0.765 | 1.081 |
| Maternal Education | 0.979 | 0.985 | 0.920 | 0.953 | 0.959 | 0.966 | 0.812 | 0.922 | 0.808 | 0.847 |
| Maternal Depression | 0.951 | 1.242 | 1.135 | 1.466 | 1.378 | 1.085 | 0.948 | 1.364 | 1.261 | 1.531 |
| Parental Occupation | 1.002 | 1.007 | 0.997 | 0.999 | 1.000 | 0.999 | 0.951 | 1.052 | 0.912 | 0.923 |
| Mat Employment | 1.943 | 1.573 | 1.128 | 1.098 | 1.477 | 1.426 | 0.987 | 1.032 | 1.064 | 1.081 |
| Painting | 1.064 | 1.053 | 1.018 | 1.019 | 1.057 | 1.055 | 0.995 | 0.994 | 1.026 | 1.042 |
| Reading | 1.014 | 1.080 | 0.995 | 1.040 | 1.064 | 1.060 | 0.997 | 1.038 | 0.977 | 1.071 |
| Library | 0.995 | 1.065 | 0.947 | 1.031 | 0.982 | 0.994 | 0.933 | 1.039 | 0.937 | 1.000 |
| N | 5506 | 5750 | 3229 | 2470 | 1994 | 2354 | 1159 | 812 | 729 | 1276 |

In the larger family size models, there were several significant disparities in the regional variables, with these differences most likely driven by the small number of individuals in certain regions in this reduced sample[25]. More importantly, there were several larger differences in variables such as maternal smoking during pregnancy, maternal depression and maternal employment, with the vast majority of these differences found in the larger family size models. These significant differences may have again been driven by the relatively small sample sizes in these models. Although I attempted to control for these differences by exact matching on each of these variables, this unfortunately resulted in the models not being able to converge. These imbalances should therefore be taken into account when interpreting the NNM results, particularly for the larger family sizes.

In general, the estimates from the NNM models were qualitatively in line with those from the OLS models shown in Tables 5.14 and 5.15. For instance, for the internalising subscale of the SDQ, there was a large last born advantage across all family sizes. Although the magnitude of these estimates was marginally lower than the corresponding estimates from the OLS models, they were still relatively large, ranging from 0.12 SD in three child families to 0.26 SD in four child families, and shown to be statistically significant. For externalising behaviour, there was evidence of a large (0.18 SD) and statistically significant last born advantage in four child families, although this association was not shown in smaller families.

Similar to the OLS estimators, there was limited evidence for an association between birth order and child cognitive ability. Although there was evidence of a statistically significant later born disadvantage for reading ability in three child families (0.14 SD), this relationship was not found within other family sizes or for any of the maths ability or pattern construction models.

### 5.6.3 Discussion

There are several aspects of the empirical results described above that are worth noting. I initially concentrate on the estimates of the relationship between family size and child outcomes. At face value, the various estimates of family size were in line with the more recent empirical literature, for instance Black *et al.,* (2005) and Angrist *et al.,* (2010). These prominent studies, along with a number of others from the literature, have argued that

[25] For instance, there were only 15 cohort children from the North East of England in the sample of children from four child families.

although there is a relatively large and statistically significant correlation between family size and various child outcomes (as predicted by the vast majority of the prominent theoretical literature), this association reduces or becomes statistically insignificant once a variety of confounding variables are controlled for, and becomes indistinguishable from zero once the potential endogeneity of family size is controlled for through the use of 2SLS models. This interpretation of the empirical results therefore implies that the conditional associations shown in the descriptive statistics and some of the OLS regression models may instead have been driven by a vector of unobserved confounding factors affecting both family size and child outcomes simultaneously. However, further investigation into the validity of the IV strategies used in this chapter *ex post* implies that the conclusion that there are no causal family size effects may be inappropriate, given that the lack of statistically significant causal estimates from the 2SLS models may instead reflect weaknesses in the respective identification strategies.

Firstly, although the sibling sex composition instrument showed strong first stage statistics (in line with the vast majority of the previous empirical literature utilising this IV strategy), and was also shown to be randomly assigned given the set of observable confounding characteristics included in the econometric models, the extremely large 2SLS estimates of family size when using this instrument (compared to those from the OLS models) cast serious doubt on the validity of the IV strategy. This is despite the fact that the estimates were in line with those of Silles (2010), the only other UK based study to have used the sibling sex composition instrument in the context of family size and child outcomes. Hahn and Hausman (2003) have argued that finding a 2SLS coefficient to be substantially larger in magnitude than the OLS coefficient can arise either because of OLS bias when the instruments are valid, or because of an improper instrument. Although the estimates from OLS models are indeed likely to be biased, the fact that *a priori* I expected the OLS models to overestimate the negative relationship between an increased family size and child outcomes indicates that the estimates from the 2SLS models, (which counterintuitively imply that the OLS models will significantly *underestimate* the true effect of family size) may also be biased.

Although it is possible these large effects from the 2SLS models may instead be explained by the fact that IV methods capture the LATE of a specific compliant subpopulation rather than the ATE for the whole population captured by OLS models, it is also possible that these extremely large empirical estimates are evidence of the instrument not being fully orthogonal to the stochastic disturbance term, with unobserved characteristics relating to both the sibling sex composition and child outcomes inflating the empirical estimates beyond feasible levels. Given these concerns regarding the true exogeneity of the sibling sex composition instrument, the empirical estimates using this IV strategy should be treated with caution.

Compared to the estimates when using the sibling sex composition instrument, the empirical estimates when using twin births instrument were quantitatively more in line with those from the OLS models and the previous empirical literature. However, although the instrument was shown to have strong first stage statistics and to be randomly assigned given the set of observable characteristics included in the empirical models, the sample size when estimating these models was relatively small compared to other prominent studies in the literature such as Black *et al.,* (2005) and Angrist *et al.,* (2010). Nelson and Startz (1990) have shown that 2SLS estimates can be severely biased and inefficient in finite samples such as these due to the significant increases in standard errors, even if the IV first stage statistics are shown to be strong. The fact that the incidence of twins within a family is a relatively rare event[26] will have only compounded these finite sample properties.

Furthermore, although the twin births IV strategy was shown to have a strong first stage relationship and be conditionally randomly assigned, the fact that the introduction of the full set of confounding covariates increased the coefficient estimate of family size in the majority of empirical models implies that these controlling variables may not have been strictly exogenous (despite Table 5.9 showing the covariates to be relatively evenly balanced between the treatment groups), and that these estimates may have also been subject to unobserved confounding. Although this phenomenon may have potentially been driven by the low probability of having a twin birth combined with the relatively small sample size, it may alternatively be evidence of a poor identification strategy. Given the issues mentioned above, the empirical estimates using the twin births IV strategy should also be treated with caution.

As well as the potential problems with the individual IV strategies, there were some further limitations when estimating the relationship between family size and child outcomes. Firstly, I was unable to assess the impact of 'completed' family size on child outcomes, and instead

[26] 85 out of 2379 cohort children included in this particular sample have a twin birth in the family (3.57%)

estimated the impact of family size when the cohort child is 7 years of age, at which point some of the families may have not yet achieved their desired number of children. Secondly, the measure of psychological well-being was reported by the parent rather than the cohort child themselves or the child's teacher, with this parental reported measure therefore potentially being subject to reporting bias. For instance, compared to a teacher reported measure, parents may be more likely to optimistically over-report the level of their child's psychological well-being (Lewis *et al.,* 2015).

Next, I concentrate on the estimates of the relationship between birth order and child outcomes. For the two measures of psychological well-being, there was evidence of a large and statistically significant last born advantage in the internalising subscale of the SDQ, as well as evidence of last born advantages for the externalising subscale of the SDQ in four child families. These estimates contradict the most prominent theoretical frameworks relating birth order to child outcomes (Zajonc 1976; Birdsall 1979), which predict that later born children should instead be at a distinct disadvantage compared to their earlier born counterparts. Although these empirical results were to a certain extent surprising, it is worth noting that these results were in line with the only other modern UK based study to investigate the relationship between birth order and the SDQ, that of Lawson and Mace (2010), which analysed the relationship using the ALSPAC cohort.

There are several mechanisms that may have driven these counterintuitive last born advantages for the measures of psychological well-being. As discussed by the studies of Parish and Wills (1993) and Hertwig *et al.,* (2002), it may be the case that later born children are born into a more settled household environment compared to earlier born children, in which parents may be older, more responsible and closer to reaching the peak of their earnings profile. These factors may in turn be more conducive to relatively higher levels of child psychological well-being compared to earlier born siblings, who may be born during periods of instability and transition.

Alternatively, it may also be the case that this positive association between later born child and higher levels of psychological well-being was driven by the relationship with older siblings. For instance, if the later born sibling has an affectionate relationship with their earlier born counterparts, the earlier born siblings may be able to provide a buffering role in response to social stresses, therefore having a protective effect on adjustment to difficult life events and potentially resulting in higher levels of psychological well-being. Although I was unable to explore this mechanism in this chapter due to data limitations, Gass *et al.,* (2007) have shown that ‘affectionate’ relationships between siblings may indeed be beneficial for children, regardless of the quality of the mother-child relationship.

Although the empirical estimates for the measures of child psychological well-being implied that there may be a later born advantage across distinct family sizes, there was very mixed evidence of an association between birth order and child cognitive ability. This is surprising, given that the majority of the more recent empirical literature, for instance Booth and Kee (2009) and Heiland (2009), have shown significant birth order disparities in child outcomes, even whilst explicitly controlling for family size. One plausible mechanism through which these mainly null findings may have manifested themselves is the fact that the older parents of later born child may have increased levels of experience, which may partially counteract the negative effects of being later born on child outcomes predicted by Zajonc (1976) and Birdsall (1979) and shown in other parts of the empirical literature.

The main limitation of the birth order models was the inability to identify within-family birth order differences, due to the cohort nature of the dataset. Although several recent studies have shown that the inclusion of family fixed effects (which in theory should control for within-family variation) makes little difference to the magnitude, statistical significance and therefore interpretation of the birth order estimates, it may be the case that the between family estimates presented in this chapter may not have appropriately accounted for the differences between families. This is despite the extensive potentially confounding variables I included in the model specifications. Given this, it should be emphasised that the birth order estimates presented in this chapter represent a conditional association rather than a true causal effect, and there is still a possibility that unobserved family level factors may have driven the relationships found between birth order and the various child outcomes.

The empirical results from this chapter may be interpreted in a number of ways. Firstly, this chapter further underlines the need to explicitly control for the relationship between family size and birth order when analysing the relationship between birth order and child outcomes, as not explicitly controlling for family size may generate spurious empirical estimates. Secondly, the mixed results regarding the association between birth order and the different measures of both psychological well-being and cognitive ability highlights the need to analyse the different subscales of child outcome measures separately. Although computationally appealing, summing measures together (such as the SDQ ‘Total Difficulties

Score') or using popular data reduction techniques such as PCA to generate a single, combined measure of child 'quality' may mask the differential effects that factors such as family size and birth order may have on different child outcome measures. Finally, the empirical estimates emphasise the difficulty in finding valid instruments to estimate causal effects in microeconometric studies, especially in relation to small sample properties and the exclusion criteria, which by definition is impossible to formally test *ex ante* in a just identified setting.

The relationship between family size and child outcomes may also be important from a policy perspective. In the UK, there are a number of measures that may impact family fertility decisions beyond parental preference, such as child tax credits, publicly funded childcare and increased benefits for single parents. Recent UK political policy, as detailed in the 2015 Budget delivered by former Chancellor of the Exchequer George Osbourne, has introduced a de facto 'two child policy', meaning that from April 2017, families with more than two children will not receive tax credits or housing benefit for their third or subsequent children. Significant decreases in welfare support such as this may incentivise families to have less children, which may come with a number of detrimental externalities. However, the empirical estimates presented in this chapter imply that the impact of potential changes in family size on child outcomes may in fact be relatively minimal or absent.

Thinking of policy implications for birth order is a more difficult task, given that by definition birth order is impossible to alter. Other empirical studies, for instance Bjorkegren and Svaleryd (2017) have argued that policies which increase parental attention on later-born siblings, such an increased child care for younger siblings, may potentially be beneficial, given the usual pattern of later born disadvantage for child outcomes predicted by a number of prominent theoretical frameworks and reported in the majority of the applied empirical literature. However, such recommendations do not take into account the fact that birth order may impact different child outcomes in different ways. Although encouraging increases in parental attention on later-born siblings may well be beneficial for measures such as child health and cognitive ability, the empirical estimates from this chapter imply that such a policy may in fact be detrimental for relative levels of child psychological well-being in the UK.

The findings presented in this chapter also have implications for users of the MCS dataset. Firstly, the findings from this chapter show the usefulness of the MCS household grid, which to date has been underused in the empirical literature. In this chapter, this data source was used to construct the sibling sex composition instrument, the twin births in the family instrument and the birth spacing variables. This underused resource represents a good opportunity for applied researchers in the field of family or household economics to investigate the impact of various measures of family composition on cohort children and their families, especially given the continuing collection of MCS data into adolescence and adulthood. Secondly, the findings from this chapter underline the importance of, where possible, utilising the sampling weights when using the MCS. As shown in Appendix 5B, there was evidence that not using the sampling weights may overestimate the conditional association between both family size and child outcomes.

There are several possible avenues for future research in this area. As shown by the studies of Henderson *et al.,* (2008), Mogstad and Wiswall (2016), Millimet *et al.,* (2011) and Fruhwirth-Schnatter *et al.,* (2014), the applied empirical literature is beginning to move beyond investigating the effect of a linear measure of family size on the mean value of child outcomes. Although investigating the relationship in a non-linear, non-parametric or distributional manner was beyond the scope of this chapter, this could be a fruitful area of future research. There are however hurdles to overcome to estimate such models, such as the very large sample sizes needed to construct multiple instruments for different family sizes in order to capture a non-linear causal effect, and the development of an estimation command which is able to take into account both the estimation of distributional causal effects and the complex survey design of datasets such as the MCS.

Secondly, although Brenoe and Molitor (2015) have estimated the distributional association between birth order and child health variables such as low birth weight, no study has specifically considered the distributional association between birth order and either child psychological well-being or cognitive ability. Analysing the distributional impacts of birth order on child outcomes is therefore another area where future research could be directed, particularly as Millimet and Wang (2011) have argued that there may be heterogeneous effects of family composition at different parts of the distribution of child outcomes.

Thirdly, although there was mixed evidence of the impact of family size and birth order on the child outcome measures used in this chapter, these two measures cannot be seen to fully capture early life child outcomes. Heckman and Conti (2012) have explicitly incorporated measures of child health into their influential life course model of development, and a recent strand of literature has indeed examined the potential impact that measures of family size and birth order may have on child health (Lundborg *et al.,* 2013; Bjorkegren and Svaleryd 2017). Investigating the relationship between birth order and child health using the MCS may be a fruitful area of future research, given the range of health measures currently contained in the study, as well as the measures that are likely to be collected in future waves of data, such as measures of adolescent health related behaviour.

Finally, as this chapter represented one of the first attempts to identify the relationship between birth order and child psychological well-being in a modern UK cohort, further research should investigate this issue using different datasets and more objective measures of child psychological well-being. This is especially relevant given that the measure of psychological well-being used in this study is reported by the parent, and that the only other modern UK based empirical study to investigate the relationship between birth order and psychological well-being (Lawson and Mace 2010) also used the SDQ as their outcome measure.

**5.7 Conclusion**

Both child psychological well-being and cognitive ability are predicted to have a significant influence on a variety of later life outcomes. Although measures of household composition such as family size and birth order may help to generate inequalities in these child outcomes, the exact nature of the relationship is not fully understood. In this chapter I contributed to the literature by investigating the impact of both family size and birth order on child psychological well-being and cognitive ability in a modern UK cohort.

For family size, the empirical estimates from OLS models showed a large and statistically significant negative conditional association between an increased family size and psychological well-being whilst controlling for a variety of potentially confounding factors. Although descriptive statistics showed a significant relationship between family size and the various measures of child cognitive ability, this relationship was reduced and became statistically insignificant once the full set of confounding factors were controlled for. Two IV strategies were used to estimate a 'true' causal effect rather than a conditional association, exploiting quasi-random variation in family size caused by the sex composition of the first two children in a family and the incidence of twin births. Although both models showed statistically insignificant causal effects of family size, similar to the majority of the recent empirical literature, the estimates from these models should be treated with a degree of caution due to evidence of unobserved confounding and small sample biases respectively.

For birth order, results showed mixed evidence of a significant relationship. For the internalising sub scale of the psychological well-being and certain externalising sub scale models, there was evidence of a relatively large and statistically significant later born advantage, with this finding robust to both OLS and NNM model specifications. Although this result was contradictory to predictions from the most prominent theoretical models of birth order, it was in accordance with the only other empirical study to investigate this issue using a modern UK cohort. Although there was evidence of later born disadvantages for child reading ability in certain family sizes, these associations were not consistent across other family sizes and different measures of cognitive ability.

The findings of this chapter highlight several empirical issues in this research area, such as the importance of fully conditioning on family size when estimating birth order effects, and the need to analyse different subscales of child outcomes separately. As well as replicating the estimates of this chapter using different datasets and more objective measures of child psychological well-being, future research should be directed at investigating the distributional relationship between family size or birth order and child outcomes rather than focussing on the means. Furthermore, measures of child health should be incorporated into analysis, as such outcomes have thus far been relatively under investigated in relation to household composition factors such as family size and birth order.

# Chapter 6. Maternal Labour Market Characteristics and Adolescent Risky Health Behaviours

## 6.1 Introduction

Both in the UK and around the globe, the labour market is changing in a number of ways. For instance, it has been reported that there are now approximately 900,000 workers on zero-hours contracts in the UK (Guardian 2016). There is also evidence of increasingly polarising wages, due to technological innovation replacing traditional 'middle wage' jobs (Holmes and Mayhew 2012), and a significant increase in the number of people working beyond retirement age (Sahlgren 2013).

Another important way in which the labour market has changed in recent years has been the increased role of women, with the rate of working age women in employment rising from approximately 53% in 1971 to over 70% in 2017 (Labour Force Survey 2017). There are several potential reasons for this increase, including the decline in the manufacturing sector and rise in the service sector since the 1960s, and a number of pieces of new legislation aimed at increasing female participation in the labour market, such as the 1970 Equal Pay Act, the 1975 Sex Discrimination Act and the 1975 Employment Protection Act. Although this increased labour supply is likely to be beneficial for families in monetary terms, and also supports normative issues related to gender equality, there are several potential spill-over effects, including having less time available to provide emotional support to children. As predicted by the past theoretical (Becker 1965) and empirical (Todd and Wolpin 2007) literatures, these decreasing time investments in children may have significant negative consequences for a range of child outcomes.

Alongside the increased role of women in the labour market, there has also been the arrival of the '24-hour' economy, driven by changes in consumption patterns, technology, industrial relations legislation and globalisation (Strazdins *et al.,* 2004). Partially due to increased demand for services at the weekend, evenings and holidays, there has been a dramatic rise in the number of workers engaging in non-standard work schedules (Presser 2005), with La Velle *et al.,* (2002) having shown that amongst dual-parent families in the USA, 43% of households contained parents who both frequently work non-standard hours.

There are several types of work that may be considered non-standard, and thus the exact definition varies across both countries and studies. For instance, Kalleberg *et al.,* (1997) define non-standard schedules as being either part-time work, temporary and on-call work, contract work and self-employment, whereas Presser (2003) define persons as working non-standard hours when they work anything other than fixed-day schedules in the previous week. Li *et al.,* (2014) have argued that in general, non-standard schedules refer to schedules in which the majority of work hours fall outside a typical daytime Monday to Friday working week.

Although these non-standard working schedules are valuable for the productivity of modern businesses, and may allow workers the flexibility to work multiple jobs or cover child care more easily (Presser and Cox 1997), it has also been argued that working such schedules is less often a parental choice and instead a non-negotiable aspect of employment (U.S. Bureau of Labour Statistics 2000). Furthermore, there is evidence that working such schedules may have a number of potential negative consequences for the employee, for example health related issues (Barnett 2006; Perry-Jenkins *et al.,* 2007; Kantermann *et al.,* 2010) and marriage instability (Presser 2003; Barnett *et al.,* 2008; Kalil *et al.,* 2010).

In addition to these studies showing the impact that working non-standard working schedules has on the health and well-being of the employee, it has been noted that there may be significant spill-over effects in various measures of child well-being, such as cognitive ability (Han and Fox 2011), psychological well-being (Dockery *et al.,* 2009) and obesity (Miller and Han 2008). However, one area that has been relatively under examined is the influence of such non-standard schedules on adolescent health related behaviour.

Adolescence is clearly a very important period of life, given the biological, psychological and emotional changes that take place, the experimentation with risky behaviours such as smoking, drinking, drug use and sexual activity, and the fact that behaviours formed in adolescence are likely to influence behaviours and outcomes in adulthood. Understanding the relationship between maternal employment and adolescent behaviours is therefore important for young people's future health prospects. The two behaviours I focus on in this chapter are smoking tobacco and drinking alcohol.

Along with the well documented obesity epidemic, smoking and drinking constitute two of the three chief lifestyle risk factors for disease and death in the UK (Davies 2012). Of the 9.6 million adult smokers in Great Britain, it is predicted that around half of these individuals will die from factors associated with the addiction, for example respiratory conditions, cardiovascular disease and various forms of cancer (ASH 2015). The potential individual health effects of drinking are also voluminous, for example high blood pressure, increased risks of liver disease, depression and various forms of cancer (Alcohol Concern 2015).

As well as individual health risks, smoking and drinking also have significant societal costs. For instance, recent research commissioned by the charity Action on Smoking and Health (ASH) has estimated that the total cost to society in England of smoking is approximately £13.9 billion annually (ASH 2015), while alcohol dependence and alcohol related crime have been estimated to cost anywhere between £8 billion and £13 billion annually (Alcohol Concern 2015).

For both smoking and drinking, research has shown that engaging in these behaviours in adolescence may have a significant impact on continuing these risky health behaviours in adulthood. For instance, the ASH report (2015) details that around two-thirds of smokers will start before the age of 18 (the legal age limit for smoking in the UK), and of those who try smoking during this period of life, between one-third and one-half will become regular smokers. For drinking, it has been reported that the earlier that an individual engages in drinking, the more likely they are to develop dependence or other alcohol-related problems in adulthood (Donaldson 2009).

As well as the impact of adolescent drinking on adult drinking behaviour, there are other potential consequences of the engagement in such risky adolescent health related behaviours. For instance, a number of studies have shown increased levels of adolescent drinking to be associated with delayed physiological development (Emanuele *et al.,* 2002), the potential engagement in risky sexual behaviour (Thomas *et al.,* 2000), worse educational outcomes (Chatterji 2006) and the increased risk of non-health related adverse consequences such as the involvement in violence or social disorder (Fergusson and Lynskey 1996).

Given the significant impact of adolescent smoking and drinking on individual health and well-being in the short and long term, a range of recent public health policies have been implemented in an attempt to decrease the incidence of these risk factors, such as the 2003 Alcohol Licensing Act, the 2003 ban of tobacco advertising and the 2007/2008 ban of smoking in public places. However, despite some evidence of promising short term effects for such interventions (Harris *et al.,* 2006; Hough and Hunter 2008; Wildman and

Hollingsworth 2013), combatting the negative effects of such health behaviours is an extremely difficult task, given how entrenched such behaviours are in large proportions of modern society.

With the relatively recent changes in the labour market and the importance of adolescent health related behaviours in shaping both present and future levels of health as a motivation, this chapter had two main aims. Using the first six waves of the UKHLS dataset, I firstly aimed to estimate the relationship between maternal labour supply and adolescent drinking and smoking, using a number of panel data models to control for individual level heterogeneity and selection in the labour market. Secondly, I aimed to estimate the association between the incidence of maternal non-standard work schedules and the adolescent risky health behaviours, using linear probability models (LPM) and random effects generalized least squares (GLS) models.

## 6.2 Previous Work

### 6.2.1 *Maternal labour supply and child outcomes*

The applied empirical literature focussing on the impact of maternal labour supply[27] on child outcomes in general is large and well developed. For instance, a multitude of studies have investigated the relationship between maternal labour supply and various dimensions of child health (Anderson *et al.,* 2003, Sleskova *et al.,* 2006; Von Hinke Kessler Scholder 2008; Ruhm 2008, Chia 2008; Liu *et al.,* 2009; Fertig *et al.,* 2009; Gennetian *et al.,* 2010; Greve 2011; Bishop 2011; Miller 2011; Morrill 2011; Morrissey *et al.,* 2011; Gwozdz *et al.,* 2013; Datar *et al.,* 2014 and Meyer 2016). Other studies have investigated the relationship between maternal labour supply and various aspects of child educational performance, cognitive ability and well-being (Blau and Grossberg 1992; Muller 1995; Waldfogel *et al.,* 2002; Vander Ven and Cullen 2004; Ruhm 2004; James-Burdemy 2005; Ruhm 2008; Bernal

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[27]As noted by Anderson *et al*., (2003), the reason for the focus in this strand of literature being mainly concerned with *maternal* labour supply rather the *paternal* labour supply is due to three main factors. Firstly, there has been a substantial increase in the number of women entering the labour market in the past 50 years. Secondly, even with these substantive increases in maternal labour force participation, it is mothers who usually still take on the majority of the childcare in modern UK society. Thirdly, as children are far more likely to live with their mother than their father if the parents are separated, there can be severe data limitations concerning father labour market behaviour in cohort and longitudinal studies.

2008; Willis and Braeur 2012; Powdthavee and Vernoit 2013 and Emisch and Francesconi 2013).

While the majority of studies have shown that increasing maternal employment levels are detrimental to child outcomes (Blau and Grossberg 1992; Muller 1995; Waldfogel *et al.,* 2002; Anderson *et al.,* 2003; Ruhm 2004; James-Burdemy 2005; Sleskova *et al.,* 2006; Von Hinke Kessler Scholder 2008; Ruhm 2008; Bernal 2008; Chia 2008; Ruhm 2008; Liu *et al.,* 2009; Fertig *et al.,* 2009; Gennetian *et al.,* 2010; Bishop 2011; Miller 2011; Morrill 2011; Morrissey *et al.,* 2011; Powdthavee and Vernoit 2013; Emisch and Francesconi 2013; Datar *et al.,* 2014 and Meyer 2016), a smaller number of studies have shown no evidence of a statistically significant relationship (Vander Ven and Cullen 2004; Greve 2011; Willis and Braeur 2012; Gwozdz *et al.,* 2013).

However, only a selected number of studies in this large literature have explicitly attempted to control for the probable endogenous relationship between maternal employment and child outcomes (Anderson *et al.,* 2003; Ruhm 2004; Von Hinke Kessler Scholder 2008; Bernal 2008; Ruhm 2008; Chia 2008; Gennetian *et al.,* 2010; Bishop 2011; Miller 2011; Morrill 2011; Emisch and Francesconi 2013; Datar *et al.,* 2014 and Meyer 2016), with the remaining studies instead relying on OLS estimation, which does not account for the fact that child outcomes may impact maternal employment, or that maternal employment and child outcomes may be jointly determined by a vector of unobservable factors.

### 6.2.2 *Maternal labour supply and adolescent risky health behaviour*

Despite the large literature relating maternal labour characteristics to child outcomes, only five empirical studies (Hillman and Sawilowsky 1991; Aughinbaugh and Gittleman 2004; Lopoo 2005; Kan 2012 and Mendolia 2016) have specifically investigated the relationship between maternal labour supply and adolescent risky health behaviours. Compared to the large literature discussed in the previous section, the findings of this smaller literature have shown more mixed results. Although the studies have mostly shown a significant conditional association between maternal labour supply and adolescent health related behaviours, once individual level heterogeneity is taken into account or IV methods are used in an attempt to control for potential omitted variable bias, the observed relationship is shown to be significantly reduced, and associated with a considerably higher level of uncertainty.

The first empirical study to explicitly analyse the relationship between maternal labour supply and adolescent risky health related behaviour was that of Hillman and Sawilowsky (1991), who estimated the association between a binary measure of maternal employment and substance abuse in early adolescence in a very small sample of 14-16 year old American children (*N*=48). Using simple descriptive statistics, the empirical results showed no association between the employment status of the mother and adolescent drinking, smoking and drug use. However, due to the statistical methods used and the limited and unrepresentative sample size, the conclusions of this study must be treated with caution.

More recently, several studies from the applied economics literature have analysed the relationship using empirical methods that explicitly attempt to control for potential unobserved individual level heterogeneity. In a seminal study, Aughinbaugh and Gittleman (2004) used a large sample of adolescents (*N*=4302) from the young adult supplement of the NLSY to examine the impact of *early life* maternal employment on the child's engagement in risky health related behaviours in adolescence. Using both child and mother fixed effects models to control for individual level heterogeneity, results showed no strong evidence of early maternal employment having a significant effect on the likelihood of participating in risky health related behaviours, with further analysis suggesting this result to be robust in various different sub group analyses. However, although the authors used a measure of early maternal employment because of the hypothesis that the first three years of a child's life are crucial for child development (Shore 1997), the authors did not take into account contemporary maternal labour supply, which may have an equivalent or even larger association than the early life measure.

Also using fixed effects models to control for unobserved heterogeneity, Lopoo (2005) used a large sample of individuals from the PSID (*N*=3035) to investigate the relationship between maternal employment and adolescent sexual activity. Results showed an increase in maternal labour supply to be associated with a dramatic decrease in the probability of a daughter having an unplanned teenage pregnancy. However, as noted by the author, this outcome measure may not fully reflect risky adolescent behaviour, as births are the end result of a sequence of decisions, including becoming sexually active, the use of contraceptives and the abortion decision (conditional on pregnancy), all of which cannot be controlled for in the empirical models.

Focussing specifically on employed mothers, Mendolia (2016) investigated how maternal working hours are related to adolescent behaviours such as life satisfaction and smoking, using a large sample of children (*N*=7153) from the youth panel of the BHPS and fixed effects estimators. In this case, results revealed no statistically significant association between mothers working full time and adolescent behaviours, with sub group analysis confirming this result to be consistent across socio-economic groups, age and gender. The author argued that possible explanations for this statistically insignificant effect include the assumption that maternal employment significantly reduced the time that parents spend with their children not standing up in practice, the increased contribution of fathers in rearing children, and the fact that the positive effects of maternal working on household income and maternal well-being may offset the negative impact of her absence.

While the use of panel data models can control for individual level heterogeneity, there may still be a set of time variant confounding characteristics that render the relationship endogenous. The only study that has attempted to capture a causal effect of maternal labour supply on child risky health related behaviours using IV methods is that of Kan (2012), who used an identification strategy based on the number of day nurseries in local level geographical areas. Using a sample of adolescents (*N*=972) from the Japanese Life Course Panel Survey, the author found that while OLS models showed little evidence of a conditional association, estimates from 2SLS models showed that sons whose mothers work full time were in fact *less likely* to smoke at school, with no significant causal effects found for daughters. The author argued that this effect may be a consequence of full time working mothers having better management skills, and therefore being more effective at supervising their children. However, it is possible that these IV estimates are misleading, as the author did not consider the possibility that families who reside in high unemployment areas may be significantly different to those who reside in low unemployment areas, and in general offers no justification for either the strength or exogeneity of the identification strategy used.

### 6.2.3 *Maternal non-standard working schedules and child outcomes*

While a large literature has explored the relationship between the number of maternal hours worked and child outcomes, a separate, smaller body of literature has specifically considered the relationship between maternal non-standard work schedules and child outcomes. Almost all using US based data, the focus of such studies was not to investigate the relationship between the quantity of maternal labour supply itself and child outcomes, but to identify the impact of the timing of these hours of work (conditional on maternal employment).

As noted in a wide ranging systematic review of this literature (Li *et al.,* 2014), this branch of empirical research has examined the impact of parental non-standard work schedules on a wide range of child outcomes, such as adolescent depression (Han and Miller 2009), social and emotional difficulties (Barton *et al.,* 1998; Strazdins *et al.,* 2004; Strazdins *et al.,* 2006; Dockery *et al.,* 2016), sleep patterns (Radosevic-Vidacek *et al.,* 2004), child obesity (Miller and Han 2008; Morrissey *et al.,* 2011; Champion *et al.,* 2012), child cognitive ability (Han 2005; Han and Fox 2011; Odom *et al.,* 2013), delinquency (Hendrix and Parcel 2014) and mental health (Dockery *et al.,* 2009). In general, this literature points to an economically small, yet statistically significant, conditional association between non-standard schedules and child outcomes, with Li *et al.,* (2014) highlighting proximal factors such as parenting skills, parental depression and the home environment as potential mediating mechanisms. However, caution is required when interpreting these results as causal, as there are also plausible mechanisms through which the relationship may be considered endogenous, such as certain child outcomes impacting maternal work schedules, and a set of unobservable characteristics jointly determining both measures.

### 6.2.4 *Maternal non-standard working schedules and adolescent risky health related behaviour*

Despite this growing literature relating parental non-standard works schedules to child outcomes, only four empirical studies (Han and Waldfogel 2007; Han *et al.,* 2010; MacPhee 2013 and Kim *et al.,* 2016) have specifically examined the relationship between maternal non-standard work schedules and adolescent risky health behaviours, despite the significant potential health and societal effects of engaging in such behaviours. To date, the evidence for a significant relationship between parental non-standard working schedules and adolescent risky health related behaviours has been mixed.

The first empirical study to consider the effect of parental work schedules on adolescent risky health related behaviours was Han and Waldfogel (2007). Using a large sample of children (*N*=12207) from the National Longitudinal Study of Youth-Child Survey (NLSY-CS) and OLS and logistic regression models, the authors identified the association between six different types of work schedule: standard, evenings, nights, rotating shifts, irregular hours and not working; and two different risky adolescent behaviours: substance use and delinquency. Results from the various models showed little evidence of a significant association between parental work schedules and adolescent risky behaviours. However, a notable exception to this finding was the significant association between rotating shifts and delinquent behaviour for single mothers. The authors attributed the overall lack of conditional association between work schedules and adolescent outcomes to the divergent links between parental work schedules and the intervening family variables such as monitoring and parental closeness.

Also using the NLSY-CS, Han *et al.,* (2010) investigated the association between parental work schedules and adolescent risky behaviours using SEM and PSM models. Empirical results suggested that mothers who often work at night spent significantly less time with their children, with this factor significantly linked to adverse adolescent behaviours such as substance use, delinquency and sexual behaviour. Such associations were not found for other work schedules, and the authors also noted that the associations found for maternal night shifts may instead be explained by the fact that such families are likely to have other characteristics that lead to poorer adolescent outcomes.

Building on the studies of Han and Waldfogel (2007) and Han *et al.,* (2010), MacPhee (2013) investigated the relationship between parental work schedules and adolescent engagement in risky behaviours. Using the Canadian National Survey of Children and Youth (NLSCY), the author investigated the different influences of standard and non-standard parental work schedules on adolescent behaviours such as stealing, fighting, drinking and illicit drug use, using probit regression models. Results showed non-standard parental work schedules to be associated with the incidences of fighting, drinking and drug taking amongst adolescent boys. Sub-group analysis counterintuitively showed non-standard working schedules in low income households to be related to a decrease in the probability of engaging in risky behaviours, with the author arguing that parents may compensate for non-standard working hours by increased monitoring, supervision and coordination.

Most recently, Kim *et al.,* (2016) used a sample of adolescents (*N*=3030) from the NLSY-CS to analyse the cumulative impact of non-standard work schedules on adolescent alcohol and cigarette use, as well as exploring some of the potential mediating mechanisms. Using path analysis, SEM and controlling for a rich set of potentially confounding variables, the authors found non-standard work schedules to be significantly associated with both outcome measures, with these associations potentially being mediated by measures of parent-child communication. Given these empirical findings, the authors further argued that there is a need for adolescent substance use interventions to explicitly target adolescents whose parents engage in non-standard working schedules.

Given the past empirical work, in this chapter I contribute to the literature in two main ways. Firstly, I contribute to the relatively small empirical literature focussing on the impact of maternal labour supply on adolescent risky health related behaviours, and am the second, after Mendolia (2016), to investigate this issue using UK data. Secondly, I contribute to the small but growing literature regarding the relationship between maternal non-standard working hours and child adolescent outcomes, and am the first to use UK data. In doing so, I am also the first to investigate the impact of both maternal labour supply and maternal non-standard works schedules on child outcomes in the same empirical study.

**6.3 Theoretical Considerations**

There are three main hypotheses that I test in the empirical analysis:

a) Is there an association between maternal employment and the incidence of adolescent smoking and drinking?
b) Is there an association between the number of hours a mother works and the incidence of adolescent drinking and smoking?
c) Is there an association between the incidence of maternal non-standard working schedules and the incidence of adolescent drinking and smoking?

In sub-sections 6.3.1 and 6.3.2 below, I present a simple household production model to demonstrate how maternal labour supply and the incidence of maternal non-standard work schedules may impact adolescent risky health behaviour. As argued by Homan (1988), although household production models come attached with several disadvantages, such as the strong neo-classical assumptions of utility maximising behaviour, full information and perfect certainty, using such models can be an elegant way of accounting for productive activities that take place within the household.

### 6.3.1 *Theoretical model*

The exploration of relationships between parental labour market supply and child outcomes can be related back to time allocation theory (Becker 1965; Leibowitz 1974, 1977; Hill and Stafford 1974). Using this general framework, classic economic models of household behaviour (Becker 1981; Behrman *et al.,* 1982; Becker and Tomes 1986) assume that households act as production units, with parents allocating their scarce time across factors such as market work, non-market work (for example housework and child care) and leisure time to maximum the household utility function, of which child outcomes are assumed to be a key component. The household maximises the utility function so that in equilibrium the marginal rate of substitution between consumption and leisure activities and the market wage rate are equal. As parental time is finite, there is a restriction on how much time the parents can spend on each of these factors. Parents may also choose to substitute time inputs for market goods in the production of child outcomes (such as taking their child to day care centres), with the exact reallocation depending on the net marginal utility of time.

Following Rosenzweig and Schultz (1983), Ruhm (2000, 2004) and von Hinke Kessler Scholder (2007)[28], the customary utility function of a static household production model described above can be sketched as:

$$U = U(Z, L)\,, \tag{6.1}$$

where utility $(U)$ is a function of consumption of commodities within the household $(Z)$ and leisure $(L)$.

As argued by Becker and Lewis (1974), child quality (proxied in this case by an adolescent's engagement in risky health behaviours) explicitly forms part of the household utility function as a household commodity $(Z)$. Parental leisure time is assumed to have a positive impact on children, as the parent is not engaged in either market or non-market work, and can therefore increase time investments into children. A series of studies have shown that mothers with increased labour supply may decrease both the quantity (Bryan and Zick 1996;

[28] The structure of the economic model is also similar to those presented by van den Brink and Groot (1997) and Brown (2009)

Gershuny 2000; Sandberg and Hofferth 2001) and quality (Hoffman 1980; Coleman 1988; Bianchi 2000) of time investments, while Del Boca *et al.,* (2012) have shown that decreased parental time investments may be detrimental for child outcomes.

The reduced form utility function displayed in equation 6.1 represents the influences of preferences and household production technology on the consumption decision. Commodities within the household are produced by combining market goods $(X)$ and time inputs $(H_n)$, for example time inputs into childcare. The household production function can therefore be represented as:

$$Z = Z(X, H_n)\ , \tag{6.2}$$

where the input factors $X$ and $H_n$ are used to produce $Z$.

It is assumed that a higher level of disposable income generated by an increased maternal labour supply will have a positive impact on children, as it increases the ability of parents to make increased and better quality investments into their children $(X)$. Although it is notoriously difficult to estimate the true causal effect of income on child outcomes due to significant levels of endogeneity (Brooks-Gunn and Duncan 1997), and also extremely difficult to identify household expenditures on children (Laezer and Michael 1988; Folbre 2008), it has been shown that there is a correlation between various measures of SES and adolescent risky health behaviours (Hanson and Chen 2007), with adolescents from lower socioeconomic backgrounds more likely to engage in certain risky behaviours.

The functional form for goods produced in the household can be represented by:

$$Z = X + Z(H_n) \tag{6.3}$$

Therefore, commodity $Z$ consists of market goods plus goods produced by the time inputs of non-market work, which importantly for this research question includes measures of child quality. The optimisation of the utility function is also subject to a time constraint and a budget constraint.

The budget constraint is given by:

$$\sum_{i=1}^{M} p_i x_i \leq I = m_o + wH_w \,, \tag{6.4}$$

where $p_i x_i$ is the price of consumption, $I$ represents total income, $m_o$ represents non-labour income and $wH_w$ represents the total labour income. Prices, non-labour income, wages and labour supplied all may affect the position of the budget constraint.

The time constraint can be represented as:

$$L + H_w + H_n = T \,, \tag{6.5}$$

with total time $(T)$ divided between hours worked $(H_w)$, hours spent in leisure $(L)$, and time spent on home production or non-market work $(H_n)$.

From the time and budget constraints, I am able to derive the full income constraint:

$$X + wH_w + wH_n = wT + m_0 = F \tag{6.6}$$

In this case, $F$ is the full income or the total income available to allocate between the consumption of market goods, leisure, and non-market production such as child care. If an individual were to maximise the utility function subject to the full income constraint, the Lagrange equation for the optimisation problem is:

$$L = U(Z(X, H_n)L) + \lambda(F - X - wL - wH_n) \tag{6.7}$$

Maximisation of the utility function yields the first order or equilibrium conditions of the model. If I exclude corner solutions (so that $0 < H_w < T, 0 < H_n < T$ and $0 < L < T$), one can show that:

$$\left(\frac{\partial U}{\partial Z}\right)\left(\frac{\partial Z}{\partial X}\right) = \lambda \tag{6.8}$$

and:

$$\left(\frac{\partial U}{\partial Z}\right)\left(\frac{\partial Z}{\partial H_N}\right) = \left(\frac{\partial U}{\partial L}\right) = \lambda w \tag{6.9}$$

From equations 6.8 and 6.9 it can be shown that:

$$\frac{\left(\frac{\partial U}{\partial Z}\right)\left(\frac{\partial Z}{\partial H_n}\right)}{\left(\frac{\partial U}{\partial Z}\right)\left(\frac{\partial Z}{\partial X}\right)} = \left(\frac{\partial Z}{\partial H_n}\right) = w\ , \tag{6.10}$$

where $(\partial Z/\ \partial H_n)$ is the marginal value of non-market work.

It can be argued that engaging in non-standard work schedules may impact the quality of parental time investments into children $(H_n)$ without significantly increasing the level of household income[29], and therefore influence of the level of market input factors $(X)$. Subsequently, although the marginal rate of substitution between non-market work and labour supply shown in equation 6.10 will likely remain relatively unchanged when a mother engages in non-standard work schedules, the quality of the non-market work is likely to decrease.

### 6.3.2 *Empirical implications*

The economic model yields ambiguous predictions about the consequences of the amount of maternal labour supply on child outcomes. If the predicted negative impact of decreased

[29] As discussed in the introduction, working non-standard work schedules is usually a non-negotiable aspect of employment, rather than a choice based on factors such as the wage rate.

time inputs caused by an increased maternal labour supply dominates the predicted positive impact of increased disposable income and therefore increased market inputs, an increased maternal labour supply may *increase* the probability of an adolescent engaging in risky health behaviours such as drinking and smoking. However, if the positive impact of the better quality child investments caused by an increased disposable income dominates the negative impact of decreased time investments, an increased maternal labour supply may *decrease* the probability of an adolescent engaging in risky health behaviours. It is therefore an empirical question as to which of the competing factors dominates. As argued by von Hinke Kessler Schroder (2007), it is also important to bear in mind that the effects of a decrease in time and child supervision and increases in income are likely to be both non-linear and heterogeneous across different household groups.

If, as expected, non-standard work schedules decrease the quality of maternal time investments, this may increase the probability of adolescents engaging in risky health behaviours. There are several mechanisms through which this relationship may manifest itself. For instance, this relationship may be mediated by levels of parent-child communication, as it has been argued that an increased level of parent-child communication may foster healthy parent-child bonds that protect children from potential risks, such as adolescent risky health related behaviours (Ennett *et al.,* 2001). Given that it has also been shown that an appropriate level of parent-child communication may be a direct function of parental work schedules (Taht and Mills 2012), it follows that parental-child communication may mediate the relationship between parental non-standard work schedules and adolescent risky health behaviour.

Another potential consequence of parents working non-standard schedules is the inability to supervise the adolescent during the evening and/or the weekend. Aizer (2004) has shown that, left unsupervised, school age children are more likely to engage in antisocial, risky or potentially dangerous behaviour (such as drinking and smoking), and therefore this can also be seen as a potential mediating pathway through which parental non-standard works schedules may increase the probability of adolescents engaging in risky health behaviours.

### 6.4 Estimation Strategy

Informed by the existing theoretical and empirical literature, I used a number of econometric techniques to: 1) estimate the association between maternal employment and adolescent risky health related behaviours; 2) estimate the association between the number of maternal working hours and adolescent risky health related behaviours; and 3) estimate the relationship between maternal non-standard working schedules and adolescent risky health related behaviours. As argued by Ruhm (2004), if I had information regarding a full vector of relevant prices, wages and individual level production shocks, then I would have been able to estimate a policy-relevant parameter of the impact of both maternal labour supply and non-standard work schedules on the engagement in risky health related behaviours. However, as such information was not available, I instead estimated reduced form models[30], controlling for a vector of child and parental characteristics assumed to confound the relationship.

To investigate the conditional association between maternal employment and adolescent risky health related behaviours, I first estimated a pooled LPM. Following this, I estimated a random effects generalised least squared (GLS) model and a fixed effects LPM (FE-LPM) model to control for unobserved individual level heterogeneity. I performed a Breush-Pagan Lagrange multiplier test (Breusch and Pagan 1979, 1980) and a Hausman test (Hausman 1978) to determine which of the model specifications provided the most efficient and consistent estimates. To further control for endogeneity, I then estimated two different 2SLS models, using the occurrence of young siblings in the family and local labour market conditions as two plausible forms of exogenous variation in maternal employment.

To estimate the relationship between the number of maternal hours worked (rather than a binary measure of maternal employment) and adolescent risky health related behaviours, I estimated LPM, GLS and FE-LPM specifications. Finally, to estimate the conditional association between the incidence of maternal non-standard work schedules and adolescent risky health related behaviours, I estimated LPM and GLS models on a sub-sample of adolescents with employed mothers. I also conducted sub-group analysis in order to

[30] Rosenzweig and Schultz (1983) refer to these reduced form models as ‘hybrid equations’, and this term is often used in the empirical literature

consider whether this relationship was consistent across different occupational and educational groups.

### 6.4.1 *Maternal employment and adolescent health related behaviour*

#### 6.4.1.1 *Pooled linear probability model*

The starting point of the empirical analysis was the LPM, which applies an OLS model to a binary dependent variable. This pooled estimator ignores the potential unobserved individual level heterogeneity associated with panel data, and fits the model as if it were a cross-sectional specification. The LPM specification I used this chapter can be given by:

$$RB_i = \beta_0 + \beta_1 EMP_i + \beta_2 \boldsymbol{x}_{ji} + \varepsilon_i \ , \tag{6.11}$$

where $i$ = 1,2,…n

In this specification, let $RB_i$ represent the incidence of a risky health behaviour (either drinking or smoking) for individual $i$, and $EMP_i$ represent a dummy variable taking the value of 1 if the mother of individual $i$ is employed and 0 otherwise, with its parameter coefficient $\beta_1$. $\boldsymbol{x}_{ji}$ represents a vector of controlling variables, with their associated parameters coefficients $\beta_2$. $\beta_0$ and $\varepsilon_{1i}$ represent the constant term and idiosyncratic error term for individual $i$ respectively.

There are several reasons why the LPM may calculate biased coefficients in a non-linear regression model, for example not giving consistent estimates of the marginal effects, and not dealing effectively with measurement error in the dependent variable (Amemiya 1997; Horace and Oaxaca 2006). Given these issues, a number of authors have argued that the marginal effects from probit or logit models should be used rather than the LPM. However, Angrist and Pischke (2009) have counter argued that using the LPM should give an extremely close estimate of the marginal effect (the effect that one is interested in), and there is in fact no theoretical basis for asserting that the probit or logit model will give a better approximation of the true marginal effect, given that the choice between the LPM, probit and logit is arbitrary. In this chapter, I estimated models using all three methods to test the robustness of the results to model specification. I calculated the LPM, probit and logit models using the *regress, probit* and *logit* commands, and clustered standard errors at the individual level.

**6.4.1.2 *Panel data models***

If there is heteroscedasticity present in the error term of the pooled LPM, the model may generate biased parameter estimates. I tested for the presence of heteroscedasticity using the Breush-Pagan Lagrange multiplier test. Under the null hypothesis that the individual-level variance component of the error term is zero, a rejection of the null hypothesis implies that a model controlling for individual heterogeneity is needed. Panel data models are able to control for individual heterogeneity that may bias the empirical estimates, as they observe individuals over multiple time periods.

The first panel data model I used was the GLS model. This model can control for unobserved individual effects which may influence measures of adolescent risky health behaviours (such as time or risk preferences) assuming that they are time invariant. The model assumes that unobserved individual level heterogeneity is unrelated to the vector of explanatory variables, by adjusting for autocorrelation in the error term (Greene 2003).

The specification of the GLS model I used can be given by:

$$RB_{it} = \beta_0 + \beta_1 EMP_{it} + \beta_2 \boldsymbol{x}_{jit} + v_i + u_{it} \,, \tag{6.12}$$

where *i* = 1, 2, … $n$ and *t* = 1,2, … $n$

In this specification, let $RB_{it}$ represent the incidence of a risky health related behaviour for individual $i$ at time $t$, and $EMP_{it}$ represent a dummy variable taking the value of 1 if the mother of individual $i$ is employed at time $t$ and 0 otherwise, with its parameter coefficient $\beta_1$. $\boldsymbol{x}_{jit}$ represents a vector of controlling variables relating to individual $i$ at time $t$, with their associated parameter coefficients $\beta_2$, and $\beta_0$ represents the constant term.

Unlike the LPM, the GLS specification requires that the error term $\varepsilon_{it}$ be represented as:

$$\varepsilon_{it} = v_i + u_{it} \,, \tag{6.13}$$

where $v_i$ represents the time invariant individual specific error term, $u_{it}$ represents the idiosyncratic error term for individual $i$ at time $t$, and $Cov[v_{it}, u_{it}|X] = 0$ for all $i, t$.

In practice, the estimates from a GLS model such as this are likely to be similar to those from the LPM with individually clustered standard errors if the panel is relatively unbalanced. This is very likely to be the case in this analysis, as the average individual only appears in just over two waves of the UKHLS dataset.

If the unobserved individual effects are correlated with one or more of the explanatory variables, then the GLS specification may give inconsistent results due to omitted variable bias. A partial solution to this problem is to remove the time invariant unobserved individual effects from the model by estimating a FE-LPM. The FE-LPM removes the time invariant unobserved individual effect $(v_i)$ from the model by mean differencing the data, and then estimating a LPM on the mean-differenced data. This leads to consistent estimates of the explanatory variables, even if the unobserved individual specific error term is correlated with one or more of the explanatory variables.

To formally test whether the GLS model or FE-LPM should be used, I implemented the Hausman Test (Hausman 1978), which tests the assumption that unobserved individual level heterogeneity is uncorrelated with the set of explanatory variables. Under the null hypothesis that individual level heterogeneity is uncorrelated with the explanatory variables, a rejection of the null hypothesis implies that the FE-LPM model should be used rather than the GLS model.

The FE-LPM specification I used in this chapter can be given by:

$$R\ddot{B}_{it} = \beta_0 + \beta_1 E\ddot{M}P_{it} + \beta_2 \ddot{\boldsymbol{x}}_{it} + \ddot{u}_{it} , \tag{6.14}$$

where *i* = 1, 2, … $n$ and *t* = 1,2, … 6

In this specification, let $R\ddot{B}_{it}$ represent a demeaned measure of the adolescent risky health related behaviour for individual $i$ and $E\ddot{M}P_i$ represent a demeaned measure of maternal employment for individual $i$, with its parameter coefficient $\beta_1$. $\ddot{\boldsymbol{x}}_i$ represents a vector of demeaned controlling variables relating to individual $i$ at time $t$, with their associated parameter coefficients $\beta_2$. $\ddot{u}_{it}$ represents the demeaned idiosyncratic error term for individual $i$ which is assumed to be unbiased, and $\beta_0$ represents the constant term. I estimated the GLS and FE-LPM specifications using the *xtreg* command, with standard errors clustered at the individual level.

#### 6.4.1.4 *Two stage least squares linear probability model*

Although the FE-LPM is able to account for individual level unobserved heterogeneity, these estimators still cannot be considered a true estimate of a causal parameter, as the model does not account for reverse causality, or changes in maternal employment which are endogenous to the outcome measures. Furthermore, the fixed effects framework is not robust to the presence of time variant omitted variables associated with both maternal labour supply and adolescent risky health related behaviours, which may render the empirical estimates endogenous.

This endogeneity issue can be shown more intuitively using a DAG. As shown in Figure 6.1, there may be a vector of unobserved characteristics ($\boldsymbol{x}_1$) which are related to both maternal employment and adolescent risky behaviours (such as ambition, ability, intelligence or time and risk preferences) that may render the relationship endogenous.

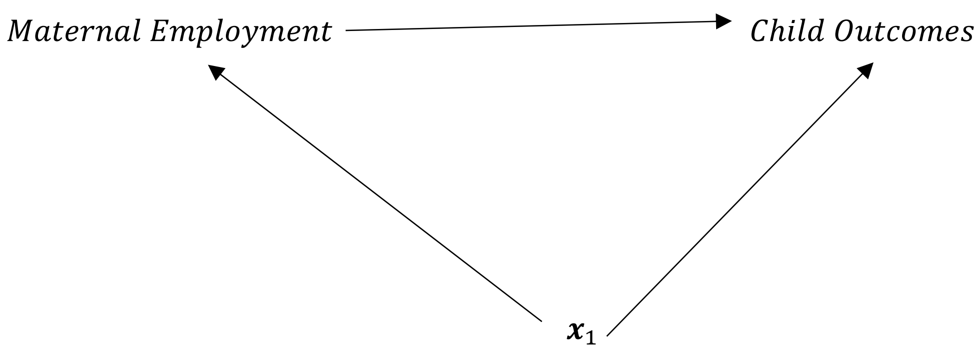


*Figure 6.1- DAG showing the effect of maternal employment on child outcomes in the presence of unobserved confounders*

One potential method of accounting for this potential endogeneity of maternal employment and isolating a causal effect is through the use of IV methods. The first IV strategy I used in this chapter was the incidence of having young siblings in the family, a strategy first implemented by Meyer (2016) to estimate the causal relationship between maternal employment and overweight children in Germany. This IV strategy is based upon the notion that the incentives for a mother to enter or re-enter the labour market will be significantly reduced if there are young children in the family, due to increased childcare needs. As argued by Meyer (2016), the opportunity costs of staying at home to look after the adolescent will be significantly lower if there is already a younger child to care for.

This IV strategy can be presented more intuitively using a DAG, shown in Figure 6.2. While Meyer (2016) used the number of younger siblings as an instrument, in this chapter I instead used the incidence of having one or more children aged 0-4 in the family, as full time education is compulsory in the UK from the age of 5, and therefore a lower time burden of childcare during working hours is required.

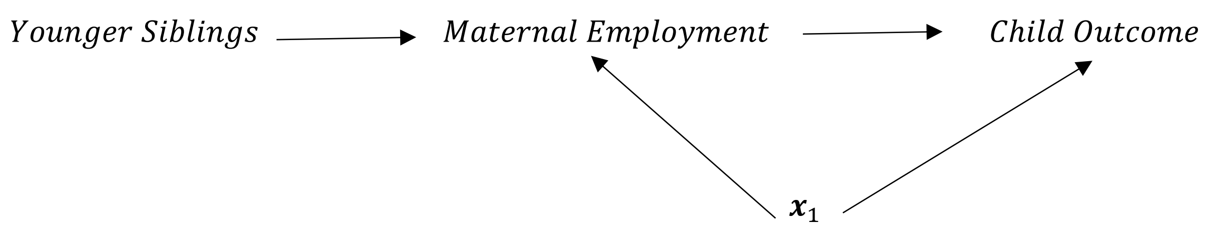


*Figure 6.2- DAG showing younger siblings acting as an instrumental variable for maternal employment in relation to child outcomes*

Although it is likely that having younger siblings will be significantly related to maternal employment, another requirement in order to obtain valid IV estimates is that the instrument must be uncorrelated with the error term, and only impact adolescent risky behaviour through changes in maternal employment. However, this assumption may not hold in practice. For example, one may expect the additional younger children to significantly impact the amount of time that a mother can allocate to other children, and will also be highly correlated with overall family size. As discussed at length in the preceding chapter, family size is almost certainly an endogenous variable in relation to child outcomes, as there is likely to be a vector of unobserved characteristics related to both variables.

Despite, these reservations regarding the true exogeneity of the IV strategy, I estimated a 2SLS-LPM, which can be shown as:

$$EMP_i = \beta_0 + \beta_1 YSIBS_i + \beta_2 \boldsymbol{x}_{ji} + \varepsilon_i \, , \tag{6.15}$$

$$RB_i = \psi_0 + \psi_1 \widehat{EMP}_i + \psi_2 \boldsymbol{x}_{ji} + \eta_{\mathrm{i}} \, , \tag{6.16}$$

where *i = 1,2,…n*

In the first stage of the model, let $EMP_i$ represent a dummy variable taking the value of 1 if the mother of individual $i$ is employed at time $t$, and 0 otherwise. $YSIBS_i$ repesents a dummy variable taking the value of 1 if the adolescent has any siblings under the age of 5 in the sample, and 0 otherwise, with its associated parameter coefficient $\beta_1$. $\boldsymbol{x}_{ji}$ represents a vector of controlling, explanatory variables with their associated parameter coefficients $\beta_2$. $\varepsilon_i$ represents the idiosyncratic error term, that is assumed to be unbiased, and $\alpha_0$ represents the constant term.

In the second stage of the model, let $RB_i$ represent the incidence of a risky health related behaviour for individual $i$. $\widehat{EMP}_i$ is a prediction of the effect of maternal employment from the first stage model, with its parameter coefficient $\psi_1$. $\boldsymbol{x}_{ji}$ represents a vector of controlling variables with their associated parameter coefficients $\psi_2$. $\psi_0$ and $\eta_{\mathrm{i}}$ represent the constant term and the idiosyncratic error term for individual $i$ respectively.

The second IV strategy I used in this chapter was a measure of local labour market conditions. This strategy has previously been used by Anderson *et al.,* (2003), Greve (2011), Bishop (2011) and Datar *et al.,* (2014). This IV strategy is based on the idea that better local labour market conditions, for example a low local unemployment rate, will be correlated with higher levels of maternal employment, and vice versa. If the residuals in a model of adolescent risky health related behaviours are not related to the local level geographic variables, the empirical model should be appropriately identified.

To construct a measure of the local labour market conditions, ideally I would have liked to link measures of the unemployment rate in a localised area, for example a Local Super Output Area (LSOA), with the geographical identifiers in the UKHLS. Unfortunately, exact variables such as the localised unemployment rate were unavailable for use. Instead, I followed the method of Plum and Knies (2015), and calculated a proxy measure of the local unemployment rate.

Specifically, I used the fact that the Geographic Accessibility dataset (GA) contains linked information from the Department for Transport's Accessibility Statistics with information from Waves A, B & C of the UKHLS in relation to access to public services, including employment centres, schools and hospitals[31]. Through the use of the GA, I was able to construct a proxy measure of the local unemployment rate. This measure was the ratio of the recipients of Jobseeker's Allowance (JSA) in the local geographical area and the users of employment centres in the same geographical area. I then subtracted the mean unemployment rate of the broad region from this measure to partially control for broad regional differences in the unemployment rate. Finally, I created a dummy variable with the value of 1 if the individual resides in an area with a proxy measure of the local unemployment rate in the 25th percentile, and 0 otherwise[32].

Although it is likely that the local labour market conditions will be significantly related to maternal employment, the instrument must be uncorrelated with the error term to be considered valid, and only impact adolescent well-being through changes in maternal employment. Cawley and Liu (2012) have argued that there are two main reasons why this instrument may not be exogenous. Firstly, it is possible that families may self-select into local areas, with the local labour market conditions potentially constituting part of this decision-making process. Secondly, studies such as Gerdtham and Ruhm (2006) have shown that macroeconomic conditions such as the local unemployment rate may also have a direct effect on individual health related outcomes through increased levels of disposable income, and it is not inconceivable that this may be extended to *adolescent* health related behaviours if part of this disposable income is directly or indirectly passed on to the adolescents. Despite these reservations regarding the true exogeneity of the IV strategy, I estimated 2SLS-LPM specifications similar to those shown in equations 6.15 and 6.16, with the local area unemployment used as the instrument rather than younger siblings. I implemented the 2SLS-LPM models using the *ivreg2* and *ivregress* commands. Due to the

[31] This information is only available for England, and therefore I excluded Scotland, Wales and Northern Ireland from this estimation sample.

[32] I used the 25th percentile as an arbitrary cut off point in line with Bloom and Knies (2015). Cut off points at the 15th percentile, 20th percentile and 30th percentile (not shown) generated similar estimates.

lack of variation over time in the two instruments, I was unable to use panel data IV methods in order to further control for individual level unobserved heterogeneity.

The estimates using the two different IV strategies will have different LATE interpretations. The younger siblings IV strategy captured the ATE of an increased maternal labour supply due to the incidence of younger siblings under the age of 5 in the household. The local labour market conditions IV strategy captured the ATE of an increased maternal labour supply caused by local area disparities in employment conditions.

### 6.4.2 *Maternal hours worked and adolescent health related behaviour*

A dummy variable of maternal employment may broadly capture the labour market status of the mother; however this measure of maternal labour supply ignores the fact that there is a wide distribution of the quantity of hours which mothers may work. To check whether not accounting for the quantity of maternal labour supply significantly impacted the interpretation of the relationship between maternal labour supply and adolescent risky health related behaviours, I estimated LPM, GLS and FE-LPM specifications using linear and quadratic measures of the number of hours worked by the mother per week. The specification I used for these models can be expressed as:

$$RB_{it} = \beta_0 + \beta_1 Hours_{it} + \beta_2 (Hours)^2{}_{it} + \beta_3 \boldsymbol{x}_{jit} + v_i + u_{it} \,, \tag{6.17}$$

where *i* = $1, 2, \dots n$ and *t* = $1,2, \dots 6$

$RB_{it}$ represents the incidence of a risky health related behaviour for individual $i$ at time $t$, with $Hours_{it}$ and $(Hours)^2{}_{it}$ representing linear and quadratic measures of the number of hours worked by the mother, with their associated parameter coefficients $\beta_1$ and $\beta_2$. $\boldsymbol{x}_{jit}$ represents a vector of controlling variables relating to individual $i$, with their associated parameter coefficients $\beta_3$, and $\beta_0$ represents the constant term.

### 6.4.3 *Maternal non-standard work schedules and adolescent health behaviour*

To estimate the relationship between the incidence of maternal non-standard work schedules and adolescent risky health related behaviours, I estimated both LPM and GLS specifications of the form:

$$RB_{it} = \beta_0 + \beta_1 NS_i + \beta_2 \boldsymbol{x}_{jit} + v_i + u_{it} \qquad if\ EMP_i = 1\ , \tag{6.21}$$

where $i$ = 1, 2, … $n$ and $t$ = 1,2,3

Let $RB_{it}$ represent the incidence of a risky health related behaviour for individual $i$, with $NS_{it}$ representing the incidence of the mother working non-standard work schedules, with its associated parameter coefficient $\beta_1$. $\boldsymbol{x}_{jit}$ represents a vector of controlling variables relating to individual $i$, including the occupational classification, the number of hours worked and the wage rate, with their associated parameter coefficients $\beta_2$. $v_i$ and $u_{it}$ represent the individual specific and idiosyncratic error terms respectively, and $\beta_0$ represents the constant.

When I estimated the RE-LPM specification, I assumed that that $v_i$ was non-zero, but not correlated with the explanatory variables. Although this assumption is unlikely to hold in practice, I was not able to control for individual level unobserved heterogeneity through the use of fixed effects or proxy fixed effects in empirical analysis. This is because the main explanatory variable of interest (the incidence of non-standard working schedules) only appears in alternate waves 2, 4 and 6 of the UKHLS, and also has very little within-person variation compared to between-person variation over time. Therefore, both fixed effects and proxy fixed effects estimates are likely to be imprecise and have extremely large standard errors, which may be too large to tolerate (Allsion 2009). The potential inconsistency of the FE-LPM and Mundlak approach RE-LPM specifications is exacerbated by the fact that the panel is also very unbalanced, which severely reduces the number of within individual comparisons available.

**6.5 Data and Variables**

In the analysis for this empirical chapter I used six waves of data drawn from the UKHLS, which was described in detail in Chapter 2. Importantly for this chapter, the UKHLS contains a youth self-completion questionnaire alongside information regarding the adult members of the household, completed by any youth aged 10-15 in the household at the time. As well as the standard set of family background variables, the youth questionnaire contains a range of questions regarding issues specific to that age range. For instance, the survey contains information regarding the use of social websites, levels of bullying at school and the use of illicit drugs. Given the extensive information regarding household level factors, the range of adolescent outcome measures and the longitudinal nature of the dataset, the UKHLS was seen as an appropriate dataset for the research question in this chapter.

### 6.5.1 *Dependent variables*

The two measures of adolescent risky health behaviour I used in this chapter were the self-reported incidence of smoking cigarettes and drinking alcohol. In the UKHLS youth self-completion survey questionnaire, the child was asked several questions related to these activities. In this case, the two questions of interest were: "*Do you ever smoke cigarettes at all?"* and *"Have you ever had an alcoholic drink? That is the whole drink, not just a sip"*.

From these questions, I created the dummy variables *EVER_SMOKE* and *EVER_DRINK,* coded as 1 if the child answered yes to the corresponding question, and 0 if they answered no in each wave. Around 36% of the pooled sample reported having have tried drinking, with around 7% of the pooled sample reporting having tried smoking. No significant gender differences were found for either measure. The risk of reporting bias impacting the truthfulness of the answers was minimal, as the adolescent completed the youth questionnaire in isolation, away from their parents.

While the wording of the question regarding smoking behaviour allowed the adolescent to transition from smoking to not smoking or vice versa on a wave by wave basis, the wording of the question regarding drinking did not, and therefore allowed for the possibility of inconsistent answers across waves from individuals (for example reporting that they have had a whole alcoholic drink during their lifetime at time $t$, yet reporting that they have never had an alcoholic drink at time $t+1$). There were two conceivable ways in which the *EVER_DRINK* variable could have been adjusted to take into account the inconsistent answers across waves. Firstly, I could have dropped all individuals who reported 'inconsistent' answers from the sample. However, employing a tactic such as this would have reduced the sample size by around 4%, and it is conceivable that the adolescent simply misunderstood the question, and answered it as though it was referring to the previous year only.

Alternatively, I could have retained the observations in the study, and adjusted the variable to take into account the inconsistent answers to the questions over time, so that a *yes* answer to the *EVER_DRINK* truly represented if the adolescent had ever answered *yes* to the questions across the different waves of data. Ultimately, it is this method that I used in empirical analysis. However, I also estimated models using the adjusted measure of adolescent drinking to check the robustness of the results to the alternative method.

### 6.5.2 *Key explanatory variables*

The first explanatory variable of interest I considered in the chapter was a binary measure of maternal employment. I constructed this measure using the *jbstat* variable, which asked each household member about their current economic activity, and coded the variable as 1 if the mother reported currently being in employment (including self-employment), and 0 otherwise. The second explanatory variable of interest I considered was the number of hours worked per week by the mother. I constructed this variable by summing the responses to various questions concerning the mother's normal weekly working hours, how much overtime the mother worked per week and the amount of time the mother worked in a second job per month (if applicable). As shown in Figure 6.3, maternal working hours were truncated, with around 33% of the mothers in the sample reporting not working any hours. Aside from this, the distribution of maternal hours worked was roughly normally distributed, with peaks around the conventional number of hours for full and part time jobs, for example 20 hours, 30 hours, 35 hours and 40 hours. For the empirical analysis, I followed the methodology of Ruhm (2008) and Mendolia (2016) and divided the total number of hours by 20, so that a one unit increase corresponded to 20 additional hours of maternal labour supply[33]. I also included a dummy variable for being self-employed, as it is has been argued that self-employed mothers may have greater flexibility regarding their working hours (Mendolia 2016), and therefore may be able to combine work with time spent with children.

[33] This also allows me to directly compare my results to those of Mendolia (2016).

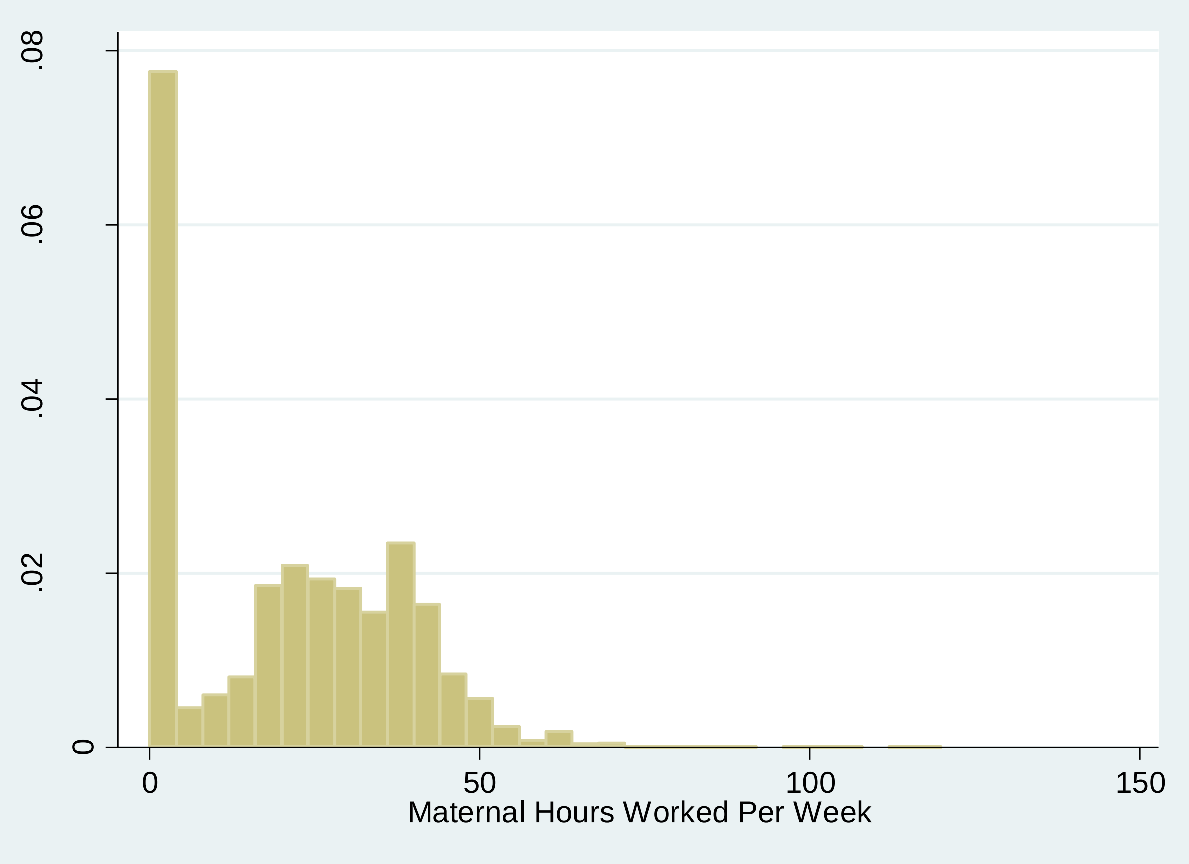


*Figure 6.3- Distribution of maternal working hours in the full estimation sample*

The third explanatory variable of interest I considered in this chapter was the incidence of non-standard maternal work schedules. I constructed this measure from the *wkends* and *wktime* variables, which asked the respondent whether they have to work at the weekend and when the works shifts take place in the day. Following the previous empirical literature, from these two questions I created a dummy variable *NON_STANDARD*, taking the value of 1 if the mother reported regularly working during the evening or regularly working at the weekend, and 0 otherwise. Of employed mothers, around 27% reported regularly working non-standard work schedules.

### 6.5.3 *Other explanatory variables*

Informed by both the theoretical and empirical literature, I also included a number of child, maternal and household characteristics in the various model specifications. Table 6.1 presents a complete list of variables and definitions used in the various models.

The first child characteristic I included was a dummy variable for gender, as Best *et al.,* (2001) have shown that the engagement in risky health behaviours may vary by gender in the UK. The region where the adolescent resides may also impact their probability of engaging in risky health behaviours, through supply side factors or local cultural norms. Therefore, I included a categorical regional variable, with categories for 10 broad areas of England and Scotland, Wales and Northern Ireland, as well as a dummy variable indicating if the adolescent lives in an urban or rural area. To control for the fact that the older children included in the survey (ages 13-15) will be far more likely to engage in smoking and drinking than younger children, I also entered child age into the regression model as a categorical variable. As noted by Contoyannis and Rice (2001), in empirical analysis either the age variable or the wave variable should be left out of the FE models due to simultaneity. In this case I excluded the wave variables from the FE-LPM specifications.

Aside from maternal labour supply, there are a number of other factors that may influence both the quantity and quality of time investments that mothers may invest in their children. The first of these characteristics I controlled for was maternal age, which was included as a linear and quadratic term. As argued by Fergusson and Woodward (1999), an increased maternal age may decrease the probability of an adolescent engaging in risky health behaviours, with this association potentially mediated through child-rearing practices and home environments experienced by children.

The second of these characteristics I controlled for was a measure of maternal mental health. As Frech and Kimbro (2011) have argued, depressed mothers are more likely to engage in negative parenting practices, for example disengagement with their children. Furthermore, Wickham *et al.,* (2015) have shown that exposure to maternal depression symptoms is associated with greater engagement in risky health behaviours from adolescents. To control for these potential effects, I included the Short Form 12-item Survey (SF-12) mental component summary as an additional explanatory variable, split into quintiles.

I also controlled for two measures of family structure: whether the mother was single and the number of children in the family. Using time use diaries, Kendig and Bianchi (2008) have shown that single mothers on average spend less time with their children than those mothers who are married or cohabit. Although these differences were shown to be relatively minor, it is still worth taking into account.

## Table 6.1- Variable labels and definitions for regression models

| Variable Name | Description | UKHLS Variable(s) used |
|---|---|---|
| ***Dependent Variables*** | | |
| EVER_DRINK | 1 = Adolescent has drunk alcohol, 0 = otherwise | *ypevralc* |
| EVER_SMOKE | 1 = Adolescent has smoked tobacco products, 0 = otherwise | *ypevrsmo* |
| ***Key Explanatory Variables*** | | |
| *EMPLOYED* | Binary measure of maternal employment. 1 = mother has a job, 0 = otherwise | *jbstat* |
| *MAT_HOURS* | Continuous measure of the number of hours a mother works per week if she has a job, divided by 20 | *jbhrs* *jbot* *j2hrs* |
| *$(MAT\_HOURS)^2$* | As above, but squared. | |
| *NON_STANDARD* | Binary measure of the incidence of 'non-standard' work schedules. 1 = if the mother reports either working at the weekend or working in the evenings. | *wkends* *wktime* |
| ***Instrumental Variables*** | | |
| *KIDS_UNDER_5* | Binary measure of the incidence of having at least one child under the age of 5 | *nch_02_dv* *nch_34_dv* |
| *LOCAL_UNEMPLOYMENT* | Proxy measure of the local unemployment rate. Number of 'at risk' users of employment centres in the local area divided by the number of users of employment centres in the local area, adjusted for broad regional differences. 1 = resides in the 25$^{th}$ percentile of local unemployment rate, 0 = otherwise | *ecall* *ecrisk* *region_dv* |
| ***Child Characteristics*** | | |
| *CHILD_AGE* | Age of child in years | *dvage* |
| *GENDER* | 0 = Child is female, 1 = Child is male | *ypsex* |
| *REGION* | Region where child resides. Entered into the model as categorical variables with categories for the 12 government office regions | *region_dv* |
| *URBAN* | Binary indicator of whether the area the child resides in is urban or rural. 1 = Urban, 0 = Rural | *urban_dv* |
| *OUT_AFTER_9* | Binary indicator of whether the child has been out unsupervised after 9pm at least once in the past month. 0= No, 1= Yes | *yplate* |
| *MEALS_WITH_FAMILY* | Indicator of how often the child eats an evening meal with the family per week. Categories for none, 1-2, 3-5, 6-7. | *ypeatlivu* |
| ***Maternal Characteristics*** | | |
| *SELF-EMPLOYED* | Binary indicator of whether mother is self-employed. 1 = self-employed, 0 = otherwise | *jbstat* |
| *MATERNAL AGE* | Mother's age at birth in years. | *age_cr* |
| *$(MATERNAL\ AGE)^2$* | As above, but squared. | *age_cr* |
| *MENTAL_HEALTH* | SF-12 Mental Component, split into quintiles. 1 = highest level of mental health problems, 5 = lowest level of mental health problems | *sf12mcs_dv* |
| *NUMBER_CHILDREN* | Number of children currently living in the household | *nchild_dv* |
| *SINGLE_HOUSEHOLD* | Marital status of mother. 1= Single/divorced/living apart; 0 = married/cohabiting | *mastat_dv* |
| *ALCOHOL_SPENDING* | Household spending per week on alcohol in pounds. | *xpaltob_g3* |
| ***Socioeconomic Characteristics*** | | |
| *WAGE* | Logarithm of hourly wage of the mother. Calculated by dividing the monthly wage by 4, and this weekly wage by 40. | *paygu_dv* *sex_cr* |
| *MATERNAL_EDUCATION* | Mothers highest educational qualification. 0 = no formal qualifications, 1 = GCSE level qualifications, 2 = A-Level/Diploma qualifications, 3 = Degree level qualifications. | *hiqual_dv* *sex_cr* |
| *MAT_NSSEC_5* | Occupation of the mother. 1 = Managerial/Professional, 2 = Intermediate, 3 = Semi/Self-Employed, 4 = Lower Supervisory and Technical, 5 = Semi-routine/routine. | *Jbnssec5_dv* *sex_cr* |
| *OWN_HOUSE* | Binary indicator of whether the mother owns the house or has a mortgage, 1= Own House, 0= Otherwise | *hsownd* |

Furthermore, a number of studies, including Bryant and Zick (1996), have shown that the amount of time parents allocate to each individual child may be inversely related to the number of children in the family.

Ideally, I would have wanted to control for smoking behaviour of parents, as it has been found that there may be significant intergenerational transmission in smoking behaviours (Gohlmann *et al.,* 2010; Brown and Van der Pol 2015). Unfortunately, the UKHLS variable regarding smoking behaviour was only collected in the second and fifth waves of data, and therefore I could not use this measure in analysis without losing a considerable proportion of the estimation sample[34]. Although I could not effectively control for parental smoking without losing significant amounts of data, I was able to partially control for parental drinking behaviour, which has also been shown to be significantly correlated with the drinking behaviour of their children (Schmidt and Tauchmann 2011). I controlled for this by including a variable which asks the main respondent the total amount spent on alcohol in the past four weeks by the household.

I also included variables designed to control for parental supervision and parent-child communication. To control for parental supervision, I included a measure of how often the adolescent was out unsupervised past 9pm in the past month. There are questions regarding parental-child communication included in the UKHLS, specifically relating to how often the adolescent talks to their parents regarding 'things that matter'. Unfortunately, these variables were only collected in waves 1, 3 and 5, and therefore could not be included in the econometric models focussing on non-standard work schedules, as information regarding work schedules was only collected in waves 2, 4 and 6. To partially control for parental-child communication, I included a measure of how often the adolescent eats an evening meal with their parents, which has been shown to be associated with measures of parent-child communication (Fulkerson *et al.,* 2011).

There are also reasons to believe that the relationship between maternal labour participation and risky health behaviours may vary by maternal educational attainment. Mothers with higher educational attainment, who are also more likely to have higher levels

[34] If I had a relatively balanced panel, I could have extrapolated the answers from the questions in waves 2 and 5 to the other waves. However, as the youth self-completion part of the panel is extremely unbalanced (the average adolescent only appears in 2 of the 6 waves of data), this method would still have involved losing a considerable amount of data, and also imposed additional assumptions regarding the dynamics of parental smoking behaviour.

of unobserved human capital, such as intelligence or ability, may spend a greater proportion of their leisure time in child related activities (Leibowitz 1974) and be more efficient at converting time inputs into high quality child investments. This relationship has also been shown in a number of empirical studies, for instance Carneiro *et al.,* (2013), who find educational attainment to be related with a large number of different child outcomes, independent of other measures of SES. Maternal educational attainment was included in empirical specifications as a categorical variable for highest educational attainment, ranging from no qualifications to degree level qualifications.

Ideally, I would have wanted to control for a number of other socioeconomic characteristics, given the potential relationship between SES and measures of adolescent risky health behaviour (Hanson and Chen 2007). However, I could not include two of the most commonly used measures of SES, parental occupation and household income, in the models investigating the relationship between maternal employment and adolescent behaviours, as they themselves can be seen as being contingent on the mother being employed. I did include a dummy variable for housing tenure as a rudimentary measure of SES, taking the value of 1 if the mother was a home owner or had a mortgage, and 0 otherwise.

However, I did include measures of occupational attainment and wage level in the models estimating the relationship between maternal non-standard work schedules and adolescent risky health behaviours. I used the five level NSSEC-5 classification as the measure of maternal occupation, with categories ranging from semi routine and routine occupations to managerial and professional occupations. I also included a logged measure of the hourly wage to account for the level of income.

### 6.5.4 *Survey weights*

Although there are a large number of sampling weights provided by the UKHLS team, due to the specific data requirements for this research question, which merged a sample from the youth survey and the main survey, and in some models only used waves 2, 4 and 6, there was no 'optimal' weighting strategy. Following discussion with staff from the UKHLS, the most appropriate 'sub-optimal' weighting strategy to use was seen to be the longitudinal or cross-sectional weights from the main survey, in the most recent wave of data used. However, there were several significant disadvantages associated with implementing a weighting strategy such as this in the estimation sample. Firstly, the use of the longitudinal sampling weights requires a balanced panel, meaning that if I were to have used such weights in analysis, the sample would have been restricted to just those individuals who have observations in all waves.

If I were to instead have used the cross-sectional weights, the sample would have been restricted to only those adolescents present in the sixth wave, which would have significantly reduced the estimation sample and ignored the panel nature of the dataset. Furthermore, due to the reduced sample size when merging the main survey with the youth survey, applying a weighting strategy based on the main survey would have resulted in a large number of strata containing only one sampling unit. Due to these strata containing a single sampling unit, there would have been insufficient information with which to compute an estimate of each individual stratum's variance, and therefore I would have been unable to compute standard errors for the regression parameters.

There are two seen to be two solutions for dealing with the problem of single sampling units within strata (Statacorp 2016). The first solution is to delete the strata with single sampling units from the estimation sample. Standard errors for the parameters from a model which includes all strata with at least two sampling units may therefore be estimated. However, using this strategy in this sample would have significantly reduced the estimation sample size, and dropping all strata which only included one sampling unit may have also introduced more bias than was previously present in the unweighted models.

The second solution to the problem of single sampling units within strata is to treat the data from those strata as though they are from different strata. Although this strategy may be appropriate when there are very few strata with single sampling units, in this case a large proportion of the observations came from strata with single sampling units. Reassigning this many observations to different strata may have once more introduced more bias than was previously present in the unweighted model.

Due to these various complications, I was unable to utilise sampling weights in the empirical analysis. Implementing either the longitudinal or cross sectional sample weights would have either meant reducing the estimation sample whilst potentially increasing levels of bias the model, or potentially increasing the level of bias in the empirical model through the wide scale reassignment of strata for individual sampling units. Therefore, it should be emphasised that although every effort was made to ensure that the results were internally valid, due to the results being unweighted, they cannot be seen as being fully representative of the distribution of the UK population.

### 6.5.5 *Missing data*

As well as the variety of explanatory variables I controlled for, ideally I would have wanted to include the ethnicity of the adolescent in the empirical models, as it has been argued there may be significant ethnic disparities in adolescent health behaviour (Blum *et al.,* 2000). However, the ethnicity variable in the UKHLS exhibited a significant amount of missing data (>6%). There were three conceivable methods that I could have used to account for this level of missing data.

Firstly, I could have dropped all observations which had missing data concerning ethnicity and conducted a complete case analysis. However, employing this method would have meant dropping a significant amount of data from the sample, which would have potentially increased the level of bias if not reporting an ethnicity was non-random. Alternatively, I could have included the ethnicity variable in the econometric models with a category for missing ethnicity. However, although this may have resulted in a larger sample size, it may have biased the results in the presence of unobserved characteristics related to not reporting an ethnicity. Finally, I could have left the ethnicity variable out of the empirical model. Although this method excludes a potentially key explanatory variable, in the main model of interest (the FE-LPM), the time invariant ethnicity variable was excluded from analysis. Consequently, it is this final method that I used. However, I also implemented the two other options mentioned above as robustness checks.

Aside from the ethnicity variable, there was relatively little missing data, with around 3% of the estimation sample having missing data on one or more of the variables. In order to check to what extent the small amount of missing data may bias the empirical estimates in this chapter, I estimated models weighted by the inverse probability of being included in the sample, using the method proposed by Bartlett (2012).

Due to the use of panel data models, I also tested for attrition, as a systematic relationship between maternal labour market characteristics, adolescent risky health behaviours and non-response may have resulted in bias in empirical models. To test for attrition bias I used the test proposed by Verbeek and Nijman (1992). I used two test variables: 1) how many waves the adolescent was present in; and 2) if the adolescent was present in the next wave.

I regressed these test variables together with a full set of controlling variables on the adolescent risky health behaviour variables in all model specifications.

### 6.5.6 *Exclusion criteria*

The two estimation samples I used in this chapter were restricted in a number of ways. Firstly, I excluded any child who did not live with their natural mother (n=687) or had a proxy respondent for the mother (n=882), as these observations did not have the requisite information regarding the key explanatory variables: maternal working hours and maternal working schedules. I also excluded a very small number of mothers who were retired or on maternity leave, due to their lack of economic activity (n=121).

Secondly, information regarding the timing of maternal working hours (i.e. whether the mother works evening or rotating shifts and whether the mother works at the weekend) was only available in waves 2, 4 and 6, and therefore I was unable to carry out analysis using these waves when investigating the impact of maternal non-standard work schedules on adolescent risky health behaviour. The non-standard working schedules equations were also restricted to women in employment and excluded those in self-employment. These changes reduced this sub sample by a further 10%. My final sample sizes were therefore 18946 observations from 8861 individuals for the full estimation sample and 5566 observations from 3983 individuals for the non-standard work schedules sub sample.

### 6.5.7 *Descriptive relationships*

Table 6.2 and Table 6.3 show the descriptive statistics for the two estimation samples. As shown, in the full estimation sample around 67% of mothers reported being in some form of employment, with around 27% of those employed mothers also reporting working non-standard work schedules. Around 36% of adolescents in the full sample reported having had an alcoholic drink, while roughly 7% of the adolescents reported having tried smoking.

| Table 6.2- Descriptive statistics for the maternal employment estimation sample (N=18946) | | | | |
|---|---|---|---|---|
| Variable Name | Mean | Std Dev | Minimum | Maximum |
| Drinking | 0.36 | 0.48 | 0 | 1 |
| Smoking | 0.07 | 0.26 | 0 | 1 |
| Mat Employment | 0.69 | 0.46 | 0 | 1 |
| Maternal Hours/20 | 1.03 | 0.87 | 0 | 6 |
| (Maternal Hours)$^2$/20 | 1.81 | 2.22 | 0 | 36 |
| Child Age | 12.52 | 1.69 | 10 | 15 |
| Female | 0.50 | 0.50 | 0 | 1 |
| North East | 0.5 | 0.21 | 0 | 1 |
| North West | 0.10 | 0.30 | 0 | 1 |
| Yorkshire/Humber | 0.08 | 0.27 | 0 | 1 |
| East Midlands | 0.07 | 0.26 | 0 | 1 |
| West Midlands | 0.09 | 0.28 | 0 | 1 |
| East England | 0.08 | 0.28 | 0 | 1 |
| London | 0.12 | 0.33 | 0 | 1 |
| South East | 0.12 | 0.32 | 0 | 1 |
| South West | 0.07 | 0.26 | 0 | 1 |
| Wales | 0.06 | 0.24 | 0 | 1 |
| Scotland | 0.09 | 0.29 | 0 | 1 |
| Northern Ireland | 0.07 | 0.26 | 0 | 1 |
| Urban | 0.77 | 0.42 | 0 | 1 |
| Self-Employed | 0.07 | 0.25 | 0 | 1 |
| Out After 9pm | 0.14 | 0.35 | 0 | 1 |
| Meals With Family | 3.17 | 0.95 | 0 | 4 |
| Maternal Age | 41.46 | 5.94 | 16 | 62 |
| (Maternal Age)$^2$ | 1754.35 | 493.06 | 256 | 3844 |
| Mat Mental Health Top Quintile | 0.20 | 0.40 | 0 | 1 |
| 2nd Quintile | 0.20 | 0.40 | 0 | 1 |
| 3rd Quintile | 0.20 | 0.40 | 0 | 1 |
| 4th Quintile | 0.23 | 0.42 | 0 | 1 |
| Bottom Quintile | 0.17 | 0.38 | 0 | 1 |
| Number of Children | 2.13 | 1.05 | 1 | 10 |
| Single Household | 0.35 | 0.48 | 0 | 1 |
| Alcohol Spending | 0.26 | 0.44 | 0 | 1 |
| Degree Level Education | 0.25 | 0.44 | 0 | 1 |
| Other Higher | 0.15 | 0.36 | 0 | 1 |
| A-Level | 0.18 | 0.39 | 0 | 1 |
| GCSE/O-Level | 0.26 | 0.44 | 0 | 1 |
| Other Qualifications | 0.08 | 0.27 | 0 | 1 |
| No Qualifications | 0.08 | 0.27 | 0 | 1 |
| Own House | 0.67 | 0.47 | 0 | 1 |

| Table 6.3- Descriptive statistics for non-standard work schedules estimation sample (N=5566) | | | | |
|---|---|---|---|---|
| Variable Name | Mean | Std Dev | Minimum | Maximum |
| Drinking | 0.37 | 0.48 | 0 | 1 |
| Smoking | 0.07 | 0.26 | 0 | 1 |
| Non-Standard Work Schedule | 0.27 | 0.44 | 0 | 1 |
| Maternal Hours | 1.48 | 0.63 | 0 | 4.9 |
| $(\text{Maternal Hours})^2$ | 2.60 | 2.05 | 0 | 24.01 |
| Child Age | 12.59 | 1.68 | 10 | 15 |
| Female | 0.50 | 0.50 | 0 | 1 |
| North East | 0.04 | 0.18 | 0 | 1 |
| North West | 0.10 | 0.30 | 0 | 1 |
| Yorkshire/Humber | 0.08 | 0.27 | 0 | 1 |
| East Midlands | 0.07 | 0.26 | 0 | 1 |
| West Midlands | 0.09 | 0.28 | 0 | 1 |
| East England | 0.09 | 0.29 | 0 | 1 |
| London | 0.09 | 0.29 | 0 | 1 |
| South East | 0.12 | 0.33 | 0 | 1 |
| South West | 0.07 | 0.26 | 0 | 1 |
| Wales | 0.08 | 0.27 | 0 | 1 |
| Scotland | 0.07 | 0.25 | 0 | 1 |
| Northern Ireland | 0.10 | 0.30 | 0 | 1 |
| Urban | 0.74 | 0.44 | 0 | 1 |
| Out After 9pm | 0.15 | 0.35 | 0 | 1 |
| Meals With Family | 3.17 | 0.96 | 0 | 4 |
| Maternal Age | 42.27 | 5.61 | 24 | 60 |
| $(\text{Maternal Age})^2$ | 1818.20 | 473.32 | 576 | 3600 |
| SF-12 Mental Health Top Quintile | 0.16 | 0.36 | 0 | 1 |
| 2nd Quintile | 0.20 | 0.40 | 0 | 1 |
| 3rd Quintile | 0.22 | 0.41 | 0 | 1 |
| 4th Quintile | 0.24 | 0.43 | 0 | 1 |
| Bottom Quintile | 0.18 | 0.39 | 0 | 1 |
| Number of Children | 1.92 | 0.84 | 1 | 6 |
| Single Household | 0.31 | 0.46 | 0 | 1 |
| Alcohol Spending | 0.31 | 0.46 | 0.00 | 1.00 |
| Degree Level Education | 0.29 | 0.45 | 0 | 1 |
| Other Higher | 0.18 | 0.38 | 0 | 1 |
| A-Level | 0.19 | 0.40 | 0 | 1 |
| GCSE/O-Level | 0.25 | 0.43 | 0 | 1 |
| Other Qualifications | 0.06 | 0.23 | 0 | 1 |
| No Qualifications | 0.03 | 0.18 | 0 | 1 |
| Own House | 0.78 | 0.41 | 0 | 1 |
| Management/Profession | 0.42 | 0.53 | 0 | 1 |
| Intermediate | 0.21 | 0.40 | 0 | 1 |
| Small Employers | 0.01 | 0.10 | 0 | 1 |
| Lower Supervisory | 0.04 | 0.20 | 0 | 1 |
| Semi Routine/Routine | 0.32 | 0.47 | 0 | 1 |
| Logarithm of Wage | 1.98 | 0.73 | 0 | 4.42 |

Appendix 6A shows bar charts of the relationships between the incidence of adolescent smoking and drinking behaviour across maternal employment status. The probability of engaging in drinking behaviour was around 7% higher amongst those adolescents with mothers who were currently in employment compared to those mothers who reported not being employed, while the probability of engaging in smoking behaviour was around 2% lower amongst those adolescents with mothers who reported being in employment compared to those who reported not being employed. Both these differences were statistically significant at the 1% level. Almost identical relationships were also found when those mothers who reported being 'currently unemployed' rather than not participating in the labour market (due to either looking after family members, being a student or being disabled) were included in the employment category (n=710).

As also shown in Appendix 6A, having a mother who worked non-standard work schedules increased the probability of engaging in adolescent drinking and smoking behaviours by around 4% and 2% respectively compared to those who did not work non-standard work schedules. These differences were again statistically significant at the 1% level.

As shown in Table 6.4, the two adolescent risky health behaviours were also extremely highly correlated. Due to this significant correlation, Oshio and Kobayashi (2010) have explored the social determinants of smoking and drinking in a bivariate probit framework, which explicitly takes into account the potential correlation between the error terms of the two outcome variables. While I did not explore this possibility in this chapter due to difficulties in controlling for individual level unobserved heterogeneity in the bivariate probit framework, this significant correlation between the outcome measures is worth noting when interpreting the results.

**Table 6.4- Correlation between adolescent drinking and smoking in the full estimation sample**

| | Full Estimation Sample | Non-Standard Schedules Sample |
|---|---|---|
| Tetrachoric Rho | 0.593 | 0.633 |
| Std Error | 0.013 | 0.023 |
| Observations | 18946 | 5566 |

## 6.6 Results and Discussion

### 6.6.1 *Maternal employment and adolescent risky health related behaviours*

#### 6.6.1.1 *Panel data models*

First, I estimated the relationship between a binary measure of maternal employment and adolescent drinking and smoking behaviours. Before estimating the full empirical models, I tested whether the estimation sample should be separated by gender. The Chow test (Chow 1960) assesses whether the coefficients are equal and the variance in the male and female 'groups' are equal. The Chow test was run in both pooled LPM and GLS models, with the output shown in Table 6.5. A post-estimation test on the female dummy variable and the interaction terms for being female indicated that the null hypothesis of equal coefficients and equal variance could not be rejected for either drinking or smoking, and therefore separate equations for males and females were not estimated.

**Table 6.5- Chow tests for the full estimation sample**

| Drinking | Smoking |
|---|---|
| $Chi^2$ (41) = 1.87 | $Chi^2$ (41) = 0.97 |
| Prob>$Chi^2$ = 0.171 | Prob>$Chi^2$ = 0.324 |

I also tested whether attrition should bias the results, using the test proposed by Verbeek and Nijman (1992). As shown in Table 6.6, the null hypothesis of random non-response from the Wald test was not rejected using both the total number of waves and the next wave as test variables. Therefore, it was assumed that non-response bias would not bias the results in this estimation sample. Table 6.7 shows a summary of the results from the LPM, GLS and FE-LPM specifications for the estimation sample. In the interests of space, the full regression output is presented in Appendices 6B and 6C.

**Table 6.6- Wald test for attrition in full estimation sample**

| | | |
|---|---|---|
| Pooled Models | | |
| # of waves respondent is present | $Chi^2$ (1) | 0.29 |
| | Prob>$Chi^2$ | 0.59 |
| If respondent is present is next wave | $Chi^2$ (1) | 0.20 |
| | Prob>$Chi^2$ | 0.65 |
| Panel Data Models | | |
| # of waves respondent is present | $Chi^2$ (1) | 0.12 |
| | Prob>$Chi^2$ | 0.72 |
| If respondent is present is next wave | $Chi^2$ (1) | 0.71 |
| | Prob>$Chi^2$ | 0.40 |

**Table 6.7- Conditional association between maternal employment and adolescent risky health behaviours in LPM, GLS and FE-LPM specifications**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Drinking | | | Smoking | | |
| | LPM | GLS | FE-LPM | LPM | GLS | FE-LPM |
| Mother Employed | 0.048*** | 0.044*** | -0.003 | -0.010** | -0.006 | -0.003 |
| | (0.008) | (0.009) | (0.018) | (0.005) | (0.005) | (0.011) |
| Breusch Pagan Test | 539.90*** | | | 6817.15*** | | |
| | (0.000) | | | (0.000) | | |
| Hausman Test | | 3091.23*** | | | 593.48*** | |
| | | (0.000) | | | (0.000) | |
| Individuals | 8861 | 8861 | 8861 | 8861 | 8861 | 8861 |
| Observations | 18946 | 18946 | 18946 | 18946 | 18946 | 18946 |
| R-squared | 0.230 | 0.228 | 0.240 | 0.072 | 0.072 | 0.057 |

*Notes*: Results from LPM, GLS and FE-LPM specifications. Clustered standard errors in parentheses. *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Each column represents a separate regression, with all models controlling for a range of child, mother and household characteristics. Full regression output for these models is shown in Appendices 6B and 6C.

As shown in columns 1-2, there was evidence of an economically small, yet statistically significant, positive association between maternal employment and the incidence of adolescent drinking in both LPM and GLS models, consistent with the descriptive relationships shown in Appendix 6A. However, as shown in column 3, this relationship was not present when the FE-LPM specification was estimated. Although this result may point to individual level unobserved heterogeneity inflating the estimates from the LPM and GLS models, this result may also stem from the nature of the maternal employment variable, which was relatively constant over time. As argued by Allison (2009), variables that are relatively time invariant can cause substantial problems in the fixed effects framework.

As shown in column 4, there was also evidence of a very small, yet statistically significant, *negative* association between maternal employment and the incidence of adolescent smoking in the LPM specification, which was consistent with the descriptive relationships shown in Appendix 6A. However, as shown in columns 5 and 6, this relationship decreased in magnitude and became statistically insignificant in both the GLS and FE-LPM specifications.

As shown by the full regression output in Appendices 6B and 6C, the other explanatory variables included in the various models mostly followed the pattern one would expect. For example, engaging in risky health behaviours was associated with being older, having a younger mother, being from a single parent family, belonging to a household who spend more money on alcohol per month, having an increased level of unsupervised time after 9pm and being less likely to eat an evening meal with their family. The two broad measures of SES that were included in these specifications (maternal educational attainment and housing tenure), also had the signs that one would expect, implying that those from lower socioeconomic groups are more likely to engage in risky health behaviours.

As shown in Tables 6.8- 6.10, these results were robust (in terms of both magnitude and statistical precision) to different model specifications (probit and logit), the alternative measure of adolescent drinking adjusted to take into account inconsistent answers across waves, and different ways of controlling for ethnicity. Furthermore, as displayed in Appendix 6D, these results were also robust to the implementation of inverse probability weights to account for levels of missing data.

**Table 6.8 - Conditional association between maternal employment and adolescent risk health related behaviours in LPM, Probit and Logit specifications**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | Drinking | | | Smoking | |
| | LPM | Probit | Logit | LPM | Probit | Logit |
| Mother Employed | 0.048*** | 0.048*** | 0.048*** | -0.010** | -0.009** | -0.010** |
| | (0.008) | (0.007) | (0.008) | (0.005) | (0.004) | (0.005) |
| Individuals | 8861 | 8861 | 8861 | 8861 | 8861 | 8861 |
| Observations | 18946 | 18946 | 18946 | 18946 | 18946 | 18946 |
| R-squared | 0.230 | 0.191 | 0.191 | 0.072 | 0.137 | 0.138 |

*Notes*: Results from LPM, GLS and FE-LPM specifications. Probit and Logit estimates are marginal effects. Clustered standard errors in parentheses. *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Each column represents a separate regression, with all models controlling for a range of child, mother and household characteristics. Full regression output for the LPM specifications is shown in Appendix 6C.

**Table 6.9 - Conditional association between maternal employment and adolescent drinking in LPM, GLS and FE-LPM specifications using alternative measure of drinking**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | Drinking Measure used in Main Text | | | Alternative Measure of Drinking | |
| | LPM | GLS | FE-LPM | LPM | GLS | FE-LPM |
| Mother Employed | 0.048*** | 0.044*** | -0.003 | 0.050*** | 0.045*** | -0.004 |
| | (0.008) | (0.009) | (0.018) | (0.008) | (0.009) | (0.018) |
| Breusch Pagan Test | 539.90*** | | | 841.56*** | | |
| | (0.000) | | | (0.000) | | |
| Hausman Test | | 3091.23*** | | | 3655.75*** | |
| | | (0.000) | | | (0.000) | |
| Individuals | 8861 | 8861 | 8861 | 8850 | 8850 | 8850 |
| Observations | 18946 | 18946 | 18946 | 18265 | 18265 | 18265 |
| R-squared | 0.230 | 0.228 | 0.240 | 0.252 | 0.250 | 0.251 |

*Notes*: Results from LPM, GLS and FE-LPM specifications with alternative measures of drinking. Columns 1-3 show the results using the drinking measure used in the main text, columns 4-6 show results using a drinking adjusted to take into account inconsistent answers across waves. Clustered standard errors in parentheses. *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Each column represents a separate regression, with all models controlling for a range of child, mother and household characteristics. Full regression out for columns 1-3 displayed in Appendix 6C.

**Table 6.10 - Conditional association between maternal employment and adolescent drinking in LPM, GLS and FE-LPM specifications when controlling for ethnicity in different ways**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Ethnicity Measure used in Main Text | | | Drop Those With Missing Ethnicity | | | Include Category for 'Missing' Ethnicity | | |
| | LPM | GLS | FE-LPM | LPM | GLS | FE-LPM | LPM | GLS | FE-LPM |
| Mother Employed | 0.048*** | 0.044*** | -0.003 | 0.046*** | 0.039*** | -0.015 | 0.043*** | 0.039*** | 0.001 |
| | (0.008) | (0.009) | (0.018) | (0.009) | (0.010) | (0.024) | (0.008) | (0.009) | (0.018) |
| Individuals | 8861 | 8861 | 8861 | 8007 | 8007 | 8007 | 8827 | 8827 | 8827 |
| Observations | 18946 | 18946 | 18946 | 13387 | 13387 | 13387 | 18821 | 18821 | 18821 |
| R-squared | 0.230 | 0.228 | 0.240 | 0.245 | 0.244 | 0.263 | 0.245 | 0.244 | 0.249 |

*Notes*: Results from LPM, GLS and FE-LPM specifications. Clustered standard errors in parentheses. *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Each column represents a separate regression, with all models controlling for a range of child, mother and household characteristics. Full regression output for columns 1-3 displayed in Appendix 6C. Full regression output for columns 4-9 was similar to that in Appendix 6C, and in the interests of space these are not displayed.

### 6.6.1.2 *Two stage least squares models*

Although the estimates from the panel data models presented in Table 6.7 controlled for unobserved individual level heterogeneity, the estimates from such models still cannot be seen to be a true causal parameter, due to the potential of reverse causality or unobserved time variant factors rendering these estimates endogenous. Therefore, I next estimated the relationship between maternal employment and adolescent risky health behaviours using 2SLS models, which explicitly attempt to control for endogeneity that may be present in the panel data models. These models used plausibly exogenous variation in levels of maternal employment in the form of having younger siblings in the family and the localised unemployment rate.

Before estimating 2SLS models, I estimated the first stage validity of the two IV strategies. To be considered valid, the instruments must satisfy two main conditions. Firstly, the instruments must be significantly related to maternal employment. Tables 6.11 and 6.12 show the formal first stage validity of the two IV strategies.

**Table 6.11- First stage estimates: effect of pre-school age siblings on the probability of mother being employed**

| | (1) | (2) |
|---|---|---|
| | No Controls | Full Set of Controls |
| Pre- School Age Siblings =1 | -0.313*** | -0.107*** |
| | (0.010) | (0.011) |
| Kleibergen-Paap LM | 747.246*** | 98.742*** |
| | (0.000) | (0.000) |
| Cragg-Donald Wald | 1117.304 | 122.856 |
| Kleibergen-Paap Wald | 944.324 | 101.123 |
| R-Squared | 0.056 | 0.274 |
| Observations | 18946 | 18946 |

*Notes:* Clustered Standard Errors in Parentheses. ***, ** & * indicates statistical significance at the 1%, 5% & 10% levels

Table 6.11 shows that having at least one sibling under the age of 5 in the household was associated with a decrease in the probability of the mother being employed by 0.107, once a full set of characteristics were controlled for. Table 6.12 shows that residing in a ‘high’ unemployment area was associated with a decrease in the probability of the mother being employed by 0.061 once a full set of confounders were controlled for.

**Table 6.12- First stage estimates: effect of living in a 'high' unemployment area on the probability of mother being employed**

| | (1) | (2) |
|---|---|---|
| | No Controls | Full Set of Controls |
| High Unemployment Area =1 | -0.243*** | -0.061*** |
| | (0.012) | (0.012) |
| Kleibergen-Paap LM | 353.547*** | 23.340*** |
| | (0.000) | (0.000) |
| Cragg-Donald Wald | 437.987 | 27.001 |
| Kleibergen-Paap Wald | 391.988 | 23.390 |
| R-Squared | 0.050 | 0.300 |
| Observations | 8267 | 8267 |

*Notes:* Clustered Standard Errors in Parentheses. ***, ** & * indicates statistical significance at the 1%, 5% & 10% levels

For both instruments, the null hypothesis of underidentifcation in the Kleibergen-Paap LM test and Cragg-Donald Wald tests was rejected at all significance levels, implying that the excluded instruments were sufficiently correlated to the assumed endogenous regressor, and should not suffer from a weak instrument problem that can cause IV models to perform poorly (Stock *et al.,* 2002).

The second condition the instruments must satisfy to be valid is that they cannot be correlated with the unbiased error term. Although this condition is untestable in a just-identified setting, the fact that I had two different forms of exogenous variation (with two different LATE interpretations) allowed me to test the joint-exogeneity of the instruments using the Hansen overidentification test, which tests the joint null hypothesis that the instruments are uncorrelated with the error term and that the excluded instruments are correctly excluded from the estimated equation (Baum *et al.,* 2015).

Table 6.13 shows the first stage validity when using both the siblings and labour market characteristics as instruments in an over-identified model. Although the null hypothesis of strict instrument exogeneity was not rejected for smoking models, this null hypothesis of exogeneity was rejected for drinking. This rejection of the null hypothesis casts doubt about the true exogeneity of the instruments in relation to the risky health behaviours, and therefore suggests the need for further investigation regarding the true exogeneity of both instruments.

**Table 6.13- First stage estimates: effect of pre-school age siblings and living in a 'high' unemployment area on the probability of mother being employed**

| | (1) | (2) |
|---|---|---|
| | Drinking | Smoking |
| Pre- School Age Siblings =1 | -0.115*** | -0.115*** |
| | (0.015) | (0.015) |
| High Unemployment Area =1 | -0.062*** | -0.062*** |
| | (0.012) | (0.012) |
| Kleibergen-Paap LM | 80.872*** | 80.872*** |
| | (0.000) | (0.000) |
| Cragg-Donald Wald | 49.085 | 49.085 |
| Kleibergen-Paap Wald | 41.555 | 41.555 |
| Hansen J Statistic | 6.480** | 0.726 |
| | (0.011) | (0.394) |
| R-Squared | 0.305 | 0.305 |
| Observations | 8267 | 8267 |

*Notes:* Clustered Standard Errors in Parentheses. ***, ** & * indicates statistical significance at the 1%, 5% & 10% levels

As a further test of exogeneity, I tested the balancing of the covariates in the 2SLS estimation samples. If IVs are truly exogenous, one would expect the covariates to be reasonably evenly balanced between the samples in which the instruments are equal to 1 and the samples in which the instruments are equal to 0. If there are systematic and statistically significant differences between the observable characteristics, this suggests that there are also significant differences in the associated unobservable characteristics, and that the instrument may not be randomly assigned. This balance was checked using two sample t-tests. Table 6.14 shows a comparison of observable characteristics for those adolescents without a sibling under 5 and those with a sibling under 5. As shown, in addition to levels of maternal employment and family size, there were significant imbalances for the majority of explanatory variables. For instance, adolescents who had at least one sibling under the age of 5 were more likely to be younger and have younger, less educated mothers.

| Table 6.14- Comparison of characteristics with and without the siblings under 5 instrument | | | | | |
|---|---|---|---|---|---|
| | Siblings Under 5 = 0 | | Siblings Under 5 = 1 | | |
| Variable | Mean | Standard Deviation | Mean | Standard Deviation | P-Value Means Diff |
| Mother Employed | 0.738 | 0.440 | 0.425 | 0.494 | 0.000 *** |
| Child Age | 12.592 | 1.682 | 12.063 | 1.661 | 0.000 *** |
| Maternal Age | 42.309 | 5.688 | 36.275 | 4.649 | 0.000 *** |
| (Maternal Age)$^2$ | 1822.404 | 480.608 | 1337.460 | 338.738 | 0.000 *** |
| Number of Children | 1.929 | 0.870 | 3.330 | 1.232 | 0.000 *** |
| Single Household | 0.348 | 0.476 | 0.335 | 0.472 | 0.199 |
| Self-Employed | 0.072 | 0.258 | 0.039 | 0.193 | 0.000 *** |
| Female | 0.495 | 0.500 | 0.524 | 0.500 | 0.006*** |
| North East | 0.036 | 0.186 | 0.040 | 0.195 | 0.357 |
| North West | 0.122 | 0.328 | 0.100 | 0.300 | 0.000 *** |
| Yorkshire/Humber | 0.088 | 0.283 | 0.075 | 0.264 | 0.027** |
| East Midlands | 0.070 | 0.250 | 0.073 | 0.261 | 0.237 |
| West Midlands | 0.087 | 0.281 | 0.097 | 0.296 | 0.075* |
| East England | 0.088 | 0.283 | 0.059 | 0.236 | 0.000 *** |
| London | 0.116 | 0.320 | 0.163 | 0.369 | 0.000 *** |
| South East | 0.120 | 0.325 | 0.098 | 0.297 | 0.001 *** |
| South West | 0.074 | 0.262 | 0.065 | 0.247 | 0.090* |
| Wales | 0.062 | 0.241 | 0.072 | 0.258 | 0.046** |
| Scotland | 0.094 | 0.291 | 0.069 | 0.254 | 0.000*** |
| Northern Ireland | 0.076 | 0.265 | 0.060 | 0.238 | 0.004*** |
| Urban | 0.755 | 0.430 | 0.836 | 0.370 | 0.000*** |
| Out After 9pm | 0.147 | 0.003 | 0.141 | 0.007 | 0.426 |
| Meals With Family | 0.317 | 0.008 | 0.318 | 0.019 | 0.501 |
| Mat Mental Health Top Quintile | 0.195 | 0.396 | 0.234 | 0.424 | 0.000*** |
| 2nd Quintile | 0.196 | 0.397 | 0.212 | 0.409 | 0.053* |
| 3rd Quintile | 0.204 | 0.403 | 0.210 | 0.407 | 0.480 |
| 4th Quintile | 0.231 | 0.421 | 0.191 | 0.393 | 0.000*** |
| Bottom Quintile | 0.175 | 0.380 | 0.152 | 0.360 | 0.004*** |
| Alcohol Spending | 45.624 | 0.523 | 32.867 | 1.033 | 0.000*** |
| Degree Level Education | 0.253 | 0.435 | 0.169 | 0.375 | 0.000*** |
| Other Higher | 0.159 | 0.366 | 0.117 | 0.322 | 0.000*** |
| A-Level | 0.185 | 0.388 | 0.176 | 0.381 | 0.276 |
| GCSE/O-Level | 0.254 | 0.435 | 0.325 | 0.469 | 0.000*** |
| Other Qualifications | 0.077 | 0.266 | 0.072 | 0.258 | 0.371 |
| No Qualifications | 0.072 | 0.259 | 0.140 | 0.347 | 0.000*** |
| Own House | 0.706 | 0.456 | 0.479 | 0.500 | 0.000 *** |
| *N* | *16025* | | *2921* | | |

*Notes:* Differences based on a two-sample t-test with unequal variances, weighted to take account of the sampling structure. *, ** & *** indicates statistical significance at the 10%, 5% & 1% levels.

**Table 6.15- Comparison of characteristics with and without the local unemployment rate instrument**

| | High Local Unemployment Rate = 0 | | High Local Unemployment Rate = 1 | | |
|---|---|---|---|---|---|
| Variable | Mean | Standard Deviation | Mean | Standard Deviation | P-Value Means Diff |
| Mother Employed | 0.724 | 0.447 | 0.481 | 0.500 | 0.000*** |
| Child Age | 12.477 | 1.691 | 12.430 | 1.689 | 0.278 |
| Maternal Age | 41.814 | 5.660 | 38.822 | 5.944 | 0.000*** |
| (Maternal Age)$^2$ | 1780.423 | 471.466 | 1542.445 | 477.970 | 0.000*** |
| Number of Children | 2.093 | 1.044 | 2.412 | 1.281 | 0.000*** |
| Single Household | 0.336 | 0.472 | 0.473 | 0.499 | 0.000*** |
| Self-Employed | 0.071 | 0.257 | 0.025 | 0.157 | 0.000*** |
| Female | 0.498 | 0.500 | 0.524 | 0.500 | 0.045** |
| North East | 0.045 | 0.208 | 0.055 | 0.229 | 0.059* |
| North West | 0.127 | 0.333 | 0.148 | 0.355 | 0.012** |
| Yorkshire/Humber | 0.092 | 0.289 | 0.109 | 0.311 | 0.022** |
| East Midlands | 0.094 | 0.292 | 0.096 | 0.295 | 0.800 |
| West Midlands | 0.100 | 0.300 | 0.136 | 0.343 | 0.000*** |
| East England | 0.111 | 0.314 | 0.092 | 0.290 | 0.017** |
| London | 0.171 | 0.376 | 0.178 | 0.382 | 0.456 |
| South East | 0.161 | 0.367 | 0.105 | 0.306 | 0.000*** |
| South West | 0.100 | 0.300 | 0.081 | 0.272 | 0.010** |
| Urban | 0.782 | 0.413 | 0.978 | 0.146 | 0.000*** |
| Out After 9pm | 0.143 | 0.004 | 0.187 | 0.009 | 0.000*** |
| Meals With Family | 3.192 | 0.012 | 3.017 | 0.023 | 0.000*** |
| Mat Mental Health Top Quintile | 0.201 | 0.400 | 0.281 | 0.449 | 0.000*** |
| 2$^{nd}$ Quintile | 0.196 | 0.397 | 0.204 | 0.403 | 0.414 |
| 3$^{rd}$ Quintile | 0.214 | 0.410 | 0.184 | 0.387 | 0.004*** |
| 4$^{th}$ Quintile | 0.244 | 0.430 | 0.165 | 0.371 | 0.000*** |
| Bottom Quintile | 0.172 | 0.378 | 0.167 | 0.373 | 0.554 |
| Alcohol Spending | 47.726 | 0.883 | 26.426 | 1.180 | 0.000*** |
| Degree Level Education | 0.287 | 0.452 | 0.107 | 0.309 | 0.000*** |
| Other Higher | 0.165 | 0.371 | 0.121 | 0.326 | 0.000*** |
| A-Level | 0.184 | 0.387 | 0.159 | 0.366 | 0.009*** |
| GCSE/O-Level | 0.252 | 0.434 | 0.305 | 0.460 | 0.000*** |
| Other Qualifications | 0.081 | 0.273 | 0.114 | 0.318 | 0.000*** |
| No Qualifications | 0.065 | 0.246 | 0.195 | 0.397 | 0.000*** |
| Own House | 0.713 | 0.452 | 0.398 | 0.490 | 0.000*** |
| *N* | *6268* | | *1999* | | |

*Notes:* Differences based on a two-sample t-test with unequal variances, weighted to take account of the sampling structure. *, ** & *** indicates statistical significance at the 10%, 5% & 1% levels.

As well as a number of regional disparities between the two samples, there were also significant differences in the levels of maternal mental health, the spending on alcohol by the household and levels of home ownership. Although these observable characteristics can be controlled for through the inclusion of the variables in the econometric models, and may be explained by the fact that I am estimating the LATE for the compliant subpopulation rather than the ATE of the whole population, the systematic and significant imbalances also strongly indicate that the controlling covariates may themselves be endogenous, and that there also may be a vector of unobservable characteristics associated with both maternal employment and adolescent health behaviours that cannot be controlled for. This indicates that this IV strategy is likely to be unsuitable for the research question, as the use of the instrument may be subject to a significant amount of unobserved confounding.

Table 6.15 shows a comparison of observable characteristics for those adolescents who reside in 'high' unemployment areas and those who do not. There were systematic and significant imbalances in almost all of the observed covariates, including maternal age, family size, maternal education attainment and home ownership. These significant differences indicate that the instrument may not be randomly assigned, potentially due to self-selection by households into certain geographic areas. Therefore, this instrument is also likely to be unsuitable for the research question, once again due to the high probability of unobserved confounding.

Despite serious reservations regarding the two IV strategies, the second stage results from the 2SLS models are shown in Table 6.16 and Table 6.17, with full regression output presented in Appendix 6E. As shown, in general the Wald estimates were qualitatively in line with the estimates from the corresponding LPM specifications displayed in Table 6.7, implying that there may be a positive causal effect of maternal employment on the adolescent drinking, yet a negative causal effect of maternal employment on adolescent smoking.

However, there were counterintuitive and unfeasibly large empirical estimates shown in column 2 of Table 6.16 and column 4 of Table 6.17, once a number of controlling characteristics were included in the specification. Although it is possible that these counterintuitive results were caused by the 2SLS models capturing the LATE for a specific compliant sub-population (compared to the LPM specifications, which capture the ATE for the whole population), it is more likely that they were due to the instrument not being randomly assigned, and controlling covariates therefore themselves being endogenous. As displayed in the full regression output in Appendix 6E, the impact of the vector of controlling variables were very similar to those shown in Appendices 6B and 6C, and mostly followed the pattern one would expect.

**Table 6.16- Maternal employment and adolescent risky health behaviour in 2SLS models using the sibling under 5 as an instrument**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Drinking | Drinking | Smoking | Smoking |
| Maternal Employment | 0.154***<br>(0.032) | -0.432***<br>(0.107) | 0.020<br>(0.017) | -0.007<br>(0.056) |
| Covariates | × | ✓ | × | ✓ |
| Observations | 18946 | 18946 | 18946 | 18946 |
| R-Squared | 0.002 | 0.075 | 0.004 | 0.072 |

*Notes:* Results from 2SLS regression models using having siblings under 5 as an instrument for maternal employment. Clustered standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%. Each column represents a separate regression, with all models controlling for a range of child, maternal, socioeconomic and household characteristics. Full regression output displayed in Appendix 6E.

**Table 6.17- Maternal employment and adolescent risky health behaviour in 2SLS models using the local unemployment rate as an instrument**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Drinking | Drinking | Smoking | Smoking |
| Maternal Employment | 0.129***<br>(0.050) | 0.098<br>(0.196) | -0.076**<br>(0.030) | -0.210<br>(0.128) |
| Covariates | × | ✓ | × | ✓ |
| Observations | 8267 | 8267 | 8267 | 8267 |
| R-Squared | 0.008 | 0.241 | 0.001 | 0.069 |

*Notes:* Results from 2SLS regression models using residing in a high unemployment area as an instrument for maternal employment. Clustered standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%. Each column represents a separate regression, with all models controlling for a range of child, maternal, socioeconomic and household characteristics. Full regression output displayed in Appendix 6E.

### 6.6.2 *Maternal hours worked and adolescent risky health behaviours*

Although the empirical estimates shown in the preceding sub-section provide inconclusive evidence of a statistically significant relationship between maternal employment and adolescent risky behaviours once individual level heterogeneity is controlled for, these findings may be due to the use of a dummy variable of maternal employment. This binary measure can be considered naïve, as it ignores the intensity of maternal labour supply. To explore this possibility, I next estimated the same regression models (LPM, GLS and FE-LPM), using a measure of the number of hours worked as the measure of maternal labour supply.

Table 6.18 shows a summary of the empirical estimates from the LPM, GLS and FE-LPM specifications using the number of maternal hours worked as the measure of maternal labour supply. In the interests of space, the full regression output is presented in Appendices 6F and 6G.

**Table 6.18- Conditional association between maternal hours worked and adolescent risk health related behaviours in LPM, GLS and FE-LPM specifications**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Drinking | | | Smoking | | |
| | LPM | GLS | FE-LPM | LPM | GLS | FE-LPM |
| Maternal Hours | 0.052*** | 0.051*** | 0.034* | -0.011 | -0.006 | 0.003 |
| | (0.009) | (0.010) | (0.019) | (0.007) | (0.007) | (0.014) |
| (Maternal Hours)$^2$ | -0.009** | -0.009** | -0.006 | 0.004 | 0.001 | -0.004 |
| | (0.004) | (0.004) | (0.007) | (0.002) | (0.002) | (0.005) |
| Breusch Pagan Test | 202.42*** | | | 6854.38*** | | |
| | (0.000) | | | (0.000) | | |
| Hausman Test | | 140.90*** | | | 604.01*** | |
| | | (0.000) | | | (0.000) | |
| Individuals | 8861 | 8861 | 8861 | 8861 | 8861 | 8861 |
| Observations | 18946 | 18946 | 18946 | 18946 | 18946 | 18946 |
| R-squared | 0.247 | 0.240 | 0.251 | 0.072 | 0.071 | 0.058 |

*Notes*: Results from LPM, GLS and FE-LPM specifications. Clustered standard errors in parentheses. *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Each column represents a separate regression, with all models controlling for a range of child, mother and household characteristics. Full regression output for these models is displayed in Appendices 6F and 6G.

As shown in columns 1-3, there was evidence of an economically small, yet statistically significant, positive association between maternal hours worked and the incidence of adolescent drinking behaviour. This result was shown to be robust to unobserved heterogeneity, given the statistical significance in the FE-LPM specification, which was assumed to be the most appropriate model specification for the research question. The statistical significance of the quadratic working hours variable in certain specifications also implies that the relationship may be non-linear.

As shown in columns 4-6, there was no evidence of an association between the number of maternal hours worked and adolescent smoking, with the magnitude of the coefficients extremely small and not statistically significant in any specification. As shown by the full regression output in Appendices 6F and 6G, the other explanatory variables included in the different model specification were similar to those shown in Appendices 6C and 6D, and mostly followed the pattern one would expect.

#### 6.6.2.1 *Sub group analysis*

Fertig *et al.,* (2009) have argued that the relationship between maternal labour market supply and adolescent outcomes may differ by maternal educational attainment, as more highly educated mothers may be better at converting their scarce time inputs into high quality time investments. Therefore, I next examined the nature of the relationship between maternal hours and adolescent risky health behaviours across broad educational groups. In this case, a mother was considered 'highly' educated if she had a degree level education or higher. Results from the preferred FE-LPM specification (as indicated by the results of the Hausman tests) are shown in Table 6.20.

As shown, there was evidence that the relationship between maternal hours worked and adolescent drinking differed by maternal educational attainment, with no evidence of a relationship in the highly educated group, yet a small, statistically significant association amongst adolescents whose mothers who had basic or some further educational qualifications. There was no evidence of an association between maternal labour supply and adolescent smoking by educational attainment.

**Table 6.19- Conditional association between maternal hours worked and adolescent risk health related behaviours in FE-LPM specifications across educational groups**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Drinking | | Smoking | |
| | Degree Level Education or Higher | Basic Qualifications | Degree Level Education or Higher | Basic Qualifications |
| Maternal Hours | 0.001 | 0.077*** | -0.001 | 0.011 |
| | (0.032) | (0.028) | (0.021) | (0.019) |
| $(\text{Maternal Hours})^2$ | 0.000 | -0.020** | (0.001) | -0.010 |
| | (0.011) | (0.010) | (0.010) | (0.007) |
| Hausman Test | 1374.00** | 2524.97*** | 253.90*** | 390.23*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Individuals | 3276 | 5585 | 3276 | 5585 |
| Observations | 7484 | 11462 | 7484 | 11462 |
| R-squared | 0.238 | 0.244 | 0.059 | 0.062 |

*Notes*: Results from FE-LPM specifications across different educational groups. Clustered standard errors in parentheses. *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Each column represents a separate regression, with all models controlling for a range of child, mother and household characteristics.

### 6.6.3 *Maternal Non-Standard Work Schedules and Adolescent Risky Health Behaviours*

Next, I estimated the relationship between maternal non-standard work schedules and adolescent risky health behaviours. I initially tested whether the models in this sample should be separated by gender. The Chow test was run on both pooled LPM and GLS models. A post-estimation test on the female dummy variable and the interaction terms for being female indicated that the null hypothesis of equal coefficients and equal variance could not be rejected for either drinking or smoking, and therefore separate equations for males and females were not estimated. The output from these tests is shown in Table 6.21.

**Table 6.20- Chow tests in non-standard schedules estimation sample**

| Drinking | Smoking |
|---|---|
| $\text{Chi}^2$ (43) = 0.19 | $\text{Chi}^2$ (43) = 0.225 |
| Prob>$\text{Chi}^2$ = 0.659 | Prob>$\text{Chi}^2$ = 0.754 |

Next, I tested whether attrition should bias the results in this sample. As shown in Table 6.22, the null hypothesis of random non-response from the Wald tests was not rejected using both the total number of waves and the next wave as test variables. Therefore, it was assumed that non-response bias would not bias the results in this sample.

| **Table 6.21- Wald test for attrition in non-standard schedules estimation sample** | | |
|---|---|---|
| | Pooled Models | |
| # of waves respondent is present | $Chi^2$ (1) | 1.86 |
| | Prob>$Chi^2$ | 0.17 |
| If respondent is present is next wave | $Chi^2$ (1) | 2.05 |
| | Prob>$Chi^2$ | 0.23 |
| | Panel Data Models | |
| # of waves respondent is present | $Chi^2$ (1) | 1.65 |
| | Prob>$Chi^2$ | 0.20 |
| If respondent is present is next wave | $Chi^2$ (1) | 1.99 |
| | Prob>$Chi^2$ | 0.21 |

Table 6.23 shows a summary of the results from the LPM and GLS specifications. Full regression output for these models is shown in Appendix 6H. It is worth reminding the reader that as well as only being estimated on employed mothers, these models were restricted to waves 2, 4 and 6, and excluded self-employed mothers due to missing data on the income variable for these individuals. Although this significantly reduced the estimation sample, estimating the empirical models with and without the inclusion of the self-employed mothers made very little difference to the empirical estimates in terms of both magnitude and statistical significance, as shown in Table 6.24. As shown in both Table 6.23 and Table 6.24, there was no evidence of an association between mothers working non-standard work schedules and either adolescent drinking or smoking behaviour, once the full vector of controlling variables were included in the model specification. This result was robust to both LPM and GLS specifications.

**Table 6.22- Conditional association between maternal non-standard work schedules and adolescent risk health related behaviours in LPM, GLS and FE-LPM specifications**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Drinking | | Smoking | |
| | LPM | GLS | LPM | GLS |
| Maternal Non-Standard Working Schedules | 0.017 | 0.015 | 0.009 | 0.009 |
| | (0.013) | (0.013) | (0.008) | (0.008) |
| Breusch Pagan Test | 186.69*** | | 2411.76*** | |
| | (0.000) | | (0.000) | |
| Individuals | 3983 | 3983 | 3983 | 3983 |
| Observations | 5566 | 5566 | 5566 | 5566 |
| R-squared | 0.269 | 0.267 | 0.078 | 0.077 |

*Notes*: Results from LPM and GLS specifications. Clustered standard errors in parentheses. *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Each column represents a separate regression, with all models controlling for a range of child, mother and household characteristics. Full regression output for these models is shown in Appendix 6H.

**Table 6.23- Conditional association between maternal non-standard work schedules and adolescent risk health related behaviours in LPM, GLS and FE-LPM specifications (excluding self-employed mothers)**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Drinking | | Smoking | |
| | LPM | GLS | LPM | GLS |
| Maternal Non-Standard Working Schedules | 0.013 | 0.011 | 0.012 | 0.013 |
| | (0.013) | (0.012) | (0.017) | (0.017) |
| Breusch Pagan Test | 205.48*** | | 2676.78*** | |
| | (0.000) | | (0.000) | |
| Individuals | 4497 | 4497 | 4497 | 4497 |
| Observations | 6333 | 6333 | 6333 | 6333 |
| R-squared | 0.266 | 0.266 | 0.079 | 0.079 |

*Notes*: Results from LPM and GLS specifications. Clustered standard errors in parentheses. *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Each column represents a separate regression, with all models controlling for a range of child, mother and household characteristics. Full regression output for these models was extremely similar to that in Appendix 6H.

As shown in the full regression output in Appendix 6H, the other variables included in the model specification also mostly followed the pattern that one would expect. For example, engaging in risky health behaviours was associated with being older, having a younger mother, being from a single parent family, belonging to a household who spend more money on alcohol, having increased levels of unsupervised time and being from a household in a lower socioeconomic group.

#### 6.6.3.1 *Sub Group Analysis*

Finally, I estimated whether this lack of association for non-standard work schedules held within different socioeconomic subgroups. Specifically, I estimated the relationship by maternal educational attainment and different occupational groups. For the purposes of the analysis, a mother was considered 'highly' educated if they had a degree level education or higher. A mother was considered to have a 'high' occupation if their occupation was managerial or professional (as defined by the NSSEC-5 classification). Results from the preferred GLS models are shown in Table 6.25 and Table 6.26.

As shown, there was very little evidence of a substantial relationship between maternal non-standard work schedules and adolescent health behaviours across the different socioeconomic groups. The only statistically significant association I found was between maternal non-standard working schedules and adolescent smoking amongst mothers who did not have a managerial or professional occupation. However, this association was extremely small in magnitude, and also only statistically significant at the 10% level.

**Table 6.24- Conditional association between maternal non-standard work schedules and adolescent risk health related behaviours in GLS specifications across educational groups**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Drinking | | Smoking | |
| | Degree Level Education or Higher | Basic Qualifications | Degree Level Education or Higher | Basic Qualifications |
| Maternal Non-Standard Work Schedules | 0.028 | 0.007 | -0.005 | 0.021* |
| | (0.020) | (0.018) | (0.011) | (0.012) |
| Breusch-Pagan Test | 79.19*** | 102.99*** | 1264.85*** | 1312.57*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Individuals | 2375 | 3191 | 2375 | 3191 |
| Observations | 1700 | 2382 | 1700 | 2382 |
| R-squared | 0.300 | 0.257 | 0.092 | 0.078 |

*Notes*: Results from GLS specifications across different educational groups. Clustered standard errors in parentheses. *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Each column represents a separate regression, with all models controlling for a range of child, mother and household characteristics. Full regression output for these models was extremely similar to that in Appendix 6H.

**Table 6.25- Conditional association between maternal non-standard work schedules and adolescent risk health related behaviours in GLS specifications across occupational groups**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Drinking | | Smoking | |
| | Managerial or Professional | Not Managerial or Professional | Managerial or Professional | Not Managerial or Professional |
| Maternal Non-Standard Work Schedules | 0.003 | 0.025 | 0.001 | 0.017 |
| | (0.020) | (0.019) | (0.011) | (0.013) |
| Breusch-Pagan Test | 124.96*** | 66.21*** | 1264.41*** | 1339.82*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Individuals | 2612 | 2954 | 2612 | 2954 |
| Observations | 1861 | 2145 | 1861 | 2145 |
| R-squared | 0.286 | 0.262 | 0.0789 | 0.088 |

*Notes*: Results from GLS specifications across different educational groups. Clustered standard errors in parentheses. *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Each column represents a separate regression, with all models controlling for a range of child, mother and household characteristics. Full regression output for these models was extremely similar to that in Appendix 6H.

### 6.6.4 Discussion

There are several aspects of the results that are worth noting. I initially concentrate on the estimates of the relationship between maternal labour supply and adolescent risky health behaviours. In general, the results from this chapter were similar with the small previous literature, which has found the association between maternal labour supply and adolescent risky health behaviours to be small in magnitude and potentially statistically insignificant once a full set of controlling characteristics are included in the model specifications. For instance, if I were to assume that the conditional association between maternal labour supply and adolescent drinking found in the preferred FE-LPM specification was indeed a true causal relationship (this is an extremely strong assumption given that there may be reverse causality or time variant unobservable factors rendering the estimates biased), an extra 20 hours of maternal labour supply would only equate to an increase of the probability of the adolescent drinking by 3.4%. Although sub-group analysis implied that this relationship may be larger for less educated mothers, the magnitude of these estimates can still be considered extremely small. Similar to the only other study in this literature which has used UK data (Mendolia 2016), there was also no evidence of an association between maternal labour supply and adolescent smoking.

There are several pathways through which this relative lack of relationship may manifest itself. On one hand, it may be the case that there is genuinely little or no effect of maternal labour market supply on adolescent health behaviours, and that mothers are able to adapt and rearrange their time in order to invest in children, as suggested by Bianchi (2000) and Sandberg and Hofferth (2001). Alternatively, it may be the case that the association between maternal labour supply and adolescent outcomes is offset by the positive aspects of maternal labour supply, such as increased household income, the mother being seen as a positive role model or allowing teenage children independence (Aughinbaugh and Gittleman 2004).

With regard to the estimates of the relationship between maternal non-standard work schedules and adolescent risky health behaviours, there was no evidence of an association between maternal non-standard work schedules and adolescent health behaviours once a number of controlling characteristics were included in the model specification. Although sub group analysis implied that there may be a statistically significant relationship between non-standard hours and smoking among those mothers who did not have a degree level education, this relationship was not consistent across different occupational groups, and was again extremely small in magnitude.

To date, the small empirical literature concerning the relationship between non-standard work schedules can be considered mixed, with two studies (Han and Waldfogel 2007 and Han *et al,.* 2010) having shown inconsistent evidence of an association between non-standard schedules and adolescent risky behaviours depending on the outcome measure, and two studies (MacPhee 2013 and Kim *et al,.* 2016) having shown evidence of small positive associations. Comparing the analysis from this chapter to those studies, there are several reasons why my results may have differed.

For example, all four of the previous studies have used data from the USA or Canada, whereas this study was the first to use data from the UK. It is possible that differences in labour market conditions or social norms in these countries may impact the nature of the relationship. Furthermore, the measures of adolescent risky behaviour are slightly different across the studies. For instance, the measure of adolescent drinking used by MacPhee (2013) was a dummy variable taking the value of 1 if the adolescent drinks alcohol *"about once or twice a month"*, whereas the measure I used in this chapter asked the adolescent if they have ever drunk a whole alcoholic drink. It is possible that subtle differences in the reporting of the adolescent risky behaviours such as this may also impact the nature of the relationship.

More generally, the null findings may be explained by the fact that mothers who have non-standard working schedules are systematically different in terms of observable characteristics compared to those who do not, and that the relationships shown in the descriptive statistics may instead be explained by a set of observable and unobservable factors related to both non-standard schedules and adolescent health behaviours. Alternatively, the estimates may be explained by mothers who have non-standard working schedules rearranging their scarce time in order to spend more time with their children.

One limitation of this particular part of analysis is that due to data constraints, I was only able to estimate the association between maternal non-standard work schedules and adolescent outcomes in three waves of data, which is potentially insufficient to fully understand how variations in maternal non-standard working schedules influence adolescent health related behaviours. This limitation also means that the preferred fixed effects regression framework could not be estimated.

The principal limitation in this chapter in general is that I did not observe the actual allocation of time made by the mother in relation to her children. Although maternal labour supply and non-standard work schedules may well be good proxies for the amount of the time spent with children and the quality of maternal time investment respectively, it could be the case that mothers who participate in the labour market rearrange their time in order to increase the quantity and quality of time investments with their children, with this unobserved behaviour potentially biasing the results using these measures.

A further limitation of the empirical analysis was the inability to fully control for endogeneity of maternal labour supply. Although the first stage strength and Wald estimators of the two different IV models I implemented suggested that both identification strategies may be valid, overidentification tests and a comparison of observable characteristics across the instrument levels showed both strategies to be unsuitable for the research question. This unsuitability was subsequently shown in the full 2SLS models, with the likely endogenous controlling covariates (caused by the instruments not being randomly assigned) changing the estimates of maternal labour supply to large and counterintuitive levels in the full estimation models. The endogeneity of the covariates also implies that there is a high probability of unobserved confounding further biasing the results from these models.

The unsuitability of the localised labour market statistics instrument implies that families may self-select into certain geographical areas, and that the estimates from such models could be biased by unobserved neighbourhood factors correlated with both maternal labour market supply and adolescent behaviour. The unsuitability of the infant siblings IV strategy also calls into question the causal estimates of maternal employment on child obesity in Germany made by Meyer (2016). The author argued that bias from the IV strategy may be minimal, due to the various unobservable endogenous factors cancelling each other out. However, aside from this, the author offered little further argument as to why the identification strategy, and therefore the results, are valid.

Although I was able to control for several important explanatory variables across the different model specifications, there were a number of important omissions that must be noted. Firstly, I was unable to control for peer effects, which have been found to have a significant effect on the decision of adolescents to initiate drinking (Lundborg 2006) and smoking (Powell *et al.,* 2005). Secondly, I could not fully control for the intergenerational transmission of drinking behaviour, and was unable to control for the transmission of smoking behaviours, with both of these factors having previously been shown to be significant channels through which adolescent risky health behaviours may manifest themselves (Wickrama *et al.,* 1999; Brown and Van der Pol 2015).

Furthermore, it is conceivable that the two binary outcome measures may have been too simplistic to capture the full nature of the adolescents' risky health related behaviour. Although the UKHLS contains some questions regarding the level of alcohol and tobacco use, these variables were unsuitable for use, due to small numbers in some categories (smoking) and significant amounts of missing data (drinking). Specifically in relation to smoking, Jones (1989) has argued that engaging in this behaviour can be seen as a two stage process, with participation and consumption being two separate individual choices. It is therefore suggested that sample selection or two-part econometric models may be more appropriate in such situations (Madden 2008; Greene *et al,.* 2017).

With these limitations in mind, there are several possible avenues for future research in this area. Given the discussion of proxy variables above, one useful area of future research would be to estimate the relationship between the actual amount of time a mother spends with her child and adolescent health related outcomes in a UK setting[35], through the use of time-use surveys. Unfortunately, there is currently no appropriate UK based dataset that has sufficient information regarding both maternal time use and adolescent health related behaviour. One recent UK based study (Del Bono *et al.,* 2016) has estimated the impact of maternal time investment on early life child outcomes using the MCS. In this case, the specific measure of maternal time input was a combined measure of various questions related to the home learning environment (the same variables which are used as explanatory variables in the second chapter), combined using PCA and validated using information from the UK Time Use Survey.

The seemingly strong correlation between household expenditure on alcohol and adolescent drinking behaviour observed in the results, as well as the inability to control for parental smoking behaviours, leads me to consider another potential area of further research: the intergenerational transmission of risky health behaviours in the UK. Although such analysis may not be possible using the UKHLS, another UK based study, the MCS, represents a more appropriate data source, given the range of historical data collected regarding parent health behaviours and the impending release of the 6th wave of data, in which data is being collected regarding both the engagement in risky health behaviours of both the cohort member and cohort member's peer group. The extensive explanatory variables included in the dataset may also allow for mediating mechanisms to be explored through mediation analysis or SEM.

Finally, given the addictive nature of smoking and excessive alcohol use, another avenue for future research is related to state dependency in the adolescent risky health behaviour. In an economic sense, state dependency refers to the fact that individuals who have experienced an event in the past are more likely to experience an event than those who

[35] See (2016) has investigated the relationship between parental supervision and adolescent risky health behaviour in a US setting using time-use data.

have not experienced the event (Heckman 1981). The use of linear panel data methods does not allow one to decompose the persistence of health and health behaviours into state dependence, unobserved heterogeneity and observable characteristics (such as maternal labour market characteristics). In order to take into account state dependence, a more sophisticated dynamic panel model is needed, such as the model implemented by Contoyannis *et al.,* (2004). Unfortunately, the highly unbalanced nature of the adolescent questionnaire of the UKHLS makes the dataset inappropriate for this methodology, and therefore a separate source of data will be needed for this issue to be addressed in a UK context.

The lack of significant association between the different labour market variables and the adolescent health related behaviours reported in this chapter has some potential policy implications. Given that a number of developed countries have introduced policies aimed at increasing levels of female labour market participation, such as childcare subsidies, it is important that the potential consequences of this increased labour market supply are fully understood. The fact that this chapter and the small empirical literature it belongs to offers little evidence of a substantial negative relationship between both maternal labour supply and the incidence of maternal non-standard work schedules on adolescent health related outcomes should therefore be reassuring to those mothers considering an increase in their labour supply or a change in their shift pattern, and policy makers aiming to increase levels of maternal employment. From a policy maker's point of view, if the goal is to decrease levels of adolescent drinking and smoking, the findings of this chapter suggest that resources may currently be better directed at determinants of adolescent health behaviours which have larger evidence bases, such as school or community based educational programmes (Sherman and Primack 2009) and increased prices (Rice *et al.,* 2010) rather than factors specifically relating to parental labour market conditions.

### 6.7 Conclusion

There have been substantial changes in the labour market in recent years, with more women entering the labour force and a significant increase in the number of people working non-standard work schedules. As a result, it has been argued both theoretically and empirically that the rise in such factors may have significant consequences for both individual and child outcomes, for example adolescent risky health behaviours. With this context, in this chapter

I contributed to the literature by investigating the relationship between both maternal labour supply and maternal non-standard works schedules and adolescent alcohol consumption and tobacco use in a modern UK household survey.

For maternal labour supply, the results showed evidence of an economically small, yet statistically significant, association between maternal hours worked and adolescent drinking, with the result robust to the inclusion of a variety of potentially confounding covariates and unobserved individual level heterogeneity. Results also implied that not appropriately controlling for selection in the labour market by the mother may underestimate this relationship. There was no evidence of an association between maternal labour market supply and adolescent smoking behaviour. Two separate 2SLS models were estimated in an attempt to control for endogeneity and estimate a causal effect rather than a conditional association, however both IV strategies were found to be inappropriate for the research question. For maternal non-standard work schedules, there was almost no evidence of a significant association with adolescent risky health behaviours, implying that mothers who work non-standard schedules may rearrange their time in order to ensure that the level of good quality time investments with their children is retained.

Future research should be directed at investigating the relationship between maternal time use and adolescent behaviours using time-use surveys, as variables such as maternal employment and work schedules may not be sufficient proxies for the quantity and quality of maternal time investment. Furthermore, the effect of parental health behaviours and peer effects on adolescent health behaviours should be further investigated, as these factors represent plausible mechanisms through which adolescents may engage in drinking and smoking.

# Chapter 7. Discussion and Conclusion

## 7.1 Research Background

Childhood and adolescence is the time when individuals form skills and behaviours that may influence the rest of their life. Despite overall levels of early life educational attainment being relatively stable (ONS 2017), and evidence that there has been a reduction in the number of adolescents engaging in risky health behaviours such as smoking, drinking and taking drugs (Association for Young People's Health 2017), there is evidence that levels of both adverse mental health conditions and child obesity are increasing (Hagell *et al,.* 2013; ONS 2016). Furthermore, it has also been shown that there are persistent and substantial inequalities in the vast majority of child outcome measures with respect to a range of personal and social circumstances (Marmot *et al,.* 2010).

The recent epidemiological and economic literatures have provided a considerable amount of evidence that a range of child outcomes, for instance cognitive ability and psychological well-being, are pivotal in shaping a variety of labour, health and socioeconomic outcomes across the life course (Heckman and Carneiro 2003; Blanden *et al.,* 2007; Goodman *et al.,* 2011; Conti *et al.,* 2016). Furthermore, behaviours begun in adolescence have been shown to contribute to adult non-communicable diseases, including those related to risky health behaviours and obesity, and may also help to shape measures of emotional and mental well-being across the life course (WHO 2016).

These child and adolescent outcomes are not simply inherited, but are created by a complex range of interconnecting factors, including the socio-political and social context, neighbourhood level factors, household characteristics and individual level determinants. In order to help young people achieve their full potential, it is important to understand the factors which may help children and adolescents to achieve the foundations for a healthy and successful life. Rather than focussing on individual dimensions, child and adolescent health and well-being needs are better tackled by combining policies and resources at these wider social determinants of health and well-being.

Previous research has identified the household (or family) unit as one of the principal influences in explaining disparities in child outcomes both between individuals and across socioeconomic groups (Cunha and Heckman 2010), mediated through proximal factors such as parental preferences, attitudes, behaviours, time allocation and the home environment.

The ‘family’ in a traditional sense can be thought of as a group of two or more people related by birth, marriage or adoption who occupy a single housing unit (US Census Bureau 2018), and is seen as both a locus of much of an individual’s social activity and the principal institution for the socialisation of children (Maccoby 1992). While economists’ interest in the family in relation to the determinants of population size can be traced back to the work of Cantillon (1730), Smith (1776) and Malthus (1798), the microeconomic analysis of the household unit can be traced back to the ‘New Household Economics’ movement, which emerged at Columbia University in the early 1960s (Grossbard-Shechtman 2001). Using this approach, the household unit is assumed to be a productive sector, which uses traditional economic concepts such as division of labour, production and distribution to determine home-based decisions such as labour supply and fertility.

Studying the role of the household unit in generating inequalities in child and adolescent outcomes using modern, nationally representative data can be seen as being a particularly relevant area of research, given the significant changes to the traditional household unit that have occurred in the past century in the UK. For instance, it has recently been reported that the traditional ‘nuclear family’ (usually defined in this context as a heterosexual married couple residing with their children) is in decline in the UK (BBC 2010). Although the traditional nuclear family is still the most common type of household in modern western society, a significant number of people are instead choosing bring up children in single parents households, live alone or live as couples without any children.

Furthermore, Cohen (2014) has argued that other substantial changes to family life in the past 50 years in the UK include the decline in the number of individuals getting married (down from 66% in 1960 to 45% in 2010), the rise of the number of women in the paid workforce and the number of remarried and co-habiting families. Large demographical changes in relation to the construction of the household are likely to impact the nature of the relationship between the household and wide range of child and adolescent outcomes, and therefore it is imperative that the true nature of these relationships are fully investigated.

**7.2 Overview of Thesis and Policy Implications**

The aim of this thesis was to better understand how household factors may contribute to inequalities in child and adolescent outcomes in the UK, using a variety of secondary data sources and a range of microeconometric methods. Specifically, I attempted to gain a better understanding of: 1) the nature of the relationship between SES and child cognitive ability; 2) the role of family size and birth order in explaining differences in child cognitive ability and psychological well-being; and 3) the relationship between maternal labour supply, maternal non-standard work schedules and adolescent risky health behaviours. An increased understanding of how household factors contribute to inequalities in childhood and adolescent outcomes should help to inform policy makers on which areas should be targeted in order to reduce levels of inequality, both in early life and across the life course.

Historically, one of the most commonly examined household factors in the social sciences has been SES, a composite measure of income, education and occupation related to the social standing or class of an individual or family. Substantial socioeconomic inequalities have been observed in areas such as health (Khanam *et al.,* 2009) and educational attainment (Carneiro and Heckman 2002) both in the UK and around the world, with such inequalities seen as a matter of social justice and therefore considered key government policy issues. As well as health and educational attainment, several previous empirical studies have examined the relationship between SES and child cognitive ability (Duncan *et al.,* 1994; Blau 1999; Feinstein 2003; Dickerson and Popli 2016), given the predicted impact that early life cognitive ability may have on various economic, social and health outcomes across the life course (Cunha and Heckman 2007). However, despite the relatively large previous literature regarding the relationship between SES and child cognitive ability, no previous empirical study had utilised the CI in estimation, despite its desirable properties as a measure of socioeconomic inequality, relative ease of computation and intuitive interpretation.

In the first empirical chapter (Chapter 4), I contributed to the literature by investigating socioeconomic inequality in child cognitive ability in the NCDS, BCS and MCS, using the CI. Changes over time in these inequalities (using dominance analysis) and their determinants (using decomposition analysis) were also explored. Results showed large socioeconomic inequalities in the majority of child cognitive tests. For the two cognitive tests that could be appropriately compared across cohorts, there was mixed evidence that the level of inequality had changed over time. Household income and parental occupational classification explained the majority of income related socioeconomic inequality in cognitive ability, while there were also roles for the level of maternal education and family size. There was little evidence of significant changes to the contributing factors over time.

It is generally acknowledged that there is a correlation between maternal educational attainment and child health outcomes (Strauss and Thomas 1995), however there is less evidence regarding its correlation with other child outcome measures such as cognitive ability. The proportion of income related socioeconomic inequality explained by the proxy measure of maternal education in both the NCDS and the MCS in Chapter 4 implies that policies or interventions designed at increasing levels of maternal education may be one way of reducing inequalities in child outcomes such as cognitive ability, mediated through proximal factors such as an increase in the quality of parental investment decisions. Rather than investing in interventions which aim to increase formal educational attainment, it has been argued that interventions with the aim of improving parenting skills in new mothers, such as the 'Preparing for Life' program recently introduced in parts of Ireland (Preparing for Life 2017), may be more effective and efficient (Devereux 2014). Carneiro *et al,.* (2013) have argued that an alternative strategy to this would be to specifically target parents in their youth, and therefore affect their level of education before they begin forming a family. The authors further argue that increases in parental education levels may also be a key transmission mechanism for intergenerational inequality, and therefore policy interventions which specifically target increases in levels of maternal education may also have significant long term benefits for both the mother and the child.

As well as measures of household SES such as parental occupation and household income, it has been predicted theoretically in the economic and psychological literatures that household composition, specifically family size and birth order, may also impact child outcomes (Becker and Tomes 1976; Zajonc 1976), mediated by the allocation of household resources between siblings. However, while a large number of empirical studies have investigated the relationship between family size, birth order and various measures of child achievement, there is substantial debate regarding whether the conditional associations found in a large number of the studies can be considered true causal relationships, or are instead spurious correlations driven by unobserved factors related to both family size and child outcomes and the substantial relationship between family size and birth order.

In the second empirical chapter (Chapter 5), I contributed to the literature by investigating the relationship between both family size and birth order and child cognitive ability and psychological well-being, using multiple exogenous forms of variation in an attempt to estimate a 'true' causal effect of family size, and explicitly accounting for the strong relationship between family size and birth order when estimating birth order effects. Analysing the determinants of child psychological well-being alongside cognitive ability can be considered important, as it has been argued that early life psychological traits may also contribute to levels of well-being across the life course, and that not accounting for such skills may overstate the returns to child cognitive ability (Heckman and Kautz 2012). Estimates from OLS models showed a significant conditional association between an increased family size and a lower level of psychological well-being, however this relationship was not shown for cognitive ability once a full set of confounding characteristics were included in the model specifications. 2SLS models showed no causal effect of family size on either outcome measure. However, the results from these models must be treated with caution, due to the possibility that small sample bias or unobserved confounding may have biased the results. For birth order, both OLS and NNM models surprisingly showed no consistent evidence of birth order effects for cognitive ability, while there was evidence of significant later born *advantages* for certain subscales of psychological well-being.

The level of fertility is a significant policy issue at the macroeconomic level, with low and/or declining fertility rates in a number of countries associated with a variety of problems, including an aging population increasingly dependent on the welfare state, and stalling levels of global economic growth. However, in the UK, several political policies have recently been introduced to incentivise parents to have less children, for example a de facto 'two child policy', which has significantly reduced the level of welfare support received by families with more than two children. At a household level, it is an increased family size that is predicted to have an adverse effect on the family. For example, having a larger family may provide mothers with less opportunity to engage in the labour market, and also may result in lower levels of parental resources for additional children. Given the inconclusiveness of the results presented in Chapter 5, whether an increased family size causally impacts levels of child cognitive ability and psychological well-being in the UK is still an unresolved issue for future empirical research. Policy makers designing interventions aimed at reducing inequalities in these early life outcome measures should therefore be cautious about including family size in the decision making process without considering its potentially strong relationship with other household characteristics.

Furthermore, even if there was undisputable evidence that family size itself causally impacts child outcomes, Bradshaw *et al,.* (2006) have argued that policy makers seeking to help larger families financially face various trade-offs. Firstly, any government policy which helps large families at the expense of small families may inadvertently increase child poverty in smaller and lone parent families, and therefore potentially increase the overall level of child poverty. Secondly, there may be both cost and effectiveness (in terms of equity) issues that must be considered. For example, improving levels of child benefit for larger families is expensive because they go to every large family whatever the level of household income. While manipulating child tax credits for large families may ensure that those who need it most receive extra help, such policies may increase the poverty trap (due to high marginal tax rates as earnings rise), and may also suffer from non-take-up. Finally, there could be potential objections from the general public regarding the extent to which increased premiums for larger families encourage 'irresponsible' child birth.

As well as family size, a number of recent popular news articles have reported that there may be significant effects of birth order on a variety of outcomes. For instance, in the past decade, the BBC website has carried headlines reporting that first born children face more pressure (BBC News 2009), are more likely to be overweight (BBC News 2014), are smarter (BBC News 2015) and receive more mental stimulation (BBC News 2017) than their later born counterparts. While these attention grabbing headlines imply that there are significant inequalities in a variety of outcomes generated within the household, accurately measuring birth order effects poses a number of methodological problems which may significantly bias the estimated parameters. The fact that the results from Chapter 5 imply that birth order may not be a significant determinant of child cognitive ability in the UK once a number of other characteristics are controlled for, and that there may in fact be an earlier born *disadvantage* for measures of psychological well-being, implies that policies aimed at putting disproportionate levels of attention and resources on later born siblings (for example the increased provision of day care for older siblings while parents are on parental leave with new-born children) may be misplaced, and such policies may in fact exacerbate inequalities in certain child outcomes within the household.

The household unit has traditionally been seen as the remit of the mother, with women expected to be responsible for household tasks such as housework, food preparation and childcare, and men expected to be the main breadwinners. Although women in the UK still do a disproportionate amount of household tasks (ONS 2016), levels of maternal labour supply have increased dramatically over the past 50 years, with this increased labour market participation seen as being an important step towards narrowing the gender wage gap (Blau 2012). Although this increased labour market participation may be beneficial for both the mother and the household in general, there may also be negative spill over effects, such as the impact on the amount of time allocated to children. Indeed, as noted by Ghez and Becker (1975): "… the raising of children requires time, especially wife's time, and goods. Thus, time and goods must be allocated between child services and other commodities". Alongside this increase in maternal labour supply in recent years, the increasingly '24 hour' economy has resulted in a number of these employment opportunities also involving the engagement in non-standard work schedules (Strazdins *et al.,* 2004).

While a large previous literature has investigated the various economic determinants of maternal labour supply and the relationship between maternal labour market activity and child outcomes such as health and cognitive ability, less attention had been paid to the potential relationship with adolescent risky health behaviours, particularly in the UK. Risky health behaviours such as drinking and smoking can be considered important behaviours to study, given their substantial health risks, significant societal costs and the fact that engaging in these behaviours in adolescence has been shown to significantly increase the probability of continuation into adulthood.

In the final empirical chapter (Chapter 6), I contributed to the literature by investigating the relationship between both maternal labour supply and maternal non-standard working schedules and adolescent drinking and smoking behaviour. Using six waves of data from the UKHLS and a variety of panel data models, results showed evidence of an economically small, yet statistically significant, conditional association between maternal labour supply and adolescent drinking, even when controlling for individual level heterogeneity. There was no evidence of a conditional association for adolescent smoking. Two IV strategies used in an attempt to identify a 'true' causal effect were found to be inappropriate for the research question. Further results showed no evidence of a significant relationship between non-standard work schedules and either adolescent risky health behaviour.

The lack of a substantial relationship between maternal labour supply and adolescent outcomes from the results in Chapter 6 implies that government policies aimed at encouraging maternal employment levels (such as increased childcare subsidies for working mothers) may not be the most effective policy strategy for decreasing levels of adolescent risky behaviour[36]. Instead, government resources may be better directed at other structural determinants of adolescent health behaviours which have larger evidence bases, in order to decrease levels of drinking and smoking both in adolescence and across the life course. It is especially important to efficiently allocate resources towards the prevention of adolescent risky health behaviours, given that there are other potential negative consequences of engaging in these behaviours, such as delayed physiological development and worse educational outcomes (Chatterji 2006).

Additionally, a number of studies (Francesconi 2002; Bernal 2008; Kabatek 2014) have argued that household decisions regarding maternal labour supply and family size are not taken in isolation, and should therefore be jointly considered in a unified modelling framework. Explicitly taking this joint decision making process into account when designing policies may result in government interventions being more efficient, given that any policy aimed at affecting either labour supply or childbearing separately is likely to have significant spill over effects on the other domain (Apps and Rees 2009; Kabatek 2014).

Overall, the research conducted in this thesis confirms the association between several household factors and a range of outcomes across childhood and adolescence in the UK. One common theme running through the three empirical chapters is the role that distal maternal characteristics, such as fertility choice, level of education or labour supply, may play in determining household inequalities in child and adolescent outcomes, mediated through proximal factors such as the quantity and quality of maternal time investments. However, imperfections in the data sources and empirical methodologies mean that a substantial amount of further research is required in order to pin down the exact magnitude of these associations, whether they in fact constitute 'true' causal effects and, if so, what the specific mediating mechanisms are through which they operate. Sophisticated measures of socioeconomic inequality, for example the CI, may be able to offer further insights into the level and determinants of socioeconomic inequality in child outcomes such as cognitive ability, while evidence from a large range of data sources and the continued application of advanced econometric techniques is needed in order to establish incontestable causal

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[36] It should be noted at this point that the evidence base for the impact of childcare subsidies on maternal labour supply is mixed in itself, with some empirical studies finding large effects (Lefebvre and Merrigan 2008), some studies finding small effects (Bettendorf *et al,.* 2015) and some studies showing no effects (Lundin *et al,.* 2008; Fitzpatrick 2010; Havnes and Mogstad 2011).

relationships between household factors and the various child and adolescent outcome measures used in this thesis.

Although a number of empirical studies have investigated the determinants of either child outcomes or adolescent outcomes in separate empirical studies, less consideration has been given to examining how different outcome measures may interact across the various different stages of childhood and adolescence (for example how child cognitive ability or psychological well-being at age 7 may be correlated with the engagement in risky health behaviours in at age 14), and how these complex, interconnecting relationships may in turn shape later life outcomes. While dynamic relationships such as these are not directly examined in this thesis, a logical extension of this work could be to more robustly investigate the pathways through which children transition through childhood and adolescence, with an aim of identifying the particular 'critical' and 'sensitive' periods which may be especially important in the development of inequalities in health, economic and social outcomes across the life course (Cunha and Heckman 2010).

However, the advanced econometric analysis needed to evaluate these dynamic relationships comes attached with a number of associated methodological issues (Popli *et al,.* 2013). Principally, such analysis requires the estimation of complex structural models which take into account the fact that measures such as health and innate ability are multidimensional in nature, and therefore must be regarded as unobservable latent variables. Moreover, a substantial amount of data is needed to account for the various latent factors and controlling covariates included in the model specification. Finally, plausible theoretical assumptions, derived from prior empirical studies, scientific knowledge or logical arguments, are needed when attaching a causal interpretation to the parameters estimated from these structural models (Bollen and Pearl 2013).

### 7.3 Strengths and Limitations

There are a number of strengths to this thesis. In the first empirical chapter (Chapter 4), I contributed to the understanding of the nature of socioeconomic inequalities in child cognitive ability in the UK in several areas, in particular whether the strength of this relationship has changed significantly over time and the analysis of some of the contributing factors that may drive income related socioeconomic inequality in child cognitive ability. Measuring income related socioeconomic inequality through the use of the CI (and related methodological tools such as dominance analysis and decomposition analysis) is novel in relation to child cognitive ability in the UK. This empirical chapter demonstrated that the CI (as well as other sophisticated measures of socioeconomic inequality such as the relative distributions method) may be useful methodological tools outside of the fields of health and health care utilisation, and could potentially be used as a complement alongside more commonly used regression based methods when analysing the relationship between SES and child outcomes such as cognitive ability.

In the second empirical chapter (Chapter 5), I contributed to the understanding of the effect of both family size and birth order on child cognitive ability and psychological well-being in the UK. When estimating the effect of family size, the use of two separate IV strategies constructed using the household grid of the MCS allowed me to control for the likely endogenous relationship between family size and child outcomes, and therefore estimate a 'true' causal effect for two specific subpopulations of the estimation sample, rather than a conditional association. When estimating the effect of birth order, the use of both OLS and NNM models within specific family sizes allowed me to control for the strong relationship between family size and birth order, take account of the probable heterogeneous birth order effects across family sizes, and also test the relationships to non-parametric assumptions.

In the third empirical chapter (Chapter 6), I contributed to the understanding of the relationship between both maternal labour supply and non-standard working schedules and adolescent risky health behaviour in the UK. When analysing the relationship between maternal labour supply and adolescent risky health behaviours, the use of fixed effects regression models allowed me to control for unobserved time-invariant individual level heterogeneity, while the failure of the two IV strategies to show the appropriate exogeneity conditions implies that these particular strategies are likely be inappropriate for research questions in this area, and should not be used in future empirical work. Additionally, as well as being novel in a UK setting, the analysis of the relationship between parental non-standard work schedules and adolescent risky health behaviours can be considered extremely policy relevant, given the significant increases in non-standard employment and the changes to household structure (for example the increasingly number of single parent households) which have occurred in the past 50 years.

As well as these strengths specific to each empirical chapter outlined above, there are also overall strengths to this thesis across the three empirical chapters. For example, the four datasets that I used across the three empirical chapters can be seen to be of extremely high quality, due to their large nationally representative samples, large number of suitable variables for inclusion in the econometric models and relatively low levels of missing data. Furthermore, in each empirical chapter I carried out a range of robustness checks in order to examine the sensitivity of my empirical results to various factors that may have biased these estimates, including missing data, alternative definitions of key variables and different empirical approaches.

However, despite these relative strengths, there are also some limitations to this thesis that must be considered. The majority of these limitations can be considered specific to each individual research question, and were explained in detail in the corresponding empirical chapter. Instead, in the remainder of this sub-section I focus on two overall limitations which are common to all three empirical chapters.

Firstly, it is possible that endogeneity may have biased the results in all three empirical chapters. Various approaches were adopted in this thesis in an attempt to address this issue, however there still remains doubt as to whether these effects can be considered causal. For instance, the OLS regression models and CI methods used in Chapter 4 do not explicitly attempt to account for endogeneity, and therefore relationships calculated from these models have to be considered conditional associations. Decomposition methods are designed to identify the contributing factors to socioeconomic inequalities, however it is again worth emphasising that this method cannot be considered a structural model or infer a direction of causality. IV methods were used in Chapter 5 and Chapter 6 in an attempt to identify 'true' causal effects. However, in both analyses there were a number of problems with the associated 2SLS models, including small sample properties, evidence that the instruments may not be strictly exogenous to the error term and potential unobserved confounding. Fixed effects models were also used in the empirical analysis in Chapter 6 to control for time invariant unobserved individual heterogeneity, but such models are unsuitable for use in short panels of data and also do not account for unobserved individual level heterogeneity that varies across time.

A second limitation across all three empirical chapters is that of external validity. The analyses presented in Chapter 4 and Chapter 5 were based on data from birth cohorts, and therefore the analyses from all three studies may be subject to specific cohort effects. Furthermore, although the estimates from the OLS models in Chapter 5 can be considered representative of the UK population due to application of the appropriate survey weights in estimation, the survey weights could not be applied when using the NNM models due to issues related to statistical software and the lack of a clear theoretical basis for using weights in the context of matching estimators (Leuven and Sianesi 2003). The parameters from the 2SLS models estimated in Chapter 5 and Chapter 6 also cannot be considered to be fully representative, as by definition they estimate the LATE for the compliant sub-population rather than the ATE at the population level. Finally, although the UKHLS is designed to be nationally representative through a complex sampling procedure and the use of a variety of survey weights, I was unable to utilise survey weights in the empirical analysis of Chapter 6 due to the specific sample of adolescents and their mothers that I used. Therefore, the results from this analysis also cannot be seen to be fully generalisable to the UK population.

**7.4 Future Research Agenda**

Although numerous individual areas for future research have been identified across the three empirical chapters (and are therefore not repeated in this sub-section), there are more general areas of future research that would build upon the knowledge and skills I have gained while undertaking this thesis, and that would be interesting to develop into, for example, a fellowship application.

The first potential area of future research stems from the difficulties in conducting cross cohort comparisons, as shown in the empirical analysis of Chapter 4. As well as generating comparable measures of SES, the CLOSER data harmonisation project (CLOSER 2017) has been developing a range of comparable variables between several UK based datasets, for example measures of body size and body composition, visual function and adult mental well-being. These newly developed measures could be used in a sensitivity analysis to test the robustness of the results from Chapter 4, however there are a number of additional questions which these variables could be used to answer. For instance, the comparable measures of SES and body size could be used to more robustly investigate the relationship between SES and measures of child health over time, while the comparable measures of adult mental well-being could be used to more accurately investigate how the relationship between multiple early life outcomes and adult mental well-being varies over both the lifecycle and across cohort, and how this may be linked to government policy. Cross cohort comparisons such as this are vital in order to understand how societal change and changes in the policy environment may impact health, economic and social outcomes in both the short term and across the life course, in order to inform future policy decisions.

A second potential area of future research stems from the difficulties in identifying valid causal effects using traditional IV methods, as shown in the empirical analysis of both Chapter 5 and Chapter 6. One relatively recent development in the area of causal inference is that of Mendelian randomization (MR), a method developed in the epidemiological literature which involves exploiting the random assignment of individuals' genotypes, and then using this random variation as a proxy for modifiable risky exposures in the first stage when implementing 2SLS models. From an economic perspective, Von Hinke Kessler Scholder *et al,.* (2011, 2012) have argued that MR presents a promising approach to estimating causal effects of modifiable risk factors on a range of outcomes[37]. There have also been several applications of this methodology in the recent economic literature, for instance Von Hinke Kessler Scholder *et al,.* (2013; 2014; 2016) and Kang *et al,.* (2016). Further developing an understanding and application of such methods may increase the knowledge base regarding the causal effects between, for example, *in utero* conditions (such as exposure to alcohol) and child health outcomes (such as obesity) on a range of later life outcomes, such as educational attainment, occupational attainment and other measures of social well-being.

However, as discussed by Von Hinke Kessler Scholder *et al,.* (2011), there are several aspects of this methodology which may inhibit the MR to calculate 'true' causal effects. Firstly, the systematic relationship between different genotypes and the outcome of interest is likely to differ significantly between subpopulations, and therefore similar to the theory underpinning the LATE, the causal effect calculated is likely to only be valid in a certain subpopulation. Secondly, it is likely that certain genotypes may be co-inherited with other variants, with this interaction potentially impacting the exclusion restriction pivotal in generating valid causal effects using IV methods. More generally, there are also problems regarding the possibility of relatively weak statistical power, the need for large amounts of complex genetic data, and the fact that the implementation of MR methods require (at the very least) a rudimentary understanding of genetics. Despite these relative shortcomings and potential difficulties, MR remains an exciting new area of research in the economic

[37] Dixon *et al,.* (2016) have argued that this method may also be useful in estimating marginal healthcare costs in the economic evaluation of health care technologies.

literature, and could be used to investigate the causal relationships between a number of policy relevant health and economic outcomes.

A third potential area of future research relates explicitly to the determinants of health inequalities. Although the child and adolescent outcomes examined in this thesis (cognitive ability, psychological well-being and risky health behaviours) may contribute to the development of health inequalities across the life cycle, government policy is also likely to play a fundamental role. There are several recent government policies that may have impacted health inequalities, such as the English health inequalities strategy introduced by the 1997 Labour government, and the policy of austerity introduced by the 2010 coalition government. Some recent empirical studies have analysed the impact of the English health inequalities strategy (Barr *et al,.* 2017) and austerity (Mattheys *et al,.* 2016) on both health outcomes and the level of health inequalities, however further research is needed before the true effect of these policies at the population level can be identified. Although there are several hurdles that need to be overcome in order to evaluate the impact of these policy measures, such as the need for a nationally representative dataset which contains both appropriate measures of health and well-being and the ability to be linked to specific geographical data, this is an area of future research with high policy relevance.

A fourth potential area of future research is related to the literature regarding the influence of 'parental investment' (also referred to in the literature as 'parental input' or 'parental involvement') on child outcomes, which is fast becoming a significant area of research in relation to child health and development (Cunha and Heckman 2007; Ermisch 2008, Aizer and Cunha 2012). The emphasis of this specific line of recent research is on the importance of parenting quality and the home environment, rather than purely monetary investments. These non-monetary investments are usually defined in terms of the quality of stimulation and support available, which can include activities such as reading to, talking to and playing with children.

Several recent empirical studies have examined parental investment and its potential impact on child outcomes in a UK setting. For instance, using data from the British Time-Use Study, Richards *et al* (2016) found that although on average parents are spending more time with their children than previously (23 minutes per day in 1975 to 80 minutes in 2015), the socioeconomic gap in this period has also increased from 20-30 minutes in 1975 to 40 minutes per day in 2015. Given these increases in both the level and inequality of parental home investments over time, the authors argue that progressive public policy specifically focussing on benefiting the most disadvantaged families is needed in order to reduce this level of inequality to acceptable levels.

In another recent study, Hernández-Alava and Popli (2017) used the MCS to estimate a dynamic factor model of child development from birth until the age of 7, including two latent measures of parental investment in their model specification. Empirical estimates displayed that family background has a significant influence on both child cognitive and non-cognitive development, with these relationships mediated by parental investments related to reading to the child and helping the child with school work. Although there are several potential difficulties in contributing to this research area, for instance accurately measuring parental investment and attributing a causal interpretation to the estimated parameters, this is a growing, policy relevant aspect of child development research that could both complement and extend the empirical work presented in this thesis.

A final area of potential future research would be to investigate how different outcome measures interact across the various different stages of childhood and adolescence, and how these complex, interconnecting relationships may in turn shape later life outcomes. Such research may be able to identify the particular 'critical' and 'sensitive' periods which may be especially important in the development of inequalities in adult outcomes across the life course. However, in practice, the advanced econometric analysis needed to evaluate these dynamic relationships comes attached with a number of complications, including the estimation of structural models to account for latent measures of child ability and health, a substantial amount of data to account for these latent factors and the various controlling variables, and the theoretical judgements needed in order to attach a causal interpretation to the parameters.

### 7.5 Concluding Remarks

The aim of this thesis was to contribute to the literature regarding the household determinants of inequalities in child and adolescent outcomes. In the first empirical chapter (Chapter 4), I contributed to the literature by investigating the socioeconomic distribution of child cognitive ability using the CI, as well as analysing whether the nature of this relationship had changed significantly over time using dominance analysis, and the factors that may contribute to the level of income related socioeconomic inequality using decomposition analysis. In the second empirical chapter (Chapter 5), I contributed to the literature regarding the impact of family size and birth order on child cognitive ability and psychological well-being, using IV models to account for the endogeneity of family size, and explicitly taking into account the strong relationship between family size and birth order when estimating birth order effects. In the final empirical chapter (Chapter 6), I contributed to the literature by analysing the relationship between both maternal labour supply and maternal non-standard working schedules on adolescent drinking and smoking behaviour in the UK, using a variety of panel data methodologies. As a complete body of work, it is hoped that the three empirical chapters together show how different household factors may contribute to the development of inequalities in various child and adolescent outcomes, which in turn may be pivotal in determining a range of health, economic and social outcomes across the life course.

# Appendix 4A - The standard error of the concentration index

As detailed by Kakwani *et al* (1997), the formulae for calculating the standard errors of the concentration index (CI) can be displayed as:

$$var(CI) = \frac{1}{n}\left[\frac{1}{n}\sum_{i=1}^{n} a_i^2 - (1 + CI)^2\right],$$

where

$$a_i = \frac{CA_i}{\mu}\,(2R_i - 1 - C) + 2 - q_{i-1} - q_i\,,$$

and

$$q_i = \frac{1}{\mu n}\sum_{\gamma=1}^{i} CA_i$$

$n$ represents the total number of people within the population, $u$ represents the mean of the total income, $R_i$ represents the socioeconomic fractional rank within the population of a member of the population $i$ and $CA_i$ represents the cognitive ability of child $i$. Additionally, $q_i$ is the coordinate of the corresponding concentration curve, with $q_{i-1}$ being the lagged value of this coordinate.

When using the 'convenient regression' method to calculate the CI, the standard error of $\beta_1$ provides a close estimate of the standard error of the CI. However, this estimate may be marginally biased due to autocorrelation. This bias can be eliminated by using a Newey-West regression estimator (Newey and West 1994) rather than linear regression estimator (O'Donnell *et al,.* 2008).

# Appendix 4B - Description of cognitive tests in the NCDS, BCS and MCS

## NCDS

| Cognitive Test | Brief Description | Scoring |
|---|---|---|
| **Age 7** | | |
| Southgate Group Reading Test | The child is either given a picture of an object or read a word, and has to ring the word describing that object or the word itself respectively. One mark is given for each correct answer. | 0-30 |
| Problem Arithmetic Test | The child is given ten problems graded in level of difficulty. The teachers are asked to read the problems to the children if necessary. | 0-10 |
| Drawing-a-Man Test | The child is asked to draw a picture of a man, with marks awarded relating to the features that were included. | 0-100 |
| Copying Designs Test | Six designs are presented to the child: a circle, square, triangle, diamond, cross and star. The children are asked to copy each design twice, with the quality of the child's responses judged by a set of criteria including general shape, symmetry and regularity of lines. | 0-12 |
| **Age 11** | | |
| General Ability Test (Verbal and Non-Verbal) | This test consists of 40 verbal and non-verbal items. The children are tested individually by teachers, who also record the answers. For verbal items, children are presented with an example set of four words linked either logically, semantically or phonologically. For the non-verbal tasks, shapes or symbols are used. Each correct answer is given one mark. | 0-40 for each subset |
| Reading Comprehension Test | The child is required to choose from a selection of 5 words which appropriately completed sentences. There are 35 questions in total, with one mark awarded for each completed sentence. | 0-35 |
| Arithmetic/Mathematics Test | 40 items involving numerical and geometric work. One mark for each question. | 0-40 |
| Copying Designs Test | The same copying designs test from the previous wave | 0-12 |

## BCS

| Age 5 | | |
|---|---|---|
| **Cognitive Test** | **Brief Description** | **Scoring** |
| Copying Designs Test | The child is asked to make two copies of eight shapes, with no time limit. A score of 0 or 1 is allocated for each drawing. | 0-8 |
| English Picture Vocabulary Test | This test is an Anglicised version of the Peabody Picture Vocabulary Test (Dunn 1959). 56 sets of four different pictures are presented to the child, with a particular word associated with each set of four pictures. The child is asked to indicate the one picture that corresponds to the given word, and given a point for each correct answer. The test is stopped if a child makes 5 incorrect answers from 8 consecutive questions, and is scaled according. | 0-56 |
| Human Figure Drawing Test | This test is a modified version of the Draw-a-Man test (Goodenough 1926). The child is asked to draw a picture of a man or woman, with marks awarded relating to the features that were included. | 0-23 |
| Complete a Profile Test | Similar to the Draw-a-Man test, the child is asked to complete an outline picture of a human face in profile by filling in features (eyes, ears etc...). Marks awarded for accuracy. | 0-16 |
| Schonell Reading Test | Reduced version of the original Schonell Reading Test. Reading ability is calculated from the ability to read words correctly. One mark for each correct answer. | 0-50 |
| **Age 10** | | |
| Shortened Edinburgh Reading Test | Test of word recognitions, which examines vocabulary, syntax, sequencing, comprehension and retention. Consists of various sections, including a picture test and matching question. One mark for each correct answer. | 0-67 |
| Friendly Maths test | Test consisted of 72 items, and tested arithmetic, number skills, fractions, algebra, geometry and statistics. One mark for each correct answer. The test is stopped if the child fails more than six consecutive items, and therefore scored accordingly. | 0-72 |
| Spelling Dictation | This task includes both real and made-up words, and therefore a test of both spelling and phonetic decoding. One point for each correct answer. | 0-50 |

| | | |
|---|---|---|
| Pictorial Language Comprehension Test | This test is based on the English Picture Language Test, and contains 71 vocabulary items, 16 sentence items and a further 13 sequence-sentence items. One mark for each correct answer. Test continues until the child makes 5 consecutive mistakes, and is weighted accordingly. | 2-100 |
| British Ability Scales Word Definitions | This subscale consists of a list of 37 words, which the child is asked to define. One mark for each correct answer. | 0-37 |
| British Ability Scales Word Similarities | This subscale consists of 21 items made up of three words. The child is asked to say what the group if items has in common. A child receives one mark for the correct group. | 0-21 |
| British Ability Scales Recall of Digits | This subscale consists of 34 items. The child is asked to listen to digits read out by a teacher and repeat them. One mark for each recall. | 0-34 |
| British Ability Scales Matrices | This subscale consists of 28 incomplete pattern arranged as a grid. The child has to complete each pattern by drawing the appropriate shape in the empty square. The assessment is stopped when the child has drawn four successive item incorrectly, and is scales accordingly. | 0-28 |

## MCS

**Age 5**

| Cognitive Test | Brief Description | Scoring |
|---|---|---|
| British Ability Scales Naming Vocabulary | To test expressive verbal ability, the child is shown a series of pictures of objects and is asked to name them. One mark for each correct answer. Number of questions answered depends on the number of correct answers, and it is therefore scaled accordingly. | 0-23 |
| British Ability Scales Pattern Construction | To test spatial problem solving, the child is asked to replicate a design using patterned squares. Number of questions answered depends on the number of correct answers, and it is therefore scaled accordingly. | 0-92 |
| British Ability Scales Picture Similarities | To test non-verbal reasoning, the child is shown a row of four pictures and is asked to identify a further congruent picture. One mark for each correct answer. Number of questions answered depends on the number of correct answers, and it is therefore scaled accordingly. | 0-170 |

| | | |
|---|---|---|
| **Age 7** | | |
| British Ability Scales Word Reading | To test educational knowledge of reading, the child is asked to read a series of words presented on a card. One mark for each correct answer. Number of questions answered depends on the number of correct answers, and it is therefore scaled accordingly. | 0-145 |
| British Ability Scales Pattern Construction | To test non-verbal reasoning, the child is shown a row of four pictures and is asked to identify a further congruent picture. One mark for each correct answer. Number of questions answered depends on the number of correct answers, and it is therefore scales accordingly. | 0-221 |
| NFER Maths Test | Covers topics such as numbers, shapes, measurement and data handling. Although there are 20 test items, the test is scored out of 12, 16 or 20 depending on the scores from the initial 7 test items. | 0-28 |
| **Age 11** | | |
| British Ability Scales Verbal Similarities Test | A series of questions where three linked items are read out to the child by the interviewer. The child is then simply asked to describe the main link between them. The test is designed to measure the child’s ability to identify and describe similarities between items. | 0-22 |

## Appendix 4C - Descriptive statistics for the alternative estimation samples

**Table 4C1 - Descriptive statistics for the estimation sample (N= 7375) used when calculating CIs in the NCDS (Age 7)**

| Variable | Mean | Std Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Maths Ability | 0.04 | 0.98 | -2.05 | 1.96 |
| Reading Ability | 0.09 | 0.94 | -3.26 | 0.93 |
| Draw A Man | 0.02 | 0.99 | -3.37 | 4.12 |
| Copying Ability | 0.04 | 0.99 | -3.50 | 2.50 |
| Parental Occupation | 3.07 | 0.88 | 1.00 | 5.00 |
| Permanent Predicted Income | 0 | 1 | -4.15 | 3.83 |
| Boy | 0.51 | 0.50 | 0.00 | 1.00 |
| North | 0.09 | 0.28 | 0 | 1 |
| North West | 0.12 | 0.33 | 0 | 1 |
| East Riding of Yorkshire | 0.08 | 0.26 | 0 | 1 |
| North Midlands | 0.07 | 0.26 | 0 | 1 |
| Midlands | 0.10 | 0.30 | 0 | 1 |
| East | 0.09 | 0.28 | 0 | 1 |
| South East | 0.15 | 0.35 | 0 | 1 |
| South | 0.06 | 0.24 | 0 | 1 |
| South West | 0.07 | 0.25 | 0 | 1 |
| Wales | 0.06 | 0.23 | 0 | 1 |
| Scotland | 0.13 | 0.33 | 0 | 1 |
| Family Size | 3.11 | 1.59 | 1 | 13 |
| Low Birth Weight | 0.04 | 0.20 | 0 | 1 |
| Preterm Birth | 0.04 | 0.19 | 0 | 1 |
| Maternal Age | 27.56 | 5.51 | 15 | 47 |
| $(\text{Maternal Age})^2$ | 790.17 | 321.23 | 225 | 2209 |
| Breastfeeding | 0.70 | 0.46 | 0 | 1 |
| Smoking in Pregnancy | 0.32 | 0.47 | 0 | 1 |
| Married | 0.98 | 0.13 | 0 | 1 |
| Maternal Education | 0.26 | 0.44 | 0 | 1 |
| Maternal Employment | 0.32 | 0.47 | 0 | 1 |

**Table 4C2 - Descriptive statistics for the full estimation sample (N=9900) in the NCDS (Age 11)**

| Variable | Mean | Std Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Non Verbal Ability | 0 | 1 | -2.74 | 2.51 |
| Verbal Ability | 0 | 1 | -2.54 | 3.02 |
| Reading Ability | 0 | 1 | -1.61 | 2.26 |
| Maths Ability | 0 | 1 | -5.58 | 2.45 |
| Copying Ability | 0 | 1 | -2.36 | 1.92 |
| Parental Occupation | 3.05 | 0.89 | 1 | 5 |
| Boy | 0.51 | 0.50 | 0 | 1 |
| North | 0.07 | 0.26 | 0 | 1 |
| North West | 0.11 | 0.32 | 0 | 1 |
| East Riding of Yorkshire | 0.08 | 0.28 | 0 | 1 |
| North Midlands | 0.08 | 0.27 | 0 | 1 |
| Midlands | 0.10 | 0.30 | 0 | 1 |
| East | 0.09 | 0.29 | 0 | 1 |
| South East | 0.17 | 0.37 | 0 | 1 |
| South | 0.06 | 0.24 | 0 | 1 |
| South West | 0.06 | 0.25 | 0 | 1 |
| Wales | 0.06 | 0.23 | 0 | 1 |
| Scotland | 0.11 | 0.31 | 0 | 1 |
| Family Size | 3.02 | 1.55 | 1 | 9 |
| Low Birth Weight | 0.04 | 0.20 | 0 | 1 |
| Preterm Birth | 0.04 | 0.19 | 0 | 1 |
| Maternal Age | 27.60 | 5.61 | 15 | 47 |
| $(\text{Maternal Age})^2$ | 793.02 | 326.92 | 225 | 2209 |
| Breastfeeding | 0.69 | 0.46 | 0 | 1 |
| Smoking in Pregnancy | 0.32 | 0.47 | 0 | 1 |
| Married | 0.97 | 0.16 | 0 | 1 |
| Maternal Education | 0.26 | 0.44 | 0 | 1 |
| Maternal Employment | 0.32 | 0.46 | 0 | 1 |

**Table 4C3 - Descriptive statistics for the estimation sample (N= 7320) used when calculating CIs in the NCDS (age 11)**

| Variable | Mean | Std Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Non Verbal Ability | 0.07 | 0.97 | -2.74 | 2.51 |
| Verbal Ability | 0.07 | 0.97 | -2.36 | 1.92 |
| Reading Ability | 0.06 | 0.99 | -2.54 | 3.02 |
| Maths Ability | 0.07 | 0.99 | -1.61 | 2.26 |
| Copying Ability | 0.02 | 0.94 | -5.58 | 2.45 |
| Parental Occupation | 3.06 | 0.87 | 1 | 5 |
| Permanent Predicted Income | 0 | 1 | -4.15 | 3.82 |
| Boy | 0.51 | 0.50 | 0 | 1 |
| North | 0.08 | 0.27 | 0 | 1 |
| North West | 0.11 | 0.31 | 0 | 1 |
| East Riding of Yorkshire | 0.08 | 0.27 | 0 | 1 |
| North Midlands | 0.07 | 0.26 | 0 | 1 |
| Midlands | 0.10 | 0.30 | 0 | 1 |
| East | 0.10 | 0.30 | 0 | 1 |
| South East | 0.15 | 0.36 | 0 | 1 |
| South | 0.06 | 0.25 | 0 | 1 |
| South West | 0.07 | 0.25 | 0 | 1 |
| Wales | 0.06 | 0.23 | 0 | 1 |
| Scotland | 0.12 | 0.33 | 0 | 1 |
| Family Size | 3.06 | 1.54 | 1 | 9 |
| Low Birth Weight | 0.04 | 0.20 | 0 | 1 |
| Preterm Birth | 0.04 | 0.19 | 0 | 1 |
| Maternal Age | 27.55 | 5.50 | 15 | 47 |
| $(\text{Maternal Age})^2$ | 789.13 | 320.09 | 225 | 2209 |
| Breastfeeding | 0.70 | 0.46 | 0 | 1 |
| Smoking in Pregnancy | 0.32 | 0.47 | 0 | 1 |
| Married | 0.98 | 0.14 | 0 | 1 |
| Maternal Education | 0.26 | 0.44 | 0 | 1 |
| Maternal Employment | 0.32 | 0.47 | 0 | 1 |

**Table 4C4 - Descriptive statistics for the full estimation sample (N=11079) in the BCS (Age 10)**

| Variable | Mean | Std Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Maths Ability | 0 | 1 | -3.53 | 2.19 |
| Reading Ability | 0 | 1 | -3.23 | 1.95 |
| BAS Definitions | 0 | 1 | -1.48 | 3.63 |
| BAS Digits | 0 | 1 | -2.15 | 1.68 |
| BAS Similarities | 0 | 1 | -2.23 | 1.58 |
| BAS Matrices | 0 | 1 | -1.72 | 1.81 |
| Parental Occupation | 3.05 | 0.84 | 1 | 5 |
| Boy | 0.52 | 0.50 | 0 | 1 |
| North | 0.06 | 0.25 | 0 | 1 |
| Yorkshire/Humberside | 0.10 | 0.29 | 0 | 1 |
| East Midlands | 0.07 | 0.26 | 0 | 1 |
| East Anglia | 0.04 | 0.19 | 0 | 1 |
| South East | 0.27 | 0.44 | 0 | 1 |
| South West | 0.08 | 0.27 | 0 | 1 |
| West Midlands | 0.11 | 0.31 | 0 | 1 |
| North West | 0.13 | 0.34 | 0 | 1 |
| Wales | 0.06 | 0.24 | 0 | 1 |
| Scotland | 0.09 | 0.29 | 0 | 1 |
| Family Size | 2.58 | 1.14 | 1 | 14 |
| Low Birth Weight | 0.05 | 0.23 | 0 | 1 |
| Preterm Birth | 0.05 | 0.22 | 0 | 1 |
| Maternal Age | 26.16 | 5.32 | 15 | 52 |
| (Maternal Age)$^2$ | 712.56 | 301.62 | 225 | 2704 |
| Breastfeeding | 0.37 | 0.48 | 0 | 1 |
| Smoking in Pregnancy | 0.40 | 0.49 | 0 | 1 |
| Married | 0.98 | 0.14 | 0 | 1 |
| Maternal Education | 0.34 | 0.47 | 0 | 1 |
| Maternal Employment | 0.44 | 0.50 | 0 | 1 |

**Table 4C5 - Descriptive statistics for the full estimation sample (N=12071) in the MCS (Age 7)**

| Variable | Mean | Std Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Maths Ability | 0 | 1 | -3.17 | 1.65 |
| Reading Ability | 0 | 1 | -3.12 | 1.86 |
| BAS Pattern Construction | 0 | 1 | -6.20 | 5.53 |
| Parental Occupation | 2.56 | 1.68 | 1 | 5 |
| Income | 0 | 1 | -1.67 | 3.88 |
| Boy | 0.50 | 0.50 | 0 | 1 |
| North East | 0.03 | 0.16 | 0 | 1 |
| North West | 0.07 | 0.26 | 0 | 1 |
| Yorkshire and Humber | 0.07 | 0.26 | 0 | 1 |
| East Midlands | 0.05 | 0.22 | 0 | 1 |
| West Midlands | 0.07 | 0.26 | 0 | 1 |
| East of England | 0.07 | 0.26 | 0 | 1 |
| London | 0.11 | 0.32 | 0 | 1 |
| South East | 0.10 | 0.30 | 0 | 1 |
| South West | 0.05 | 0.23 | 0 | 1 |
| Wales | 0.14 | 0.35 | 0 | 1 |
| Scotland | 0.13 | 0.33 | 0 | 1 |
| Northern Ireland | 0.10 | 0.31 | 0 | 1 |
| Family Size | 2.54 | 1.07 | 1 | 10 |
| Low Birth Weight | 0.07 | 0.26 | 0 | 1 |
| Preterm Birth | 0.08 | 0.27 | 0 | 1 |
| Maternal Age | 28.95 | 5.72 | 15 | 51 |
| $(\text{Maternal Age})^2$ | 870.61 | 331.01 | 225 | 2601 |
| Breastfeeding | 0.70 | 0.46 | 0 | 1 |
| Smoking in Pregnancy | 0.15 | 0.35 | 0 | 1 |
| Married | 0.64 | 0.48 | 0 | 1 |
| Maternal Education | 0.28 | 0.45 | 0 | 1 |
| Maternal Employment | 0.65 | 0.48 | 0 | 1 |

**Table 4C6 - Descriptive statistics for the full estimation sample (N=11971) in the MCS (Age 11)**

| Variable | Mean | Std Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Verbal Ability | 0 | 1 | -3.53 | 2.19 |
| Parental Occupation | 2.54 | 1.68 | 1 | 5 |
| Income | 0 | 1 | -2.05 | 4.57 |
| Boy | 0.50 | 0.50 | 0 | 1 |
| North East | 0.03 | 0.16 | 0 | 1 |
| North West | 0.08 | 0.27 | 0 | 1 |
| Yorkshire and Humber | 0.07 | 0.26 | 0 | 1 |
| East Midlands | 0.05 | 0.22 | 0 | 1 |
| West Midlands | 0.07 | 0.26 | 0 | 1 |
| East of England | 0.07 | 0.25 | 0 | 1 |
| London | 0.12 | 0.32 | 0 | 1 |
| South East | 0.10 | 0.30 | 0 | 1 |
| South West | 0.05 | 0.23 | 0 | 1 |
| Wales | 0.15 | 0.35 | 0 | 1 |
| Scotland | 0.12 | 0.32 | 0 | 1 |
| Northern Ireland | 0.10 | 0.30 | 0 | 1 |
| Family Size | 2.57 | 1.10 | 1 | 11 |
| Low Birth Weight | 0.07 | 0.26 | 0 | 1 |
| Preterm Birth | 0.08 | 0.27 | 0 | 1 |
| Maternal Age | 28.98 | 5.72 | 14 | 51 |
| (Maternal Age)$^2$ | 872.70 | 331.08 | 196 | 2601 |
| Breastfeeding | 0.71 | 0.45 | 0 | 1 |
| Smoking in Pregnancy | 0.15 | 0.35 | 0 | 1 |
| Married | 0.64 | 0.48 | 0 | 1 |
| Maternal Education | 0.29 | 0.45 | 0 | 1 |
| Maternal Employment | 0.63 | 0.50 | 0 | 1 |

# Appendix 4D - Full regression output from OLS regression models in Tables 4.11 and 4.12 (NCDS)

**Table 4D1-Age 7**

| | Reading | | Maths | | Drawing | | Copying | |
|---|---|---|---|---|---|---|---|---|
| White | 0.130*** | (0.031) | 0.108*** | (0.032) | 0.041 | (0.033) | 0.082** | (0.033) |
| Boy | -0.254*** | (0.017) | 0.089*** | (0.018) | -0.079*** | (0.019) | 0.049*** | (0.019) |
| Low Birth Weight | -0.251*** | (0.049) | -0.216*** | (0.047) | -0.203*** | (0.048) | -0.207*** | (0.050) |
| Preterm Birth | -0.026 | (0.050) | -0.048 | (0.051) | -0.079 | (0.052) | -0.052 | (0.051) |
| Region | | | | | | | | |
| North | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| North West | -0.040 | (0.038) | -0.093** | (0.043) | 0.006 | (0.040) | 0.054 | (0.042) |
| East and West Riding | -0.119*** | (0.043) | -0.143*** | (0.047) | 0.223*** | (0.045) | 0.035 | (0.047) |
| North Midlands | -0.122*** | (0.044) | -0.171*** | (0.047) | 0.097** | (0.044) | -0.053 | (0.047) |
| Midlands | -0.159*** | (0.041) | -0.212*** | (0.046) | 0.204*** | (0.043) | -0.100** | (0.045) |
| East | -0.083** | (0.041) | -0.197*** | (0.047) | 0.117*** | (0.044) | 0.059 | (0.046) |
| South East | -0.149*** | (0.037) | -0.177*** | (0.042) | 0.129*** | (0.040) | 0.074* | (0.041) |
| South | -0.161*** | (0.045) | -0.219*** | (0.051) | 0.190*** | (0.050) | 0.108** | (0.051) |
| South West | -0.214*** | (0.045) | -0.135*** | (0.049) | 0.159*** | (0.047) | 0.029 | (0.049) |
| Wales | -0.141*** | (0.049) | 0.015 | (0.053) | 0.124** | (0.052) | 0.004 | (0.053) |
| Scotland | 0.258*** | (0.036) | -0.193*** | (0.043) | -0.048 | (0.041) | -0.147*** | (0.044) |
| Family Size | -0.119*** | (0.006) | -0.040*** | (0.006) | -0.058*** | (0.006) | -0.067*** | (0.006) |
| Maternal Age | 0.063*** | (0.014) | 0.034** | (0.014) | 0.051*** | (0.014) | 0.045*** | (0.014) |
| $(\text{Maternal Age})^2$ | -0.001*** | (0.000) | -0.001** | (0.000) | -0.001*** | (0.000) | -0.001*** | (0.000) |
| Parents Married | 0.238*** | (0.064) | 0.207*** | (0.060) | 0.089 | (0.062) | 0.166*** | (0.060) |
| Smoking During Pregnancy | -0.088*** | (0.019) | -0.069*** | (0.020) | -0.041** | (0.020) | -0.064*** | (0.020) |
| Breastfed | 0.091*** | (0.020) | 0.060*** | (0.021) | 0.088*** | (0.021) | 0.109*** | (0.021) |
| Maternal Employment | 0.048** | (0.019) | 0.023 | (0.021) | -0.043** | (0.021) | 0.013 | (0.021) |
| Maternal Education | 0.242*** | (0.019) | 0.252*** | (0.023) | 0.157*** | (0.023) | 0.167*** | (0.023) |
| Observations | 10921 | | 10921 | | 10921 | | 10921 | |
| R-squared | 0.149 | | 0.066 | | 0.054 | | 0.059 | |

*Notes:* Full Regression Output from OLS regression models. Robust standard errors in parentheses. ***significant at 1%, ** at 5%, * at 1%

## Table 4D2 -Age 11

| | Verbal | | Non-Verbal | | Maths | | Reading | | Copying | |
|---|---|---|---|---|---|---|---|---|---|---|
| White | 0.309*** | (0.089) | 0.392*** | (0.093) | 0.303*** | (0.089) | 0.281*** | (0.082) | 0.131 | (0.088) |
| Boy | -0.213*** | (0.018) | -0.028 | (0.018) | 0.050*** | (0.018) | 0.001 | (0.018) | 0.046** | (0.019) |
| Low Birth Weight | -0.230*** | (0.049) | -0.237*** | (0.047) | -0.225*** | (0.045) | -0.190*** | (0.049) | -0.144*** | (0.054) |
| Preterm Birth | -0.022 | (0.053) | -0.064 | (0.054) | -0.029 | (0.049) | -0.059 | (0.053) | -0.098* | (0.057) |
| Region | | | | | | | | | | |
| North | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| North West | 0.145*** | (0.044) | 0.128*** | (0.044) | 0.056 | (0.044) | 0.063 | (0.043) | -0.088** | (0.044) |
| East and West Riding | -0.068 | (0.046) | -0.005 | (0.046) | -0.075* | (0.045) | -0.028 | (0.046) | 0.015 | (0.049) |
| North Midlands | 0.039 | (0.047) | 0.047 | (0.047) | -0.070 | (0.046) | -0.022 | (0.045) | -0.001 | (0.049) |
| Midlands | -0.021 | (0.045) | 0.043 | (0.045) | -0.150*** | (0.044) | -0.077* | (0.044) | -0.100** | (0.047) |
| East | 0.026 | (0.044) | 0.101** | (0.044) | -0.042 | (0.045) | -0.003 | (0.044) | -0.023 | (0.046) |
| South East | 0.022 | (0.041) | 0.106*** | (0.041) | -0.078* | (0.041) | 0.031 | (0.041) | -0.064 | (0.043) |
| South | 0.058 | (0.049) | 0.114** | (0.050) | -0.035 | (0.050) | 0.003 | (0.048) | 0.055 | (0.053) |
| South West | 0.088* | (0.049) | 0.181*** | (0.048) | -0.069 | (0.048) | -0.043 | (0.048) | 0.025 | (0.053) |
| Wales | 0.106** | (0.053) | 0.112** | (0.052) | 0.040 | (0.050) | -0.061 | (0.050) | -0.066 | (0.056) |
| Scotland | 0.089** | (0.042) | 0.027 | (0.042) | 0.143*** | (0.042) | 0.063 | (0.041) | -0.134*** | (0.046) |
| Family Size | -0.113*** | (0.006) | -0.105*** | (0.006) | -0.097*** | (0.006) | -0.133*** | (0.006) | -0.046*** | (0.007) |
| Maternal Age | 0.059*** | (0.014) | 0.057*** | (0.014) | 0.081*** | (0.014) | 0.067*** | (0.014) | 0.043*** | (0.016) |
| $(\text{Maternal Age})^2$ | -0.001*** | (0.000) | -0.001*** | (0.000) | -0.001*** | (0.000) | -0.001*** | (0.000) | -0.001** | (0.000) |
| Parents Married | 0.105* | (0.059) | 0.107* | (0.060) | 0.176*** | (0.055) | 0.086 | (0.060) | 0.055 | (0.061) |
| Smoking in Pregnancy | -0.128*** | (0.020) | -0.128*** | (0.020) | -0.169*** | (0.019) | -0.105*** | (0.019) | -0.047** | (0.021) |
| Breastfed | 0.105*** | (0.021) | 0.136*** | (0.021) | 0.120*** | (0.020) | 0.117*** | (0.020) | 0.097*** | (0.021) |
| Maternal Employment | 0.069*** | (0.021) | 0.068*** | (0.021) | 0.086*** | (0.021) | 0.123*** | (0.021) | 0.018 | (0.022) |
| Maternal Education | 0.321*** | (0.022) | 0.321*** | (0.022) | 0.387*** | (0.023) | 0.383*** | (0.022) | 0.142*** | (0.023) |
| Observations | 9900 | | 9900 | | 9900 | | 9900 | | 9900 | |
| R-squared | 0.159 | | 0.155 | | 0.181 | | 0.191 | | 0.041 | |

*Notes:* Full Regression Output from OLS regression models. Robust standard errors in parentheses. ***significant at 1%, ** at 5%, * at 1%

## Appendix 4E - Applying inverse probability weighting to check the bias from missing data (NCDS)

**Table 4E1- Regression output from logit model used to calculate IPWs (NCDS)**

| | |
|---|---|
| Mother Employed | 0.028 |
| | (0.046) |
| Maternal Education | -0.070 |
| | (0.047) |
| Maternal Age | 0.153*** |
| | (0.029) |
| (Maternal Age)$^2$ | -0.003*** |
| | (0.000) |
| Parents Married | 0.985*** |
| | (0.102) |
| White | 2.186*** |
| | (0.046) |
| Observations | 14967 |
| Pseudo R-Squared | 0.181 |

*Notes:* Coefficients from a logit regression model. Robust standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%

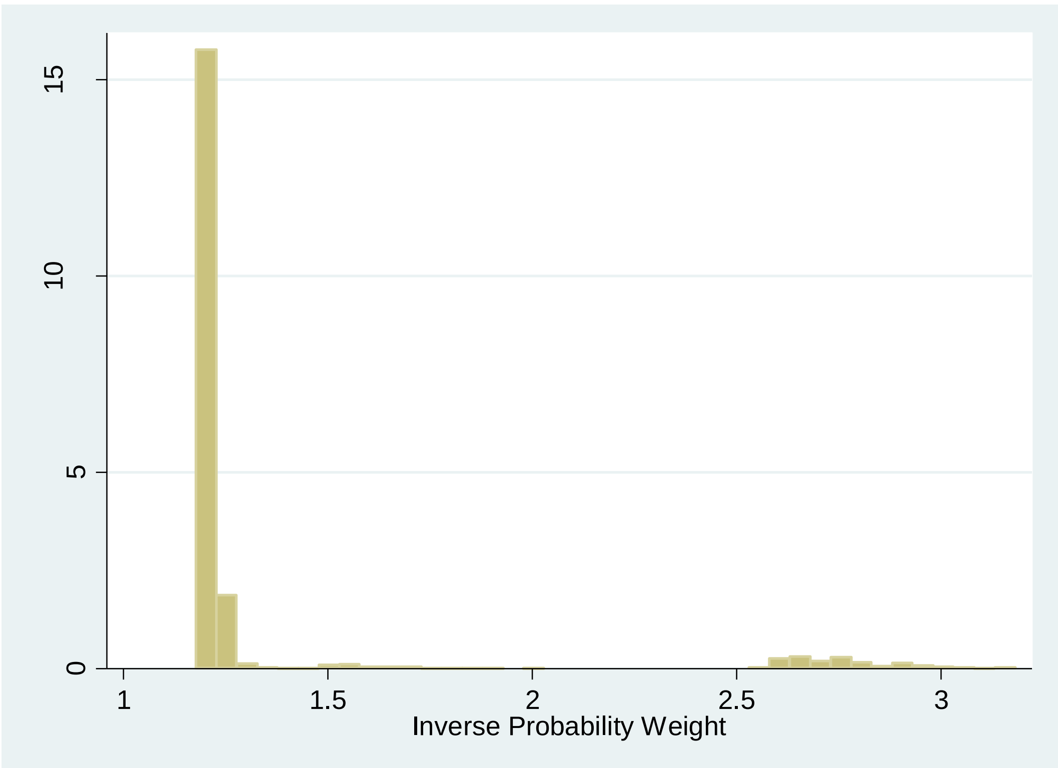



*Figure 4E1- Distribution of Inverse Probability Weights in the NCDS*

**Table 4E2 - Unweighted results of the relationship between SES and child cognitive ability estimated by OLS regression models (NCDS Age 7)**

| | (1) Reading | | (2) Maths | | (3) Drawing | | (4) Copying | |
|---|---|---|---|---|---|---|---|---|
| Parental Social Class | | | | | | | | |
| I | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| II | -0.116*** | (0.032) | -0.172*** | (0.045) | -0.094* | (0.049) | -0.088** | (0.044) |
| III | -0.316*** | (0.030) | -0.366*** | (0.041) | -0.218*** | (0.046) | -0.213*** | (0.040) |
| IV | -0.461*** | (0.037) | -0.465*** | (0.046) | -0.309*** | (0.050) | -0.277*** | (0.045) |
| V | -0.663*** | (0.050) | -0.545*** | (0.056) | -0.411*** | (0.059) | -0.405*** | (0.056) |
| Observations | 10921 | | 10921 | | 10921 | | 10921 | |
| R-squared | 0.149 | | 0.066 | | 0.054 | | 0.059 | |

*Notes:* Summary of empirical estimates. Robust standard errors in parentheses. *** Significant at 1%, ** at 5%, * at 10%.

**Table 4E3 - Weighted results of the relationship between SES and child cognitive ability estimated by OLS regression models (NCDS Age 7)**

| | (1) Reading | | (2) Maths | | (3) Drawing | | (4) Copying | |
|---|---|---|---|---|---|---|---|---|
| Parental Social Class | | | | | | | | |
| I | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| II | -0.101*** | (0.036) | -0.155*** | (0.048) | -0.087* | (0.053) | -0.102** | -0.155*** |
| III | -0.331*** | (0.034) | -0.374*** | (0.044) | -0.223*** | (0.050) | -0.213*** | -0.374*** |
| IV | -0.471*** | (0.042) | -0.468*** | (0.049) | -0.301*** | (0.055) | -0.289*** | -0.468*** |
| V | -0.659*** | (0.054) | -0.547*** | (0.059) | -0.407*** | (0.063) | -0.424*** | -0.547*** |
| Observations | 10921 | | 10921 | | 10921 | | 10921 | |
| R-squared | 0.151 | | 0.070 | | 0.053 | | 0.057 | |

*Notes:* Summary of empirical estimates. Robust standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

## Appendix 4F - Full regression output from Tables 4.14 and 4.15 (BCS)

**Table 4F1 - Age 5**

| | Drawing | | Copying | | Profile | | Vocabulary | |
|---|---|---|---|---|---|---|---|---|
| White | 0.036 | (0.042) | 0.124*** | (0.041) | 0.007 | (0.043) | 0.565*** | (0.051) |
| Boy | -0.220*** | (0.016) | 0.007 | (0.018) | 0.042** | (0.019) | 0.137*** | (0.020) |
| Low Birth Weight | -0.107*** | (0.041) | -0.269*** | (0.044) | -0.045 | (0.044) | -0.283*** | (0.053) |
| Preterm Birth | -0.038 | (0.043) | -0.087* | (0.045) | -0.109** | (0.046) | -0.018 | (0.052) |
| Region | | | | | | | | |
| North | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| Yorkshire/Humberside | 0.015 | (0.040) | -0.120*** | (0.045) | 0.042 | (0.048) | -0.024 | (0.051) |
| East Midlands | -0.074 | (0.046) | -0.157*** | (0.048) | 0.129** | (0.051) | 0.007 | (0.055) |
| East Anglia | -0.030 | (0.050) | -0.117** | (0.059) | 0.045 | (0.060) | -0.039 | (0.064) |
| South East | 0.059* | (0.034) | -0.047 | (0.039) | 0.176*** | (0.041) | 0.069 | (0.043) |
| South West | -0.025 | (0.042) | -0.060 | (0.047) | 0.131*** | (0.050) | 0.006 | (0.053) |
| West Midlands | 0.027 | (0.038) | -0.166*** | (0.043) | 0.150*** | (0.046) | -0.087* | (0.049) |
| North West | 0.036 | (0.037) | 0.020 | (0.042) | 0.053 | (0.044) | -0.022 | (0.047) |
| Wales | 0.065 | (0.044) | -0.045 | (0.050) | 0.052 | (0.053) | -0.116** | (0.057) |
| Scotland | 0.053 | (0.041) | -0.431*** | (0.045) | 0.262*** | (0.050) | -0.040 | (0.054) |
| Family Size | -0.057*** | (0.008) | -0.113*** | (0.008) | -0.041*** | (0.009) | -0.169*** | (0.010) |
| Maternal Age | 0.010 | (0.013) | 0.084*** | (0.014) | 0.000 | (0.014) | 0.117*** | (0.016) |
| $(\text{Maternal Age})^2$ | -0.000 | (0.000) | -0.001*** | (0.000) | 0.000 | (0.000) | -0.002*** | (0.000) |
| Parents Married | 0.018 | (0.064) | 0.146** | (0.067) | 0.009 | (0.069) | 0.263*** | (0.074) |
| Smoking in Pregnancy | -0.059*** | (0.017) | -0.070*** | (0.019) | 0.028 | (0.020) | -0.071*** | (0.021) |
| Breastfed | 0.065*** | (0.017) | 0.103*** | (0.019) | 0.089*** | (0.020) | 0.045** | (0.021) |
| Maternal Employment | 0.038** | (0.017) | 0.029 | (0.018) | -0.011 | (0.019) | 0.000 | (0.020) |
| Maternal Education | 0.070*** | (0.018) | 0.197*** | (0.021) | 0.038* | (0.021) | 0.189*** | (0.022) |
| Observations | 11167 | | 11167 | | 11167 | | 8616 | |
| R-squared | 0.042 | | 0.101 | | 0.018 | | 0.134 | |

*Notes:* Full Regression Output from OLS regression models. Robust standard errors in parentheses. ***significant at 1%, ** at 5%, * at 1%

**Table 4F2 - Age 10 (Part 1)**

| | Maths | | Reading | | Definitions | | Digits | |
|---|---|---|---|---|---|---|---|---|
| White | -0.301*** | (0.047) | -0.239*** | (0.043) | -0.139** | (0.061) | 0.013 | (0.057) |
| Boy | -0.551*** | (0.042) | -0.451*** | (0.039) | -0.327*** | (0.056) | -0.017 | (0.052) |
| Low Birth Weight | -0.661*** | (0.048) | -0.586*** | (0.046) | -0.415*** | (0.059) | -0.017 | (0.057) |
| Preterm Birth | -0.839*** | (0.058) | -0.733*** | (0.057) | -0.535*** | (0.065) | -0.078 | (0.065) |
| Region | | | | | | | | |
| North | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| Yorkshire/Humber | -0.104** | (0.048) | -0.094** | (0.047) | -0.080* | (0.044) | -0.191*** | (0.044) |
| East Midlands | -0.091* | (0.050) | -0.038 | (0.050) | -0.067 | (0.047) | -0.159*** | (0.046) |
| East Anglia | -0.077 | (0.067) | -0.025 | (0.063) | -0.218*** | (0.058) | -0.374*** | (0.062) |
| South East | -0.105** | (0.041) | -0.076* | (0.040) | -0.132*** | (0.038) | -0.335*** | (0.038) |
| South West | -0.118** | (0.051) | -0.051 | (0.050) | -0.232*** | (0.049) | -0.418*** | (0.050) |
| West Midlands | -0.205*** | (0.046) | -0.134*** | (0.045) | -0.058 | (0.042) | -0.170*** | (0.041) |
| North West | 0.015 | (0.044) | 0.072* | (0.043) | -0.052 | (0.041) | -0.135*** | (0.040) |
| Wales | -0.035 | (0.054) | -0.077 | (0.052) | -0.214*** | (0.050) | -0.294*** | (0.051) |
| Scotland | 0.160*** | (0.046) | 0.183*** | (0.045) | 0.047 | (0.044) | -0.137*** | (0.044) |
| Family Size | -0.121*** | (0.010) | -0.163*** | (0.010) | -0.125*** | (0.008) | -0.029*** | (0.009) |
| Maternal Age | 0.068*** | (0.015) | 0.067*** | (0.015) | 0.051*** | (0.014) | 0.023 | (0.015) |
| (Maternal Age)$^2$ | -0.001*** | (0.000) | -0.001*** | (0.000) | -0.001*** | (0.000) | -0.000 | (0.000) |
| Parents Married | 0.063 | (0.082) | 0.045 | (0.079) | 0.008 | (0.066) | -0.014 | (0.071) |
| Smoking in Pregnancy | -0.152*** | (0.020) | -0.160*** | (0.020) | -0.099*** | (0.019) | -0.032 | (0.020) |
| Breastfed | 0.084*** | (0.021) | 0.123*** | (0.021) | 0.122*** | (0.020) | 0.006 | (0.021) |
| Maternal Employment | -0.023 | (0.019) | -0.028 | (0.019) | -0.035* | (0.019) | 0.003 | (0.020) |
| Maternal Education | 0.378*** | (0.022) | 0.390*** | (0.022) | 0.239*** | (0.022) | 0.065*** | (0.022) |
| Observations | 9181 | | 9187 | | 10790 | | 10790 | |
| R-squared | 0.151 | | 0.172 | | 0.091 | | 0.017 | |

*Notes:* Full Regression Output from OLS regression models. Robust standard errors in parentheses. ***significant at 1%, ** at 5%, * at 1%

**Table 4F3 - Age 10 (Part 2)**

| Reading | Similarities | | Matrices | | Spelling | | Vocabulary | |
|---|---|---|---|---|---|---|---|---|
| White | 0.029 | (0.059) | -0.007 | (0.060) | 0.151*** | (0.052) | 0.213*** | (0.047) |
| Boy | -0.043 | (0.053) | -0.106* | (0.055) | -0.155*** | (0.022) | 0.052*** | (0.019) |
| Low Birth Weight | -0.069 | (0.058) | -0.142** | (0.061) | -0.210*** | (0.054) | -0.149*** | (0.046) |
| Preterm Birth | -0.177*** | (0.065) | -0.286*** | (0.070) | -0.031 | (0.052) | 0.017 | (0.046) |
| Region | | | | | | | | |
| North | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| Yorks/Humber | -0.136*** | (0.042) | -0.129*** | (0.050) | -0.218*** | (0.052) | -0.151*** | (0.043) |
| East Midlands | -0.111** | (0.044) | -0.072 | (0.052) | -0.198*** | (0.055) | -0.080* | (0.047) |
| East Anglia | -0.309*** | (0.061) | -0.242*** | (0.068) | -0.385*** | (0.073) | -0.248*** | (0.064) |
| South East | -0.285*** | (0.036) | -0.264*** | (0.043) | -0.350*** | (0.044) | -0.234*** | (0.038) |
| South West | -0.356*** | (0.049) | -0.306*** | (0.056) | -0.266*** | (0.056) | -0.129*** | (0.047) |
| West Midlands | -0.094** | (0.039) | -0.080* | (0.047) | -0.125** | (0.050) | -0.068* | (0.041) |
| North West | -0.133*** | (0.038) | -0.054 | (0.046) | -0.124** | (0.048) | -0.113*** | (0.040) |
| Wales | -0.253*** | (0.050) | -0.278*** | (0.060) | -0.314*** | (0.059) | -0.233*** | (0.052) |
| Scotland | -0.097** | (0.042) | -0.133*** | (0.051) | 0.142*** | (0.048) | -0.084** | (0.041) |
| Family Size | -0.066*** | (0.009) | -0.061*** | (0.010) | -0.078*** | (0.010) | -0.087*** | (0.009) |
| Maternal Age | 0.039*** | (0.014) | 0.048*** | (0.016) | 0.035** | (0.016) | 0.032** | (0.015) |
| $(\text{Maternal Age})^2$ | -0.001** | (0.000) | -0.001*** | (0.000) | -0.001* | (0.000) | -0.000* | (0.000) |
| Parents Married | 0.008 | (0.070) | 0.010 | (0.086) | -0.002 | (0.078) | 0.024 | (0.070) |
| Smoking in Pregnancy | -0.047** | (0.020) | -0.084*** | (0.023) | -0.029 | (0.023) | -0.047** | (0.020) |
| Breastfed | 0.057*** | (0.021) | 0.080*** | (0.023) | 0.037 | (0.024) | 0.058*** | (0.021) |
| Maternal Employment | -0.014 | (0.019) | -0.018 | (0.022) | -0.025 | (0.022) | -0.016 | (0.020) |
| Maternal Education | 0.078*** | (0.022) | 0.147*** | (0.025) | 0.123*** | (0.025) | 0.087*** | (0.022) |
| Observations | 10790 | | 8573 | | 8255 | | 10790 | |
| R-squared | 0.025 | | 0.037 | | 0.048 | | 0.031 | |

*Notes:* Full regression output from OLS specifications. Robust standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

## Appendix 4G - Applying inverse probability weighting to check for bias from missing data (BCS)

**Table 4G1 - Regression output from logit model used to calculate IPWs (BCS)**

| | |
|---|---|
| Mother Employed | -0.014 |
| | (0.065) |
| Maternal Education | 0.053 |
| | (0.068) |
| Maternal Age | 0.219*** |
| | (0.041) |
| (Maternal Age)$^2$ | -0.003*** |
| | (0.001) |
| Parents Married | 3.087*** |
| | (0.090) |
| White | 0.530*** |
| | (0.114) |
| Observations | 12546 |
| Pseudo R-Squared | 0.174 |

*Notes:* Coefficients from a logit regression model. Robust standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%

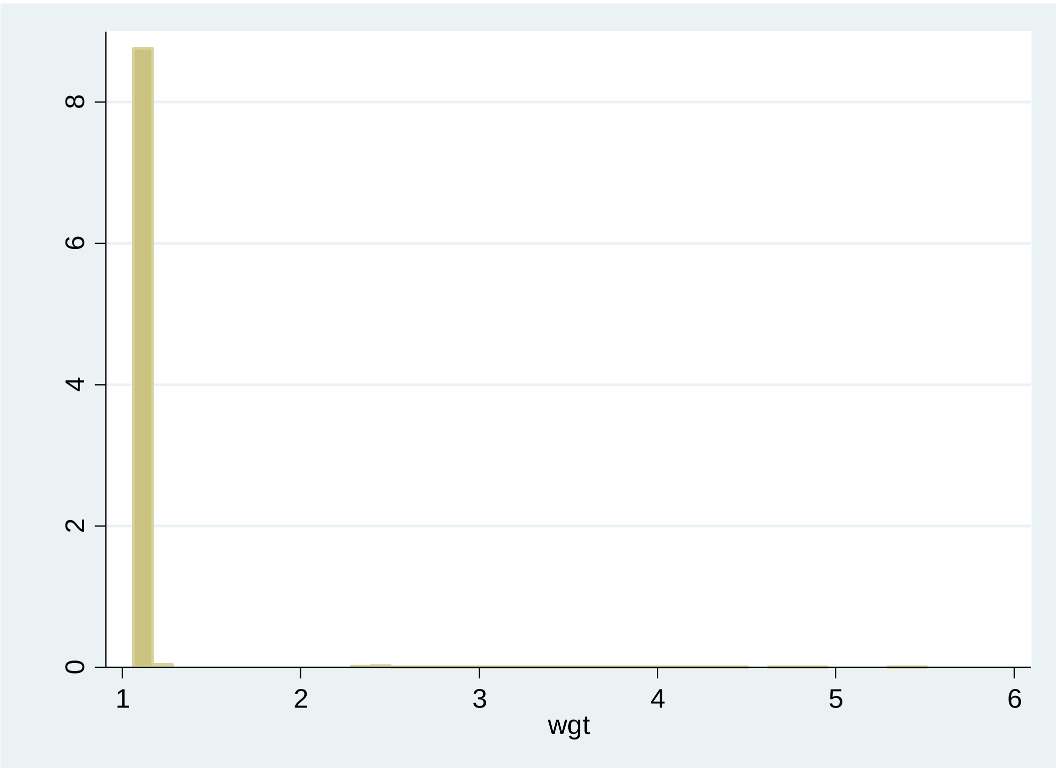



*Figure 4G1- Distribution of Inverse Probability Weights in the BCS*

**Table 4G2 - Unweighted results of the relationship between SES and child cognitive ability estimated by OLS regression models (BCS Age 5)**

| | (1) Drawing | | (2) Copying | | (3) Profile | | (4) Vocabulary | |
|---|---|---|---|---|---|---|---|---|
| Parental Social Class | | | | | | | | |
| I | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| II | -0.055 | (0.040) | -0.125*** | (0.046) | -0.049 | (0.050) | -0.160*** | (0.051) |
| III | -0.147*** | (0.035) | -0.286*** | (0.041) | -0.132*** | (0.045) | -0.215*** | (0.045) |
| IV | -0.190*** | (0.041) | -0.400*** | (0.047) | -0.154*** | (0.051) | -0.349*** | (0.051) |
| V | -0.301*** | (0.049) | -0.541*** | (0.056) | -0.317*** | (0.059) | -0.582*** | (0.062) |
| Observations | 11167 | | 11167 | | 11167 | | 8616 | |
| R-squared | 0.042 | | 0.101 | | 0.018 | | 0.134 | |

*Notes:* Summary of empirical estimates. Robust standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

**Table 4G3 - Weighted results of the relationship between SES and child cognitive ability estimated by OLS regression models (BCS Age 5)**

| | (1) Drawing | | (2) Copying | | (3) Profile | | (4) Vocabulary | |
|---|---|---|---|---|---|---|---|---|
| Parental Social Class | | | | | | | | |
| I | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| II | -0.063 | (0.040) | -0.126*** | (0.046) | -0.049 | (0.050) | -0.166*** | (0.051) |
| III | -0.154*** | (0.036) | -0.293*** | (0.042) | -0.138*** | (0.045) | -0.225*** | (0.045) |
| IV | -0.197*** | (0.042) | -0.407*** | (0.048) | -0.163*** | (0.051) | -0.345*** | (0.052) |
| V | -0.304*** | (0.050) | -0.535*** | (0.059) | -0.293*** | (0.062) | -0.561*** | (0.057) |
| Observations | 11167 | | 11167 | | 11167 | | 8616 | |
| R-squared | 0.042 | | 0.101 | | 0.018 | | 0.134 | |

*Notes:* Summary of empirical estimates. Robust standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

# Appendix 4H - Full regression output from OLS regression models in Tables 4.16-4.18 (MCS)

**Table 4H1- Age 5**

| | Verbal Similarities | | Vocabulary | | Pattern | |
|---|---|---|---|---|---|---|
| White | 0.042 | (0.042) | 0.680*** | (0.051) | 0.278*** | (0.038) |
| Low Birth Weight | -0.130*** | (0.046) | -0.137*** | (0.049) | -0.212*** | (0.041) |
| Boy | -0.113*** | (0.022) | -0.060*** | (0.019) | -0.170*** | (0.020) |
| Preterm Birth | 0.011 | (0.042) | 0.070* | (0.042) | -0.082** | (0.041) |
| Family Size | -0.039*** | (0.011) | -0.110*** | (0.009) | -0.045*** | (0.011) |
| Region | | | | | | |
| North East | (Omitted) | | (Omitted) | | (Omitted) | |
| North West | 0.222*** | (0.083) | 0.117* | (0.068) | 0.174* | (0.099) |
| Yorkshire/Humberside | 0.014 | (0.061) | -0.011 | (0.072) | 0.052 | (0.102) |
| East Midlands | 0.183*** | (0.066) | 0.178** | (0.073) | 0.105 | (0.092) |
| West Midlands | 0.004 | (0.058) | 0.061 | (0.076) | 0.135 | (0.085) |
| East of England | -0.006 | (0.092) | 0.111 | (0.092) | 0.052 | (0.102) |
| London | 0.143* | (0.073) | 0.054 | (0.080) | 0.204** | (0.090) |
| South East | 0.095 | (0.065) | 0.073 | (0.073) | 0.228** | (0.093) |
| South West | 0.066 | (0.072) | 0.151** | (0.072) | 0.117 | (0.110) |
| Wales | 0.179*** | (0.056) | 0.052 | (0.065) | 0.239*** | (0.084) |
| Scotland | 0.056 | (0.059) | 0.154** | (0.069) | 0.055 | (0.093) |
| Northern Ireland | 0.317*** | (0.065) | 0.140* | (0.080) | 0.134 | (0.086) |
| Maternal Age | 0.041** | (0.017) | 0.056*** | (0.013) | 0.029** | (0.015) |
| (Maternal Age)$^2$ | -0.001** | (0.000) | -0.001*** | (0.000) | -0.000* | (0.000) |
| Parents Married | -0.007 | (0.023) | 0.005 | (0.021) | 0.024 | (0.022) |
| Smoking in Pregnancy | -0.027 | (0.029) | 0.027 | (0.023) | -0.067** | (0.031) |
| Breastfed | 0.158*** | (0.025) | 0.098*** | (0.022) | 0.101*** | (0.023) |
| Maternal Employment | 0.083*** | (0.020) | 0.068*** | (0.021) | 0.022 | (0.021) |
| Maternal Education | 0.133*** | (0.023) | 0.238*** | (0.020) | 0.160*** | (0.024) |
| Observations | 13592 | | 13592 | | 13592 | |
| R-Squared | 0.056 | | 0.185 | | 0.076 | |

*Notes:* Summary of empirical estimates. Taylor linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

**Table 4H2 - Age 7**

| | Reading | | Maths | | Pattern | |
|---|---|---|---|---|---|---|
| White | -0.095** | (0.044) | 0.232*** | (0.052) | 0.325*** | (0.048) |
| Low Birth Weight | -0.110** | (0.051) | -0.233*** | (0.048) | -0.220*** | (0.052) |
| Boy | -0.159*** | (0.019) | 0.020 | (0.021) | -0.065*** | (0.019) |
| Preterm Birth | -0.063 | (0.050) | -0.016 | (0.050) | -0.048 | (0.047) |
| Family Size | -0.080*** | (0.011) | -0.043*** | (0.011) | -0.030*** | (0.012) |
| Region | | | | | | |
| North East | (Omitted) | | (Omitted) | | (Omitted) | |
| North West | -0.005 | (0.079) | 0.070 | (0.102) | -0.027 | (0.073) |
| Yorkshire/Humberside | -0.067 | (0.080) | -0.048 | (0.092) | -0.110 | (0.075) |
| East Midlands | -0.061 | (0.087) | 0.036 | (0.099) | -0.043 | (0.062) |
| West Midlands | -0.011 | (0.082) | 0.062 | (0.085) | -0.057 | (0.070) |
| East of England | -0.073 | (0.084) | -0.089 | (0.105) | 0.005 | (0.069) |
| London | 0.111 | (0.087) | 0.119 | (0.097) | -0.033 | (0.069) |
| South East | -0.064 | (0.076) | -0.063 | (0.091) | 0.051 | (0.059) |
| South West | -0.026 | (0.085) | -0.002 | (0.092) | -0.008 | (0.067) |
| Wales | -0.286*** | (0.083) | 0.075 | (0.078) | 0.084 | (0.057) |
| Scotland | -0.131* | (0.076) | -0.119 | (0.083) | 0.000 | (0.060) |
| Northern Ireland | -0.280*** | (0.077) | 0.067 | (0.082) | 0.064 | (0.063) |
| Maternal Age | 0.054*** | (0.016) | 0.028* | (0.015) | 0.033** | (0.015) |
| (Maternal Age)$^2$ | -0.001*** | (0.000) | -0.000* | (0.000) | -0.001** | (0.000) |
| Parents Married | 0.066*** | (0.025) | 0.038 | (0.025) | 0.024 | (0.026) |
| Smoking in Pregnancy | -0.056* | (0.029) | 0.012 | (0.035) | 0.002 | (0.031) |
| Breastfed | 0.108*** | (0.022) | 0.113*** | (0.027) | 0.145*** | (0.022) |
| Maternal Employment | 0.066*** | (0.024) | 0.071*** | (0.027) | 0.055** | (0.027) |
| Maternal Education | 0.220*** | (0.024) | 0.188*** | (0.026) | 0.175*** | (0.027) |
| Observations | 12071 | | 12071 | | 12071 | |
| R-Squared | 0.134 | | 0.094 | | 0.085 | |

*Notes:* Summary of empirical estimates. Taylor linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

| **Table 4H3 - Age 7** | | |
|---|---|---|
| | Verbal Ability | |
| White | -0.062 | (0.051) |
| Low Birth Weight | 0.076 | (0.049) |
| Boy | 0.072*** | (0.020) |
| Preterm Birth | -0.036 | (0.061) |
| Family Size | -0.069*** | (0.011) |
| Region | | |
| North East | (Omitted) | |
| North West | 0.403*** | (0.135) |
| Yorkshire/Humberside | -0.108 | (0.118) |
| East Midlands | 0.091 | (0.129) |
| West Midlands | 0.047 | (0.130) |
| East of England | 0.040 | (0.120) |
| London | 0.206* | (0.117) |
| South East | 0.065 | (0.126) |
| South West | 0.034 | (0.135) |
| Wales | 0.178 | (0.121) |
| Scotland | -0.018 | (0.118) |
| Northern Ireland | 0.285** | (0.116) |
| Maternal Age | 0.017 | (0.015) |
| $(\text{Maternal Age})^2$ | -0.000 | (0.000) |
| Parents Married | 0.021 | (0.025) |
| Smoking in Pregnancy | 0.012 | (0.031) |
| Breastfed | 0.103*** | (0.025) |
| Maternal Employment | 0.035 | (0.023) |
| Maternal Education | 0.266*** | (0.021) |
| Observations | 11971 | |
| R-Squared | 0.116 | |

*Notes:* Summary of empirical estimates. Taylor linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

## Appendix 4I - Applying inverse probability weighting to check for bias from missing data (MCS)

**Table 4I1 - Regression output from logit model used to calculate IPWs (MCS)**

| | |
|---|---|
| Mother Employed | 0.623*** |
| | (0.059) |
| Maternal Education | 0.107 |
| | (0.066) |
| Maternal Age | 0.355*** |
| | (0.035) |
| (Maternal Age)$^2$ | -0.006*** |
| | (0.001) |
| Parents Married | 0.329*** |
| | (0.065) |
| White | 0.664*** |
| | (0.073) |
| Observations | 13457 |
| Pseudo R-Squared | 0.052 |

*Notes:* Coefficients from logit regression model. Taylor linearized errors in parentheses. *** significant at 1%, ** at 5%, * at 10%

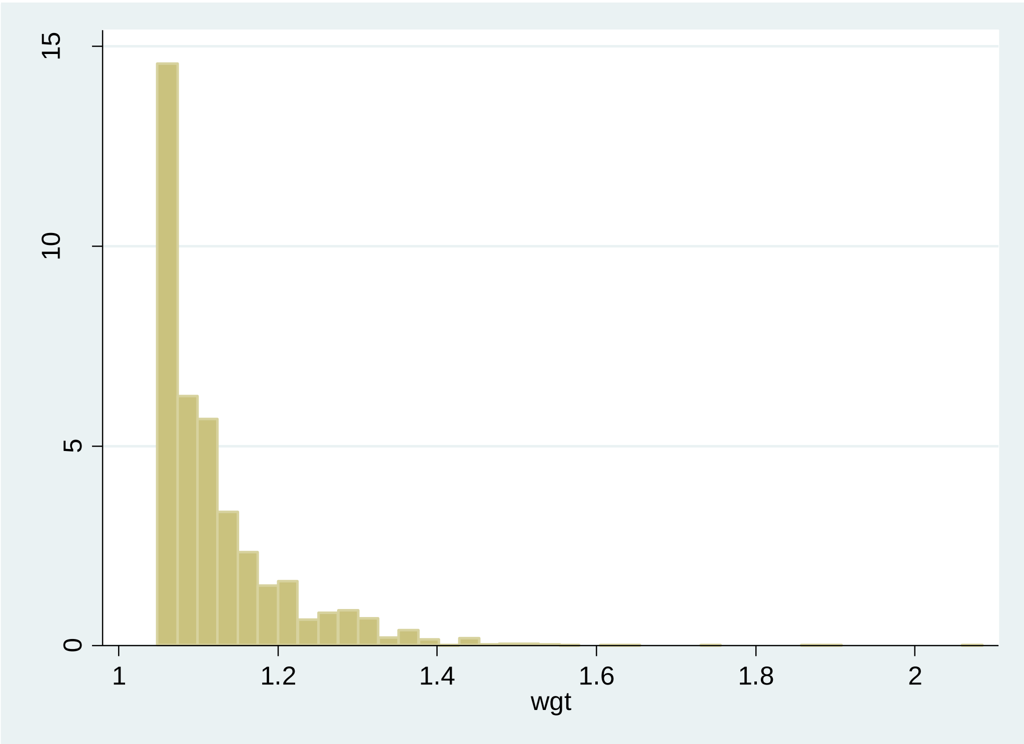



*Figure 4I1 - Distribution of Inverse Probability Weights in the MCS*

**Table 4I2 - Unweighted results of the relationship between SES and child cognitive ability estimated by OLS regression models (MCS Age 7)**

| | (1) Reading | | (2) Maths | | (3) Pattern | |
|---|---|---|---|---|---|---|
| Parental Social Class | | | | | | |
| I | (Omitted) | | (Omitted) | | (Omitted) | |
| II | -0.139*** | (0.026) | -0.193*** | (0.028) | -0.141*** | (0.027) |
| III | -0.257*** | (0.036) | -0.218*** | (0.038) | -0.103*** | (0.037) |
| IV | -0.282*** | (0.033) | -0.234*** | (0.034) | -0.179*** | (0.032) |
| V | -0.348*** | (0.027) | -0.333*** | (0.028) | -0.278*** | (0.027) |
| Observations | 12071 | | 12071 | | 12071 | |
| R-squared | 0.141 | | 0.090 | | 0.082 | |

*Notes:* Summary of empirical estimates. Taylor linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

**Table 4I3 - Weighted results of the relationship between SES and child cognitive ability estimated by OLS regression models (MCS Age 7)**

| | (1) Reading | | (2) Maths | | (3) Pattern | |
|---|---|---|---|---|---|---|
| Parental Social Class | | | | | | |
| I | (Omitted) | | (Omitted) | | (Omitted) | |
| II | -0.141*** | (0.032) | -0.191*** | (0.032) | -0.149*** | (0.033) |
| III | -0.271*** | (0.042) | -0.232*** | (0.041) | -0.109*** | (0.038) |
| IV | -0.323*** | (0.037) | -0.278*** | (0.043) | -0.198*** | (0.040) |
| V | -0.356*** | (0.031) | -0.347*** | (0.031) | -0.293*** | (0.033) |
| Observations | 12071 | | 12071 | | 12071 | |
| R-squared | 0.134 | | 0.094 | | 0.085 | |

*Notes:* Summary of empirical estimates. Taylor linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

# Appendix 5A - The strengths and difficulties questionnaire

For each item, the parent/carer/teacher is asked to either indicate whether the comment is ‘Not True’, ‘Somewhat True’ or ‘Certainly True’, given the child’s behaviour in the last six months or the previous school year.

***Emotional Problems***

1. [Child] often complains of headaches…
2. Has many worries…
3. Is often unhappy, downhearted…
4. Is nervous or clingy in new situations…
5. Has many fears, easily scared…

***Conduct Problems***

1. [Child] often has temper tantrums…
2. Is generally obedient…
3. Fights with other children…
4. Lies or cheats…
5. Steals from home, school or elsewhere …

***Hyperactivity***

1. [Child] is restless or overactive…
2. Is constantly fidgeting or squirming…
3. Is easily distracted…
4. Thinks things out before acting…
5. Sees tasks through to the end…

***Peer Relationship Problems***

1. [Child] is rather solitary, tends to play alone…
2. Has at least one good friend…
3. Is generally liked by other children…
4. Is picked on or bullied…
5. Gets on better with adults than other children…

***Prosocial Behaviour***

1. [Child] is considerate of other people's feelings…
2. Shares readily with other children…
3. Helpful if someone is hurt…
4. Kind to younger children…
5. Often volunteers to help others…

## Appendix 5B - Comparing OLS regression models with and without the implementation of the MCS sampling survey weights

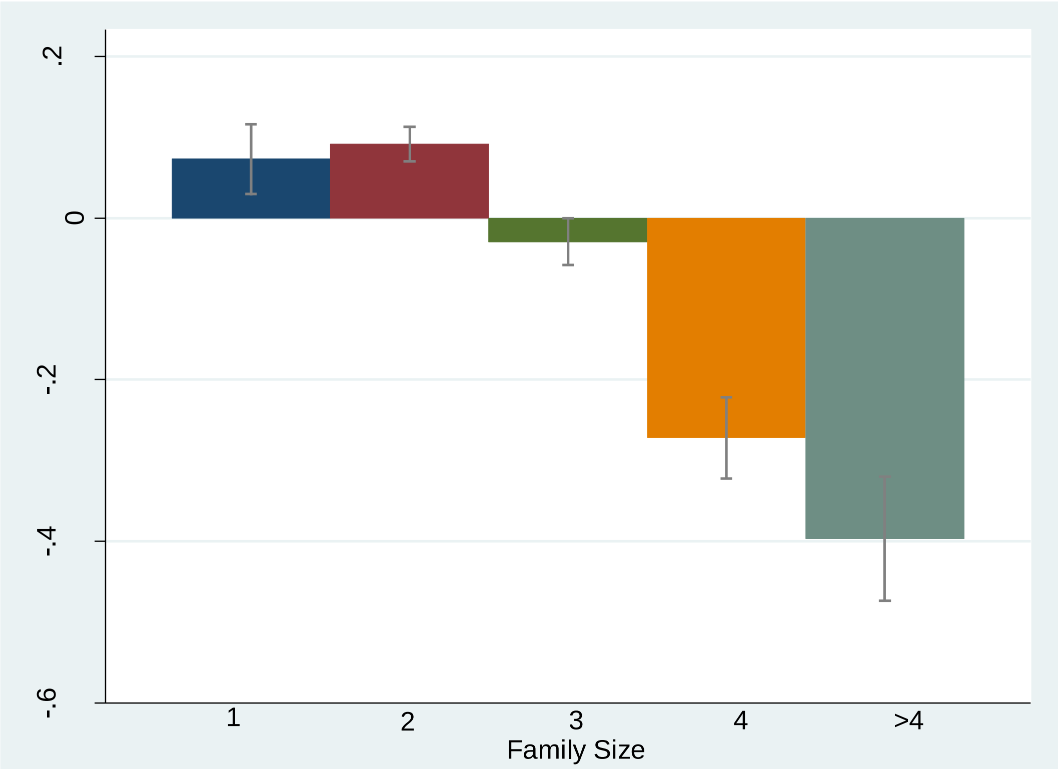
**Table 5B1- OLS regression models with and without the implementation of the MCS sampling survey weights**

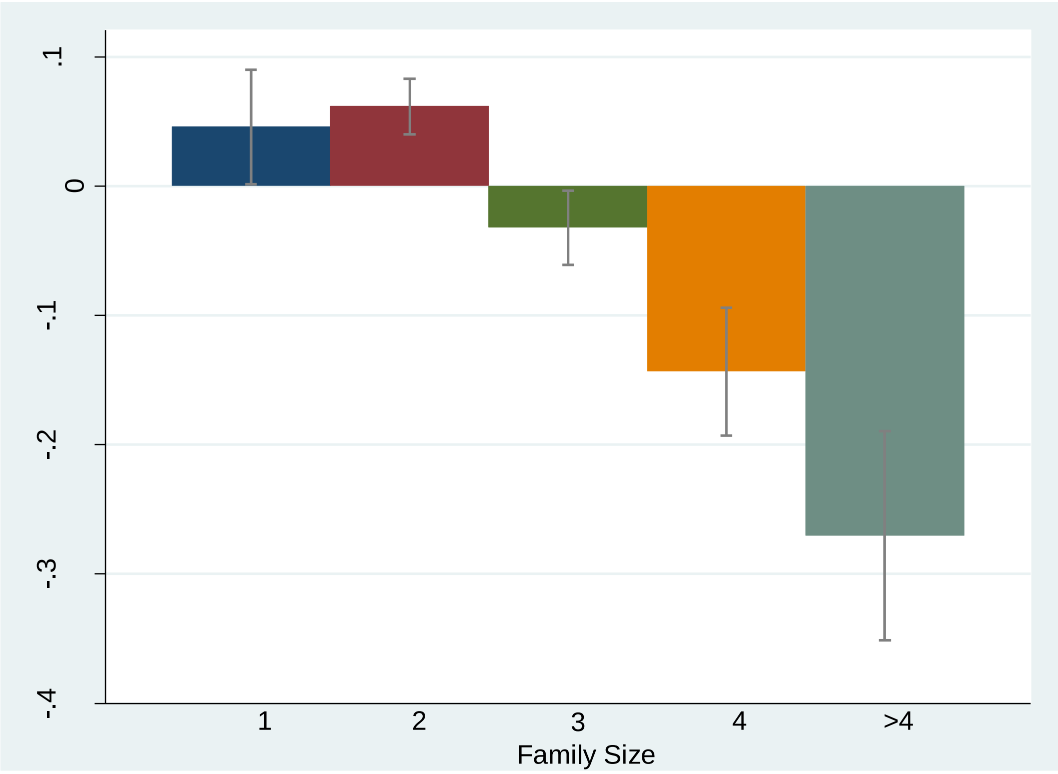
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | Internalising | | Externalising | | Reading | | Maths | | Pattern | |
| | Full Estimation Sample | No Survey weights | Full Estimation Sample | No Survey weights | Full Estimation Sample | No Survey weights | Full Estimation Sample | No Survey weights | Full Estimation Sample | No Survey weights |
| Family Size = 2 | -0.001 | -0.021 | -0.077* | -0.107*** | -0.022 | -0.068** | -0.031 | -0.060* | 0.032 | 0.029 |
| | (0.046) | (0.035) | (0.043) | (0.035) | (0.041) | (0.034) | (0.042) | (0.036) | (0.044) | (0.036) |
| Family Size = 3 | -0.128** | -0.142*** | -0.126** | -0.123*** | -0.059 | -0.099** | -0.062 | -0.094** | 0.007 | 0.008 |
| | (0.053) | (0.042) | (0.054) | (0.041) | (0.052) | (0.040) | (0.050) | (0.043) | (0.048) | (0.043) |
| Family Size = 4 | -0.222*** | -0.281*** | -0.144* | -0.173*** | -0.118** | -0.149*** | -0.072 | -0.099* | -0.060 | 0.007 |
| | (0.070) | (0.055) | (0.078) | (0.054) | (0.060) | (0.052) | (0.063) | (0.056) | (0.063) | (0.056) |
| Family Size = >4 | -0.238** | -0.295*** | -0.180** | -0.170** | -0.084 | -0.133** | -0.107 | -0.115 | -0.136 | -0.040 |
| | (0.093) | (0.069) | (0.088) | (0.069) | (0.083) | (0.067) | (0.086) | (0.071) | (0.092) | (0.071) |
| Observations | 11796 | 11,796 | 11796 | 11,796 | 11796 | 11,796 | 11796 | 11,796 | 11796 | 11,796 |
| R-Squared | 0.141 | 0.139 | 0.165 | 0.161 | 0.203 | 0.211 | 0.118 | 0.110 | 0.111 | 0.103 |

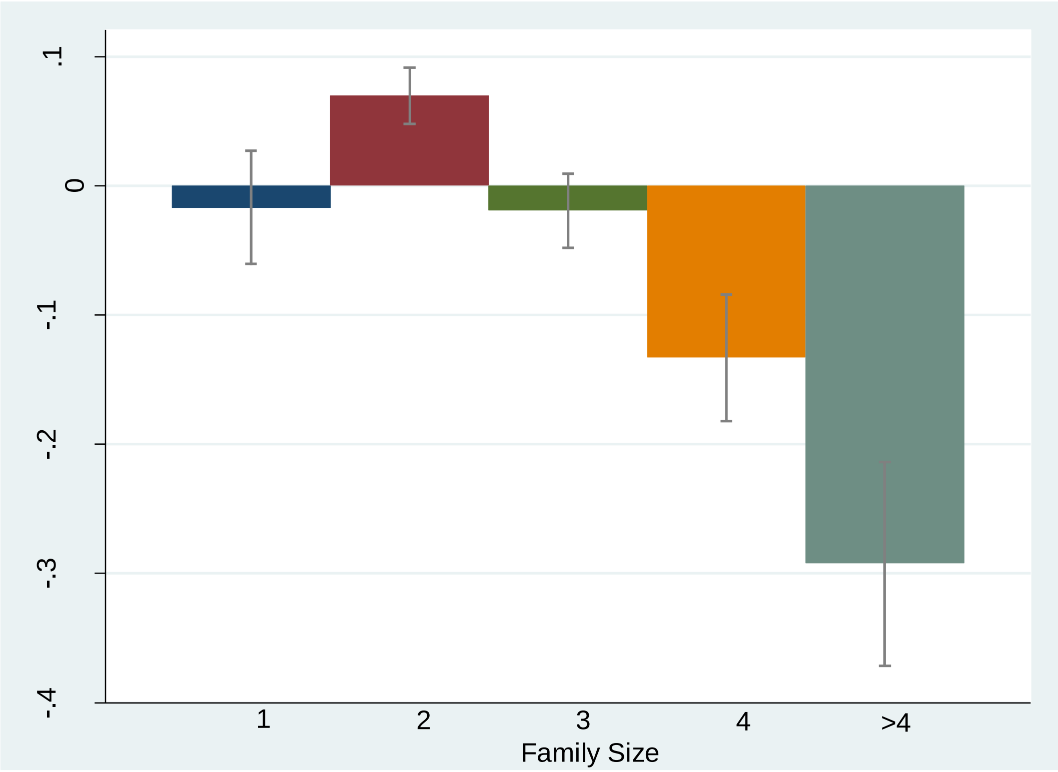
*Notes:* Results from OLS regression models. Omitted category is only children (Family Size = 1).Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%. Each column represents a separate regression, with all models controlling for a range of child, maternal, socioeconomic and household characteristics. Columns 1, 3, 5, 7 & 9 are estimates from the full regression sample. Columns 2, 4 , 6, 8 & 10 are the same regressions, without the implementation of the MCS sampling survey weights

# Appendix 5C - Descriptive relationships

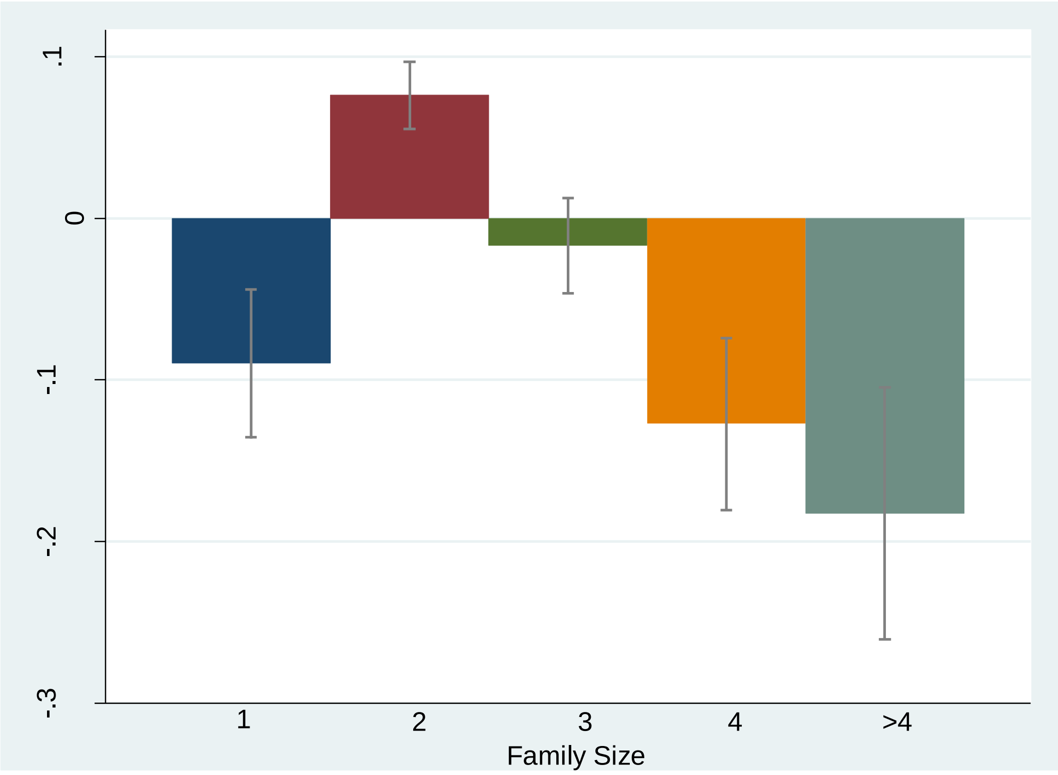
***1) Family Size and Cognitive Ability***

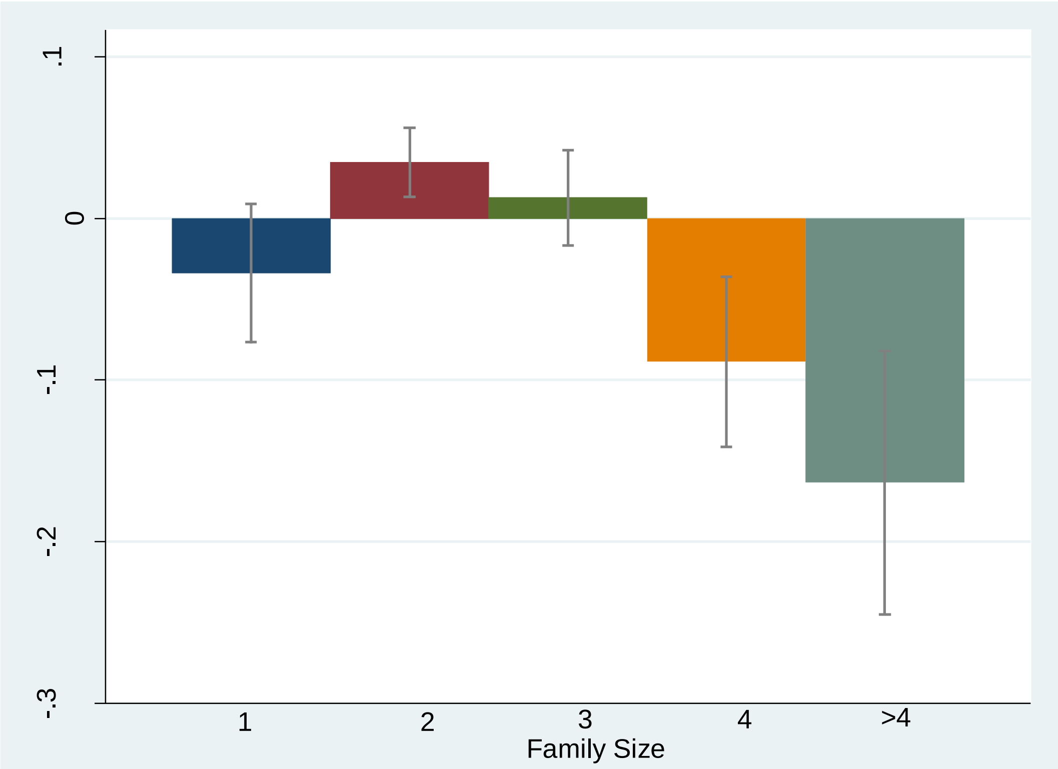


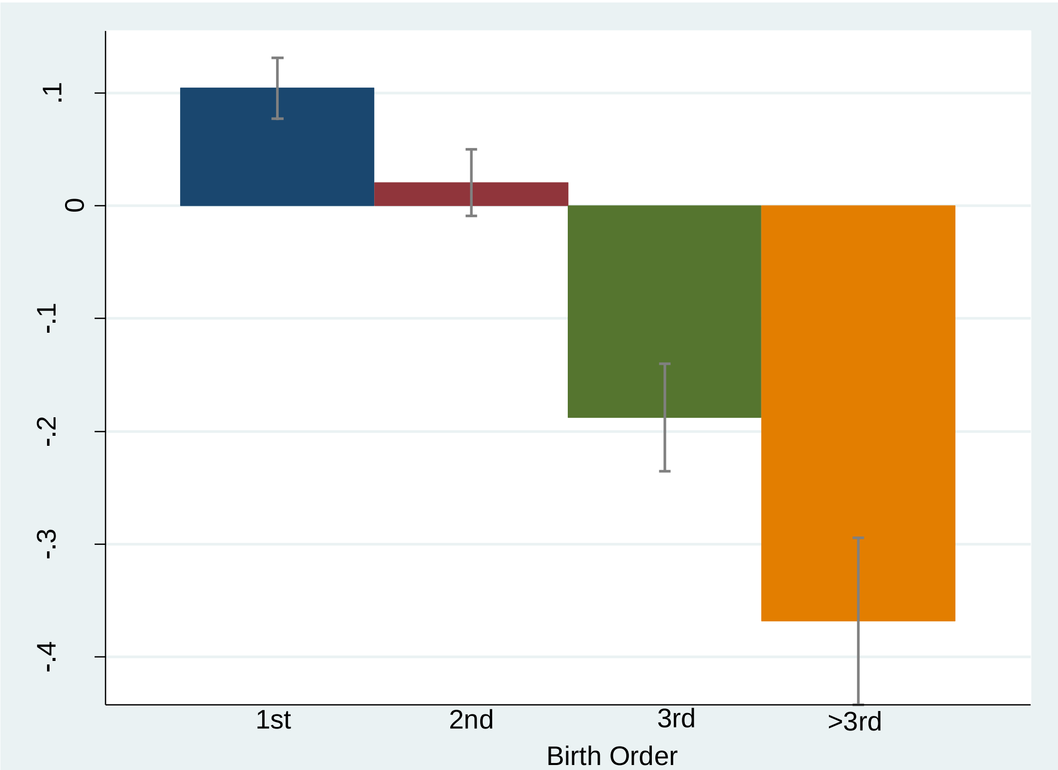


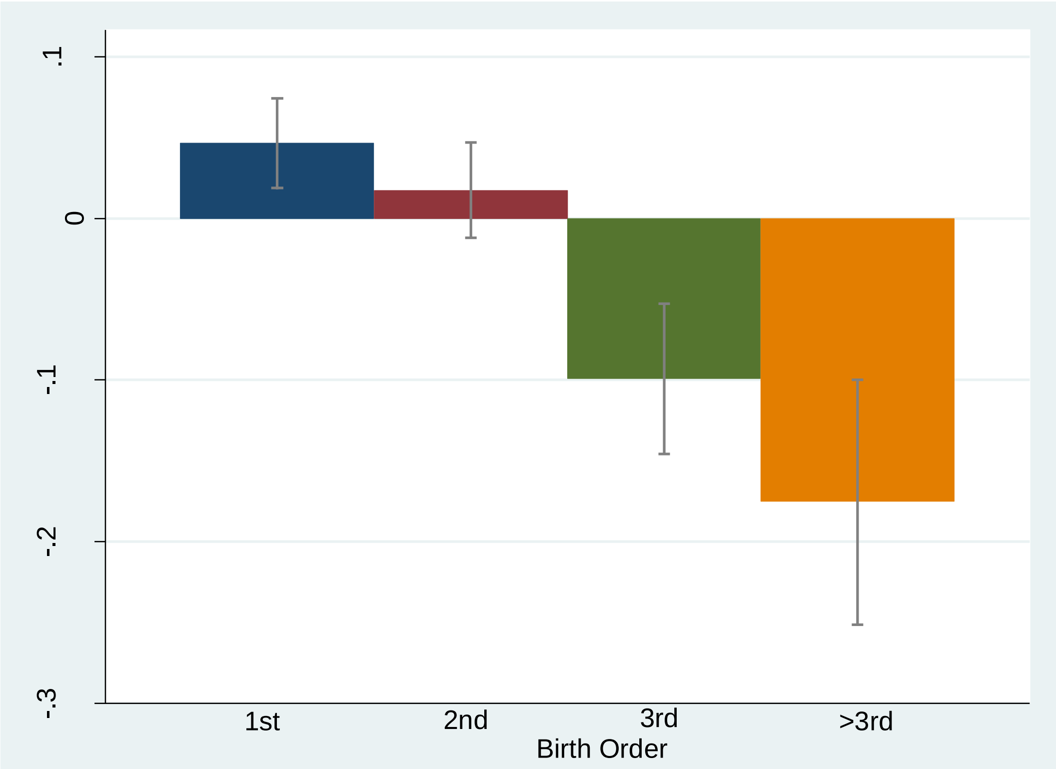

***2) Family Size and Psychological Well-Being***

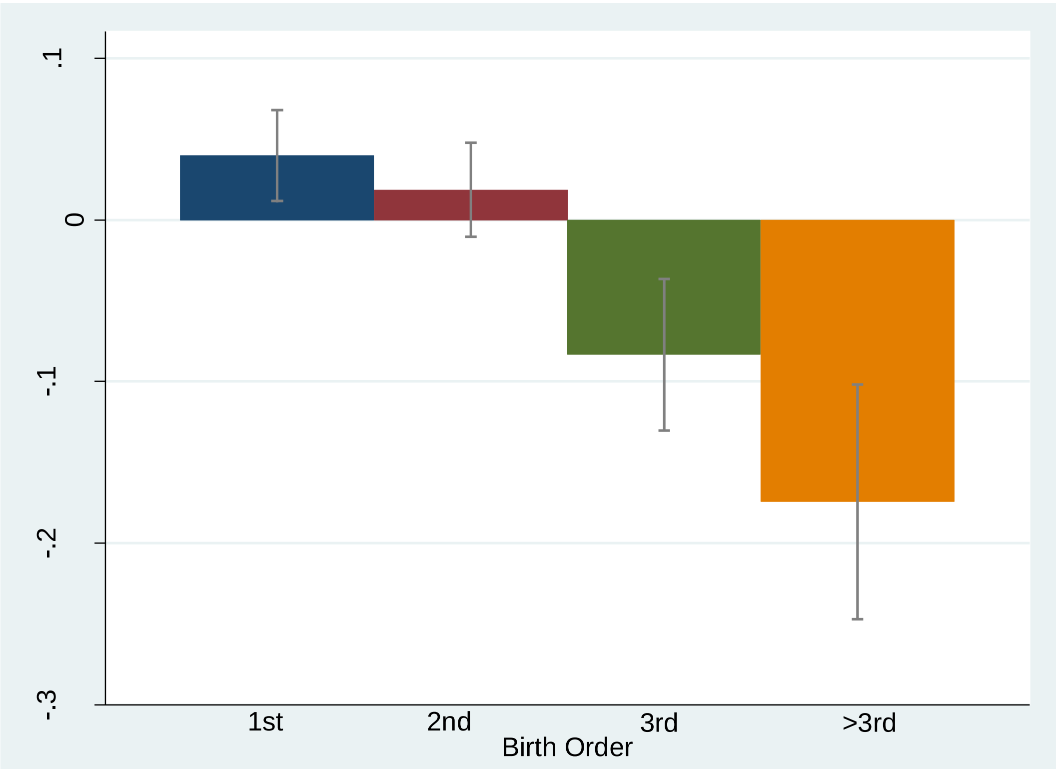




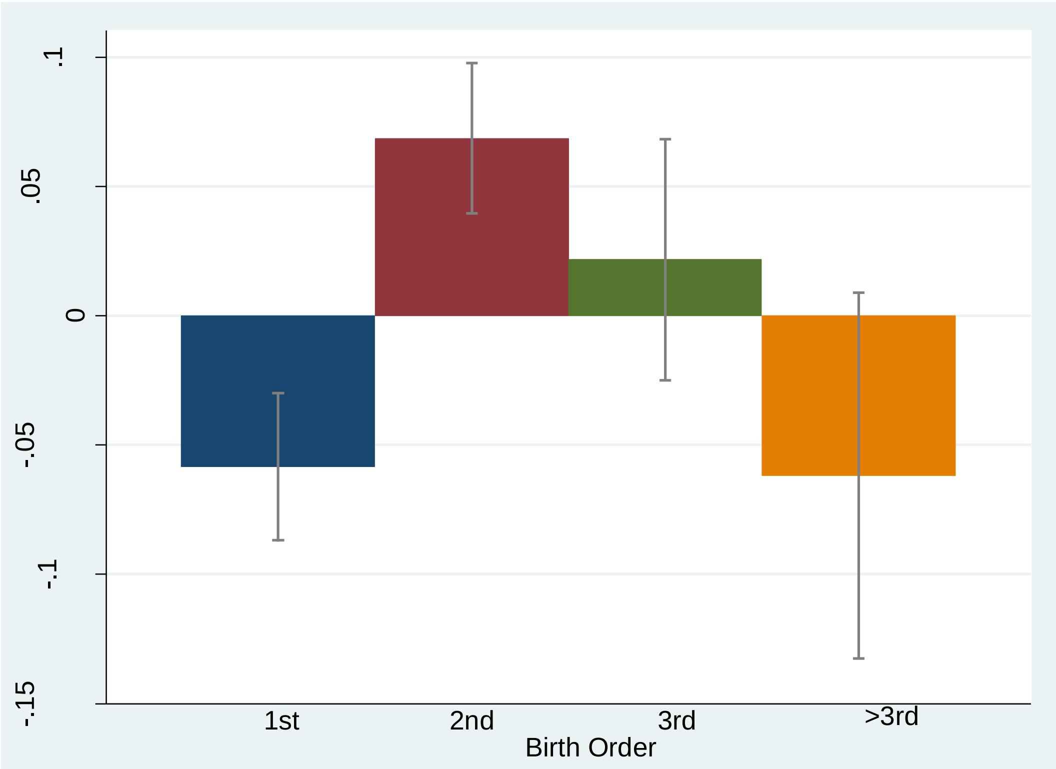

### *3) Birth Order and Cognitive Ability*

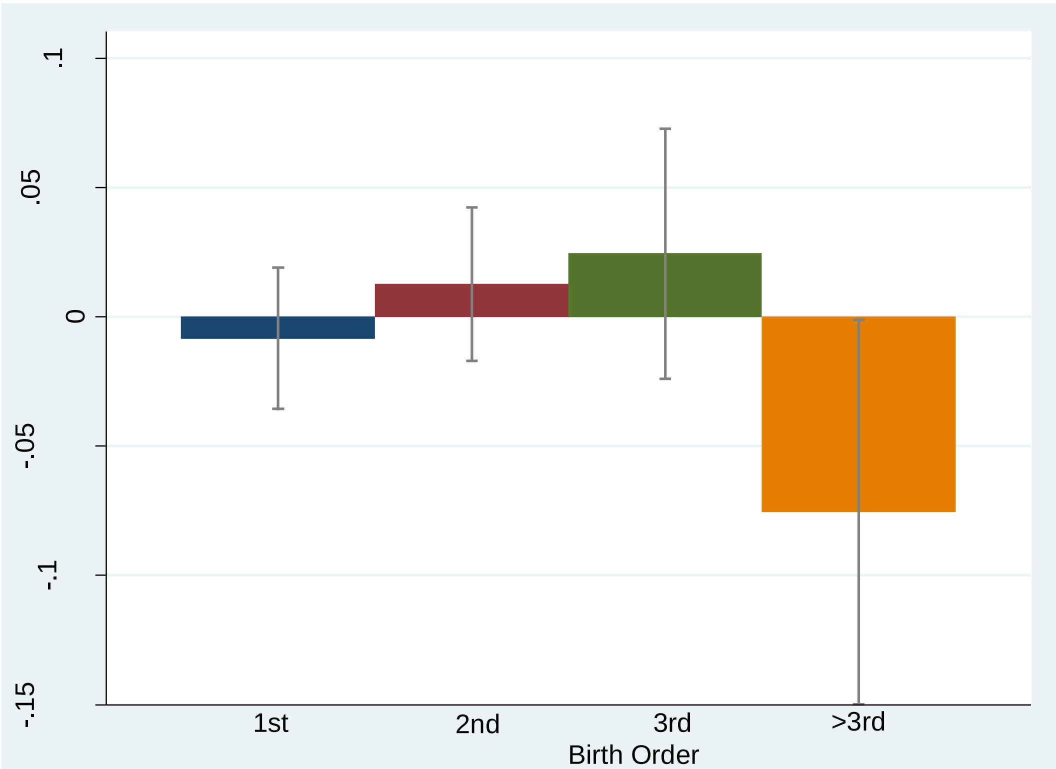



.1
0
-.1
-.2
-.3
1st
2nd
3rd
>3rd
Birth Order


.1
0
-.1
-.2
-.3
1st
2nd
3rd
>3rd
Birth Order

*4) Birth Order and Psychological Well-Being*



# Appendix 5D - Full regression output from Table 5.4

| | Internalising | | Externalising | | Reading | | Maths | | Pattern | |
|---|---|---|---|---|---|---|---|---|---|---|
| Birth Order | | | | | | | | | | |
| First Born | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Second Born | 0.146*** | (0.026) | -0.005 | (0.028) | -0.089*** | (0.029) | -0.010 | (0.027) | -0.002 | (0.030) |
| Third Born | 0.283*** | (0.040) | 0.083* | (0.046) | -0.201*** | (0.045) | -0.012 | (0.040) | -0.010 | (0.043) |
| > Third Born | 0.385*** | (0.077) | 0.081 | (0.076) | -0.244*** | (0.068) | 0.048 | (0.067) | 0.118 | (0.074) |
| Average Birth Spacing | 0.036*** | (0.011) | 0.035*** | (0.012) | 0.005 | (0.010) | -0.003 | (0.011) | 0.002 | (0.012) |
| (Average Birth Spacing)$^2$ | -0.003*** | (0.001) | -0.002* | (0.001) | -0.001 | (0.001) | -0.001 | (0.001) | -0.001 | (0.001) |
| Boy | -0.029 | (0.021) | -0.310*** | (0.020) | -0.143*** | (0.019) | 0.068*** | (0.022) | -0.038* | (0.020) |
| London | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| North East | 0.033 | (0.060) | 0.001 | (0.060) | -0.067 | (0.072) | 0.014 | (0.098) | 0.092 | (0.067) |
| North West | 0.062 | (0.044) | 0.010 | (0.047) | -0.099* | (0.055) | 0.055 | (0.105) | 0.041 | (0.078) |
| Yorkshire/Humber | -0.112** | (0.049) | -0.032 | (0.050) | -0.172** | (0.068) | -0.082 | (0.098) | -0.032 | (0.073) |
| East Midlands | 0.004 | (0.051) | 0.006 | (0.060) | -0.154** | (0.061) | -0.030 | (0.088) | 0.025 | (0.054) |
| West Midlands | -0.047 | (0.056) | -0.095* | (0.052) | -0.127** | (0.060) | -0.008 | (0.083) | 0.012 | (0.063) |
| East England | -0.158*** | (0.051) | -0.061 | (0.048) | -0.232*** | (0.060) | -0.176* | (0.096) | 0.054 | (0.063) |
| South East | -0.104** | (0.048) | 0.013 | (0.048) | -0.197*** | (0.047) | -0.163** | (0.081) | 0.103* | (0.057) |
| South West | -0.113** | (0.054) | 0.001 | (0.054) | -0.160** | (0.065) | -0.146* | (0.087) | 0.016 | (0.067) |
| Wales | 0.002 | (0.047) | 0.040 | (0.048) | -0.387*** | (0.062) | -0.033 | (0.074) | 0.137** | (0.053) |
| Scotland | 0.009 | (0.043) | 0.019 | (0.048) | -0.296*** | (0.052) | -0.259*** | (0.074) | 0.035 | (0.058) |
| Northern Ireland | 0.028 | (0.046) | 0.027 | (0.048) | -0.463*** | (0.057) | 0.048 | (0.079) | 0.127** | (0.060) |
| White | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Indian | -0.074 | (0.096) | 0.032 | (0.057) | 0.362*** | (0.058) | 0.127 | (0.098) | -0.064 | (0.087) |
| Pakistani | -0.182*** | (0.065) | 0.066 | (0.061) | 0.364*** | (0.071) | -0.221*** | (0.083) | -0.392*** | (0.080) |
| Bangladeshi | -0.310*** | (0.099) | 0.211*** | (0.062) | 0.462*** | (0.091) | -0.112 | (0.097) | -0.141* | (0.083) |
| Black Caribbean | -0.163** | (0.077) | -0.092 | (0.091) | -0.057 | (0.065) | -0.247*** | (0.081) | -0.479*** | (0.089) |
| Black African | 0.049 | (0.075) | 0.196** | (0.097) | 0.110 | (0.092) | -0.178* | (0.101) | -0.440*** | (0.081) |
| Other | -0.132* | (0.071) | 0.172** | (0.072) | 0.065 | (0.076) | -0.012 | (0.079) | 0.061 | (0.086) |
| Preterm Birth | -0.045 | (0.054) | 0.021 | (0.049) | -0.052 | (0.051) | -0.023 | (0.049) | -0.053 | (0.048) |
| Low Birth Weight | -0.194*** | (0.054) | -0.297*** | (0.056) | -0.118** | (0.056) | -0.201*** | (0.048) | -0.188*** | (0.051) |
| Poor Maternal Health | | | | | | | | | | |
| Excellent Health | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Very Good Health | -0.086*** | (0.023) | -0.099*** | (0.027) | 0.045* | (0.024) | 0.007 | (0.028) | 0.066** | (0.026) |
| Good Health | -0.207*** | (0.026) | -0.199*** | (0.030) | -0.074*** | (0.026) | -0.080** | (0.032) | 0.001 | (0.029) |
| Fair Health | -0.257*** | (0.040) | -0.225*** | (0.040) | -0.035 | (0.038) | -0.019 | (0.046) | 0.083** | (0.039) |
| Poor Health | -0.461*** | (0.091) | -0.342*** | (0.080) | -0.215** | (0.084) | -0.230*** | (0.074) | -0.115 | (0.087) |
| Breastfeeding | | | | | | | | | | |
| Never Breastfed | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Under 3 Months | 0.026 | (0.025) | 0.051** | (0.026) | 0.067*** | (0.024) | 0.070** | (0.028) | 0.100*** | (0.027) |

## Appendix 5D - Full regression output from Table 5.4 (continued)

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 3-6 Months | 0.091** | (0.037) | 0.065* | (0.033) | 0.062* | (0.033) | 0.095*** | (0.036) | 0.208*** | (0.035) |
| Over 6 Months | 0.088** | (0.037) | 0.125*** | (0.040) | 0.095** | (0.040) | 0.137*** | (0.048) | 0.145*** | (0.044) |
| Pregnant Smoking | 0.024 | (0.033) | -0.152*** | (0.029) | -0.014 | (0.031) | 0.028 | (0.033) | -0.005 | (0.032) |
| Maternal Age | 0.017 | (0.017) | 0.029* | (0.017) | 0.049*** | (0.015) | 0.023 | (0.016) | 0.038** | (0.016) |
| (Maternal Age)$^2$ | -0.000 | (0.000) | -0.000 | (0.000) | -0.001*** | (0.000) | -0.000 | (0.000) | -0.001** | (0.000) |
| Income | | | | | | | | | | |
| Lowest Quintile | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| 2nd Quintile | 0.016 | (0.043) | -0.011 | (0.039) | -0.020 | (0.036) | 0.011 | (0.036) | 0.027 | (0.034) |
| 3rd Quintile | 0.115** | (0.047) | 0.037 | (0.038) | 0.040 | (0.033) | 0.050 | (0.039) | 0.013 | (0.038) |
| 4th Quintile | 0.123*** | (0.046) | 0.086** | (0.043) | 0.040 | (0.037) | 0.081* | (0.043) | 0.093** | (0.041) |
| Top Quintile | 0.215*** | (0.048) | 0.122*** | (0.043) | 0.144*** | (0.041) | 0.186*** | (0.048) | 0.132*** | (0.043) |
| Maternal Education | | | | | | | | | | |
| No Formal Qualifications | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| GCSE | 0.132*** | (0.041) | 0.125*** | (0.039) | 0.088** | (0.038) | 0.073* | (0.037) | 0.102*** | (0.032) |
| A-Level/Diploma | 0.179*** | (0.049) | 0.190*** | (0.047) | 0.178*** | (0.047) | 0.150*** | (0.044) | 0.199*** | (0.040) |
| Degree | 0.167*** | (0.051) | 0.253*** | (0.051) | 0.324*** | (0.048) | 0.304*** | (0.046) | 0.329*** | (0.044) |
| Maternal Depression | -0.589*** | (0.039) | -0.398*** | (0.036) | -0.067** | (0.034) | -0.062* | (0.034) | -0.036 | (0.028) |
| Parental Occupation | | | | | | | | | | |
| Managerial/Profession | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Intermediate | 0.012 | (0.036) | -0.006 | (0.034) | -0.034 | (0.033) | -0.097*** | (0.034) | -0.079** | (0.032) |
| Semi/Self Employed | 0.011 | (0.044) | 0.028 | (0.042) | -0.178*** | (0.042) | -0.119*** | (0.041) | 0.001 | (0.037) |
| Lower Supervisory | -0.059 | (0.054) | -0.074 | (0.051) | -0.181*** | (0.044) | -0.175*** | (0.047) | -0.080* | (0.047) |
| Semi Routine | -0.082* | (0.048) | -0.171*** | (0.038) | -0.243*** | (0.034) | -0.232*** | (0.038) | -0.231*** | (0.038) |
| Maternal Employment | 0.037 | (0.029) | -0.002 | (0.027) | 0.067*** | (0.023) | 0.060** | (0.028) | -0.018 | (0.025) |
| Drawing/Painting | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Once or twice a month | 0.087 | (0.141) | 0.036 | (0.125) | 0.131 | (0.096) | 0.153 | (0.099) | -0.109 | (0.098) |
| Once or twice a week | 0.074 | (0.130) | 0.013 | (0.114) | 0.203** | (0.091) | 0.129 | (0.091) | 0.129 | (0.086) |
| Several Times a Week | 0.073 | (0.136) | -0.073 | (0.115) | 0.264*** | (0.094) | 0.147 | (0.093) | 0.151* | (0.083) |
| Almost Every Day | 0.026 | (0.136) | -0.075 | (0.119) | 0.288*** | (0.094) | 0.133 | (0.094) | 0.233*** | (0.085) |
| Every Day | 0.018 | (0.135) | -0.107 | (0.117) | 0.250*** | (0.092) | 0.092 | (0.096) | 0.259*** | (0.087) |
| Help with Reading | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Once or twice a month | 0.023 | (0.034) | -0.024 | (0.031) | 0.007 | (0.030) | 0.043 | (0.031) | -0.003 | (0.030) |
| Once or twice a week | 0.005 | (0.032) | -0.059* | (0.035) | -0.032 | (0.030) | -0.028 | (0.038) | 0.005 | (0.034) |
| Several Times a Week | 0.093 | (0.066) | -0.093 | (0.093) | 0.202*** | (0.076) | 0.177** | (0.080) | 0.168** | (0.080) |
| Almost Every Day | 0.042 | (0.127) | 0.188 | (0.143) | 0.359** | (0.148) | 0.080 | (0.159) | 0.318** | (0.149) |
| Every Day | 0.061 | (0.209) | 0.112 | (0.128) | 0.398*** | (0.027) | 0.233*** | (0.029) | 0.169*** | (0.028) |
| Trips to the Library | | | | | | | | | | |

# Appendix 5D - Full regression output from Table 5.4 (continued)

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Less than once a week | -0.052 | (0.041) | -0.019 | (0.036) | -0.022 | (0.035) | -0.057 | (0.039) | -0.030 | (0.034) |
| Once or twice a month | 0.042 | (0.029) | 0.036 | (0.030) | 0.108*** | (0.028) | 0.088*** | (0.028) | 0.080*** | (0.026) |
| Once or twice a week | 0.030 | (0.028) | 0.103*** | (0.031) | 0.116*** | (0.030) | 0.053* | (0.030) | 0.047* | (0.027) |
| Several Times a Week | 0.017 | (0.044) | 0.083* | (0.043) | 0.184*** | (0.041) | 0.168*** | (0.046) | 0.026 | (0.045) |
| Almost Every Day | -0.062 | (0.125) | 0.040 | (0.128) | 0.219** | (0.110) | 0.125 | (0.116) | 0.061 | (0.139) |
| Every Day | -0.013 | (0.211) | -0.035 | (0.248) | 0.270 | (0.262) | 0.404 | (0.382) | 0.053 | (0.289) |
| Observations | 11796 | | 11796 | | 11796 | | 11796 | | 11796 | |
| R-squared | 0.141 | | 0.165 | | 0.203 | | 0.118 | | 0.111 | |

*Notes:* Full Regression Output from OLS regression models. Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

## Appendix 5E - Applying inverse probability weighting to check the robustness of the empirical estimates to missing data

**Table 5E1- Regression Output from Logit Model**

| | |
|---|---|
| Top Income Quintile | (omitted) |
| Second Income Quintile | 0.241*** |
| | (0.077) |
| Third Income Quintile | 0.696*** |
| | (0.099) |
| Fourth Income Quintile | 0.651*** |
| | (0.113) |
| Bottom Income Quintile | 1.146*** |
| | (0.142) |
| No Formal Qualifications | (omitted) |
| GSCE Level Qualifications | 0.868*** |
| | (0.072) |
| A-Level/Diploma Qualifications | 1.105*** |
| | (0.113) |
| Degree Level Qualifications | 0.821*** |
| | (0.126) |
| White | (omitted) |
| Indian | -0.302 |
| | (0.791) |
| Pakistani | -0.693 |
| | (0.780) |
| Bangladeshi | -1.217 |
| | (0.787) |
| Black Caribbean | -0.295 |
| | (0.794) |
| Black African | -1.264 |
| | (0.786) |
| Other | -0.819 |
| | (0.788) |
| Maternal Age | 0.187*** |
| | (0.039) |
| $(\text{Maternal Age})^2$ | -0.003*** |
| | (0.001) |
| Maternal Employment | 0.678*** |
| | (0.071) |
| Observations | 13,200 |
| Pseudo R-Squared | 0.162 |

*Notes:* Coefficients from logit regression model. Taylor linearized errors in parentheses. *** significant at 1%, ** at 5%, * at 10%

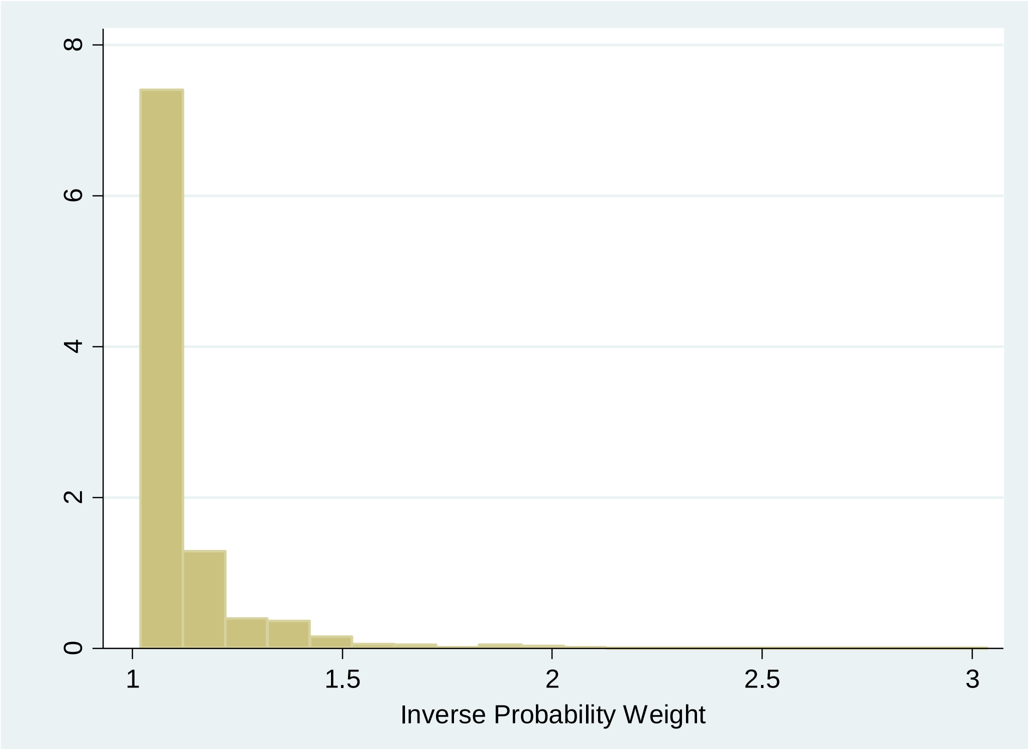



*Figure 5E1- Distribution of IPWs*

**Table 5E2 - Regression output from OLS models with and without the implementation of inverse probability weights**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | Internalising | | Externalising | | Reading | | Maths | | Pattern | |
| | Unweighted | IPW | Unweighted | IPW | Unweighted | IPW | Unweighted | IPW | Unweighted | IPW |
| Family Size = 2 | -0.021 | -0.010 | -0.107*** | -0.098*** | -0.068** | -0.074** | -0.060* | -0.062* | 0.029 | 0.027 |
| | (0.035) | (0.038) | (0.035) | (0.036) | (0.034) | (0.035) | (0.036) | (0.037) | (0.036) | (0.036) |
| Family Size = 3 | -0.142*** | -0.132*** | -0.123*** | -0.113*** | -0.099** | -0.097** | -0.094** | -0.099** | 0.008 | 0.004 |
| | (0.042) | (0.045) | (0.041) | (0.043) | (0.040) | (0.041) | (0.043) | (0.043) | (0.043) | (0.043) |
| Family Size = 4 | -0.281*** | -0.270*** | -0.173*** | -0.165*** | -0.149*** | -0.149*** | -0.099* | -0.102* | 0.007 | 0.009 |
| | (0.055) | (0.063) | (0.054) | (0.058) | (0.052) | (0.055) | (0.056) | (0.056) | (0.056) | (0.057) |
| Family Size = >4 | -0.295*** | -0.283*** | -0.170** | -0.171** | -0.133** | -0.115* | -0.115 | -0.124* | -0.040 | -0.062 |
| | (0.069) | (0.076) | (0.069) | (0.074) | (0.067) | (0.070) | (0.071) | (0.074) | (0.071) | (0.073) |
| | 11796 | 11,796 | 11796 | 11,796 | 11796 | 11,796 | 11796 | 11,796 | 11796 | 11,796 |
| Observations | 11796 | 11796 | 11796 | 11796 | 11796 | 11796 | 11796 | 11796 | 11796 | 11796 |
| R-Squared | 0.139 | 0.147 | 0.161 | 0.162 | 0.211 | 0.213 | 0.110 | 0.117 | 0.103 | 0.110 |

*Notes:* Results from OLS regression models. Omitted category is only children (Family Size = 1).Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%. Each column represents a separate regression, with all models controlling for a range of child, maternal, socioeconomic and household characteristics. Columns 1, 3, 5, 7 & 9 are unweighted estimates from the full regression sample. Columns 2, 4 , 6, 8 & 10 are the same regressions, weighted to by the inverse probability of being a complete case

# Appendix 5F - Full Regression Output from Tables 5.10 and 5.11

| | Internalising | | Externalising | | Reading | | Maths | | Pattern | |
|---|---|---|---|---|---|---|---|---|---|---|
| Second Born | 0.159** | (0.069) | 0.026 | (0.073) | -0.029 | (0.063) | 0.026 | (0.067) | 0.063 | (0.069) |
| Average Birth Spacing | 0.042 | (0.032) | 0.042 | (0.035) | 0.035 | (0.029) | 0.009 | (0.032) | 0.033 | (0.035) |
| (Average Birth Spacing)² | -0.004 | (0.002) | -0.003 | (0.003) | -0.003 | (0.002) | -0.002 | (0.003) | -0.003 | (0.003) |
| Boy | -0.095*** | (0.033) | -0.384*** | (0.037) | -0.133*** | (0.035) | 0.081** | (0.035) | -0.009 | (0.036) |
| London | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| North East | -0.001 | (0.097) | 0.013 | (0.094) | -0.207** | (0.094) | -0.084 | (0.114) | 0.009 | (0.096) |
| North West | 0.058 | (0.068) | 0.037 | (0.066) | -0.167*** | (0.058) | 0.003 | (0.099) | 0.045 | (0.086) |
| Yorkshire/Humber | -0.092 | (0.069) | -0.047 | (0.069) | -0.269*** | (0.083) | -0.123 | (0.105) | -0.081 | (0.090) |
| East Midlands | -0.013 | (0.075) | -0.016 | (0.085) | -0.173** | (0.074) | -0.053 | (0.094) | 0.028 | (0.079) |
| West Midlands | -0.024 | (0.080) | -0.094 | (0.069) | -0.143** | (0.060) | -0.025 | (0.081) | -0.027 | (0.073) |
| East England | -0.175** | (0.069) | -0.021 | (0.069) | -0.295*** | (0.057) | -0.188** | (0.087) | 0.049 | (0.071) |
| South East | -0.097 | (0.059) | 0.033 | (0.067) | -0.267*** | (0.050) | -0.166** | (0.079) | 0.092 | (0.064) |
| South West | -0.095 | (0.070) | 0.008 | (0.071) | -0.174** | (0.070) | -0.203** | (0.078) | 0.006 | (0.074) |
| Wales | 0.027 | (0.059) | 0.035 | (0.065) | -0.443*** | (0.069) | -0.069 | (0.073) | 0.084 | (0.066) |
| Scotland | 0.003 | (0.061) | 0.006 | (0.068) | -0.361*** | (0.060) | -0.299*** | (0.076) | 0.034 | (0.069) |
| Northern Ireland | 0.031 | (0.052) | 0.056 | (0.063) | -0.518*** | (0.060) | 0.011 | (0.079) | 0.178** | (0.074) |
| White | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Indian | -0.102 | (0.123) | -0.075 | (0.084) | 0.285*** | (0.080) | 0.093 | (0.119) | -0.170 | (0.112) |
| Pakistani | -0.191 | (0.132) | 0.212* | (0.121) | 0.435*** | (0.129) | -0.240** | (0.112) | -0.322** | (0.133) |
| Bangladeshi | -0.402** | (0.186) | 0.299** | (0.119) | 0.533*** | (0.176) | -0.048 | (0.126) | -0.001 | (0.138) |
| Black Caribbean | -0.161* | (0.095) | -0.081 | (0.114) | -0.043 | (0.082) | -0.242*** | (0.090) | -0.400*** | (0.104) |
| Black African | 0.199* | (0.103) | 0.369*** | (0.104) | 0.024 | (0.133) | -0.114 | (0.142) | -0.308*** | (0.114) |
| Other | -0.123 | (0.092) | 0.134 | (0.095) | -0.004 | (0.098) | -0.015 | (0.112) | -0.001 | (0.122) |
| Preterm Birth | -0.006 | (0.062) | 0.058 | (0.060) | -0.029 | (0.069) | -0.034 | (0.070) | -0.032 | (0.061) |
| Low Birth Weight | -0.221*** | (0.063) | -0.315*** | (0.067) | -0.135** | (0.065) | -0.225*** | (0.055) | -0.201*** | (0.062) |
| Poor Maternal Health | | | | | | | | | | |
| Excellent Health | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Very Good Health | -0.107*** | (0.030) | -0.126*** | (0.034) | 0.007 | (0.027) | -0.025 | (0.032) | 0.043 | (0.031) |
| Good Health | -0.219*** | (0.037) | -0.198*** | (0.037) | -0.076** | (0.034) | -0.098** | (0.039) | -0.005 | (0.037) |
| Fair Health | -0.252*** | (0.049) | -0.259*** | (0.050) | -0.020 | (0.051) | 0.017 | (0.059) | 0.076 | (0.052) |
| Poor Health | -0.480*** | (0.121) | -0.258*** | (0.098) | -0.193* | (0.101) | -0.198** | (0.089) | -0.178* | (0.105) |
| Breastfeeding | | | | | | | | | | |
| Never Breastfed | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Under 3 Months | 0.024 | (0.032) | 0.034 | (0.035) | 0.089*** | (0.029) | 0.094*** | (0.034) | 0.087*** | (0.033) |
| 3-6 Months | 0.093** | (0.047) | 0.064 | (0.048) | 0.107** | (0.042) | 0.155*** | (0.045) | 0.190*** | (0.045) |

## Appendix 5F - Full Regression Output from Tables 5.10 and 5.11 (continued)

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Over 6 Months | 0.090* | (0.049) | 0.127** | (0.053) | 0.150*** | (0.053) | 0.179*** | (0.056) | 0.168*** | (0.059) |
| Pregnant Smoking | -0.023 | (0.044) | -0.176*** | (0.041) | -0.031 | (0.039) | 0.063 | (0.041) | -0.001 | (0.039) |
| Maternal Age | 0.008 | (0.024) | 0.032 | (0.025) | 0.063*** | (0.022) | 0.041* | (0.022) | 0.030 | (0.023) |
| $(\text{Maternal Age})^2$ | -0.000 | (0.000) | -0.000 | (0.000) | -0.001*** | (0.000) | -0.001** | (0.000) | -0.001* | (0.000) |
| Income | | | | | | | | | | |
| Lowest Quintile | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| 2nd Quintile | 0.011 | (0.055) | -0.023 | (0.052) | -0.000 | (0.042) | -0.032 | (0.047) | 0.020 | (0.049) |
| 3rd Quintile | 0.059 | (0.059) | -0.003 | (0.048) | 0.067 | (0.043) | 0.040 | (0.050) | -0.011 | (0.054) |
| 4th Quintile | 0.065 | (0.061) | 0.006 | (0.058) | 0.039 | (0.051) | 0.053 | (0.060) | 0.058 | (0.061) |
| Top Quintile | 0.163** | (0.075) | 0.059 | (0.072) | 0.114* | (0.064) | 0.130* | (0.074) | 0.075 | (0.073) |
| Maternal Education | | | | | | | | | | |
| No Formal Qualifications | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| GCSE | 0.166*** | (0.054) | 0.087 | (0.053) | 0.044 | (0.045) | 0.040 | (0.046) | 0.077* | (0.042) |
| A-Level/Diploma | 0.194*** | (0.056) | 0.180*** | (0.058) | 0.113** | (0.052) | 0.119** | (0.052) | 0.160*** | (0.049) |
| Degree | 0.171** | (0.069) | 0.236*** | (0.073) | 0.303*** | (0.061) | 0.285*** | (0.069) | 0.370*** | (0.065) |
| Maternal Depression | -0.615*** | (0.051) | -0.387*** | (0.046) | -0.048 | (0.043) | -0.066 | (0.043) | -0.043 | (0.039) |
| Parental Occupation | | | | | | | | | | |
| Managerial/Profession | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Intermediate | -0.043 | (0.054) | -0.062 | (0.046) | -0.060 | (0.046) | -0.140*** | (0.050) | -0.118** | (0.048) |
| Semi/Self Employed | 0.049 | (0.050) | 0.025 | (0.050) | -0.180*** | (0.050) | -0.115*** | (0.042) | -0.008 | (0.043) |
| Lower Supervisory | -0.029 | (0.061) | -0.128** | (0.062) | -0.170*** | (0.058) | -0.170*** | (0.057) | -0.138** | (0.058) |
| Semi Routine | -0.108 | (0.066) | -0.238*** | (0.050) | -0.266*** | (0.045) | -0.264*** | (0.046) | -0.340*** | (0.049) |
| Maternal Employment | 0.020 | (0.041) | -0.025 | (0.036) | 0.038 | (0.035) | 0.049 | (0.040) | -0.086** | (0.036) |
| Drawing/Painting | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Once or twice a month | 0.044 | (0.181) | -0.002 | (0.151) | 0.075 | (0.126) | 0.082 | (0.139) | -0.314** | (0.140) |
| Once or twice a week | 0.033 | (0.164) | -0.039 | (0.143) | 0.159 | (0.116) | 0.101 | (0.127) | -0.263** | (0.131) |
| Several Times a Week | 0.052 | (0.167) | -0.137 | (0.138) | 0.200* | (0.119) | 0.111 | (0.129) | -0.281** | (0.126) |
| Almost Every Day | -0.025 | (0.168) | -0.137 | (0.142) | 0.227* | (0.119) | 0.096 | (0.131) | -0.368*** | (0.128) |
| Every Day | -0.000 | (0.172) | -0.160 | (0.135) | 0.213* | (0.119) | 0.082 | (0.134) | -0.360*** | (0.129) |
| Help with Reading | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Once or twice a month | 0.068* | (0.040) | -0.054 | (0.038) | 0.028 | (0.036) | 0.061 | (0.037) | 0.020 | (0.040) |
| Once or twice a week | 0.048 | (0.042) | -0.062 | (0.041) | 0.012 | (0.036) | -0.016 | (0.047) | 0.025 | (0.045) |
| Several Times a Week | 0.098 | (0.093) | -0.056 | (0.116) | 0.270*** | (0.104) | 0.293*** | (0.095) | 0.229** | (0.100) |
| Almost Every Day | 0.216 | (0.165) | 0.330** | (0.148) | 0.483** | (0.233) | 0.377* | (0.197) | 0.294* | (0.169) |
| Every Day | 0.078** | (0.038) | 0.080** | (0.035) | 0.392*** | (0.033) | 0.231*** | (0.036) | 0.186*** | (0.035) |

## Appendix 5F - Full Regression Output from Tables 5.10 and 5.11 (continued)

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Trips to the Library | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Less than once a week | -0.049 | (0.051) | -0.056 | (0.047) | -0.035 | (0.043) | -0.054 | (0.045) | -0.020 | (0.044) |
| Once or twice a month | 0.043 | (0.040) | 0.046 | (0.037) | 0.079** | (0.033) | 0.071** | (0.034) | 0.034 | (0.033) |
| Once or twice a week | 0.013 | (0.042) | 0.103** | (0.041) | 0.099*** | (0.038) | 0.045 | (0.038) | 0.012 | (0.036) |
| Several Times a Week | 0.039 | (0.055) | 0.078 | (0.054) | 0.189*** | (0.051) | 0.167*** | (0.053) | -0.057 | (0.060) |
| Almost Every Day | -0.060 | (0.180) | -0.000 | (0.182) | 0.107 | (0.136) | 0.085 | (0.133) | -0.013 | (0.171) |
| Every Day | -0.075 | (0.191) | -0.714** | (0.286) | 0.054 | (0.255) | 0.511 | (0.435) | -0.015 | (0.363) |
| First Born is Boy | 0.060** | (0.026) | 0.090*** | (0.031) | -0.012 | (0.030) | -0.010 | (0.029) | -0.056* | (0.030) |
| Second Born is Boy | 0.014 | (0.030) | 0.041 | (0.034) | -0.011 | (0.031) | 0.003 | (0.031) | -0.027 | (0.033) |
| Observations | 7885 | | 7885 | | 7885 | | 7885 | | 7885 | |
| R-squared | 0.139 | | 0.150 | | 0.154 | | 0.109 | | 0.072 | |

*Notes:* Full Regression Output from 2SLS regression models. Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

# Appendix 5G - Full Regression Output from Table 5.12 and 5.13

| | Internalising | | Externalising | | Reading | | Maths | | Pattern | |
|---|---|---|---|---|---|---|---|---|---|---|
| Second Born | 0.033 | (0.056) | -0.102* | (0.057) | -0.088 | (0.056) | 0.021 | (0.054) | 0.033 | (0.061) |
| Average Birth Spacing | 0.070 | (0.063) | 0.155** | (0.062) | -0.017 | (0.065) | 0.077 | (0.067) | 0.039 | (0.061) |
| (Average Birth Spacing)$^2$ | -0.008 | (0.008) | -0.019** | (0.009) | 0.005 | (0.010) | -0.016 | (0.010) | -0.008 | (0.008) |
| Boy | -0.119** | (0.049) | -0.338*** | (0.048) | -0.154*** | (0.043) | 0.020 | (0.043) | -0.114** | (0.045) |
| London | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| North East | 0.174 | (0.169) | 0.039 | (0.157) | -0.192 | (0.149) | -0.114 | (0.137) | 0.102 | (0.158) |
| North West | 0.206* | (0.107) | 0.162 | (0.105) | -0.145 | (0.097) | 0.057 | (0.118) | 0.128 | (0.116) |
| Yorkshire/Humber | -0.082 | (0.131) | -0.209* | (0.119) | -0.219* | (0.112) | -0.118 | (0.111) | 0.151 | (0.134) |
| East Midlands | -0.079 | (0.134) | -0.007 | (0.129) | -0.070 | (0.130) | 0.132 | (0.134) | 0.185 | (0.125) |
| West Midlands | -0.023 | (0.136) | -0.114 | (0.101) | -0.087 | (0.108) | 0.085 | (0.090) | 0.186* | (0.106) |
| East England | -0.195* | (0.109) | 0.051 | (0.100) | -0.314*** | (0.095) | -0.160 | (0.099) | 0.221** | (0.107) |
| South East | -0.187 | (0.125) | 0.046 | (0.110) | -0.033 | (0.094) | -0.064 | (0.090) | 0.394*** | (0.101) |
| South West | -0.169 | (0.126) | 0.065 | (0.095) | -0.039 | (0.110) | -0.054 | (0.097) | 0.252** | (0.122) |
| Wales | 0.027 | (0.112) | 0.094 | (0.099) | -0.367*** | (0.115) | -0.004 | (0.094) | 0.273*** | (0.105) |
| Scotland | 0.175* | (0.102) | 0.087 | (0.085) | -0.207** | (0.098) | -0.274*** | (0.098) | 0.230** | (0.105) |
| Northern Ireland | 0.086 | (0.102) | 0.147 | (0.093) | -0.450*** | (0.099) | 0.067 | (0.098) | 0.346*** | (0.117) |
| White | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Indian | 0.176 | (0.140) | 0.185 | (0.127) | 0.534*** | (0.126) | 0.232 | (0.155) | -0.057 | (0.156) |
| Pakistani | -0.294** | (0.128) | 0.160 | (0.124) | 0.407*** | (0.086) | -0.349*** | (0.099) | -0.381*** | (0.128) |
| Bangladeshi | -0.527** | (0.233) | 0.393*** | (0.129) | 0.590*** | (0.209) | 0.020 | (0.177) | 0.049 | (0.154) |
| Black Caribbean | -0.120 | (0.188) | -0.111 | (0.249) | 0.101 | (0.150) | -0.392*** | (0.127) | -0.161 | (0.143) |
| Black African | 0.067 | (0.171) | 0.411*** | (0.144) | 0.315* | (0.185) | -0.166 | (0.191) | -0.454*** | (0.139) |
| Other | -0.172 | (0.172) | 0.054 | (0.210) | 0.098 | (0.155) | -0.007 | (0.164) | 0.330* | (0.190) |
| Preterm Birth | -0.143 | (0.114) | -0.075 | (0.120) | -0.158 | (0.107) | -0.068 | (0.111) | -0.137 | (0.112) |
| Low Birth Weight | -0.073 | (0.122) | -0.109 | (0.108) | -0.105 | (0.101) | -0.180* | (0.096) | -0.130 | (0.102) |
| Poor Maternal Health | | | | | | | | | | |
| Excellent Health | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Very Good Health | -0.130** | (0.062) | -0.177*** | (0.066) | -0.009 | (0.058) | -0.022 | (0.051) | 0.055 | (0.055) |
| Good Health | -0.226*** | (0.070) | -0.189*** | (0.069) | -0.123* | (0.064) | -0.015 | (0.058) | -0.016 | (0.056) |
| Fair Health | -0.157 | (0.098) | -0.284*** | (0.100) | -0.058 | (0.091) | 0.075 | (0.092) | 0.066 | (0.085) |
| Poor Health | -0.394* | (0.234) | -0.177 | (0.198) | -0.301 | (0.198) | -0.158 | (0.165) | -0.075 | (0.192) |
| Breastfeeding | | | | | | | | | | |
| Never Breastfed | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Under 3 Months | 0.084 | (0.073) | 0.040 | (0.059) | 0.158*** | (0.060) | 0.174*** | (0.054) | 0.043 | (0.054) |
| 3-6 Months | 0.180* | (0.101) | 0.099 | (0.088) | 0.167** | (0.083) | 0.293*** | (0.079) | 0.226*** | (0.079) |

## Appendix 5G - Full Regression Output from Table 5.12 and 5.13 (continued)

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Over 6 Months | 0.229** | (0.102) | 0.127 | (0.111) | 0.169* | (0.102) | 0.238** | (0.106) | 0.197** | (0.095) |
| Pregnant Smoking | -0.009 | (0.079) | -0.095 | (0.077) | -0.044 | (0.062) | 0.132* | (0.074) | 0.134* | (0.076) |
| Maternal Age | 0.013 | (0.049) | 0.069 | (0.050) | 0.047 | (0.039) | 0.023 | (0.040) | -0.012 | (0.042) |
| (Maternal Age)$^2$ | -0.000 | (0.001) | -0.001 | (0.001) | -0.001 | (0.001) | -0.000 | (0.001) | 0.000 | (0.001) |
| Income | | | | | | | | | | |
| Lowest Quintile | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| 2nd Quintile | 0.025 | (0.087) | -0.084 | (0.090) | -0.027 | (0.066) | -0.077 | (0.074) | -0.069 | (0.081) |
| 3rd Quintile | 0.023 | (0.107) | -0.017 | (0.089) | 0.090 | (0.074) | 0.006 | (0.082) | -0.070 | (0.097) |
| 4th Quintile | 0.142 | (0.103) | 0.056 | (0.114) | 0.045 | (0.080) | 0.014 | (0.095) | -0.052 | (0.100) |
| Top Quintile | 0.322*** | (0.108) | 0.124 | (0.106) | 0.225** | (0.089) | 0.242** | (0.095) | 0.107 | (0.115) |
| Maternal Education | | | | | | | | | | |
| No Formal Qualifications | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| GCSE | 0.188** | (0.088) | 0.147* | (0.086) | -0.008 | (0.072) | 0.025 | (0.081) | 0.104 | (0.068) |
| A-Level/Diploma | 0.149 | (0.104) | 0.193* | (0.109) | 0.117 | (0.094) | 0.087 | (0.100) | 0.205** | (0.099) |
| Degree | 0.153 | (0.106) | 0.287*** | (0.103) | 0.290*** | (0.093) | 0.222** | (0.102) | 0.342*** | (0.093) |
| Maternal Depression | -0.627*** | (0.085) | -0.328*** | (0.081) | 0.009 | (0.067) | -0.064 | (0.073) | -0.024 | (0.069) |
| Parental Occupation | | | | | | | | | | |
| Managerial/Profession | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Intermediate | 0.112 | (0.087) | 0.025 | (0.083) | -0.141** | (0.067) | -0.172** | (0.086) | -0.170** | (0.084) |
| Semi/Self Employed | 0.014 | (0.097) | -0.029 | (0.089) | -0.113 | (0.079) | -0.049 | (0.083) | -0.003 | (0.082) |
| Lower Supervisory | 0.086 | (0.106) | -0.138 | (0.121) | -0.201** | (0.094) | -0.172* | (0.101) | -0.154 | (0.110) |
| Semi Routine | -0.065 | (0.114) | -0.250*** | (0.087) | -0.249*** | (0.069) | -0.287*** | (0.070) | -0.421*** | (0.072) |
| Maternal Employment | 0.034 | (0.067) | -0.075 | (0.064) | 0.047 | (0.056) | 0.095 | (0.063) | -0.016 | (0.058) |
| Drawing/Painting | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Once or twice a month | 0.183 | (0.375) | 0.213 | (0.349) | 0.378 | (0.242) | 0.136 | (0.218) | -0.077 | (0.236) |
| Once or twice a week | 0.261 | (0.337) | 0.217 | (0.319) | 0.418* | (0.229) | 0.161 | (0.199) | 0.020 | (0.246) |
| Several Times a Week | 0.193 | (0.357) | 0.000 | (0.312) | 0.472* | (0.242) | 0.158 | (0.211) | -0.109 | (0.241) |
| Almost Every Day | 0.057 | (0.345) | 0.047 | (0.316) | 0.431* | (0.237) | 0.147 | (0.214) | -0.166 | (0.237) |
| Every Day | 0.107 | (0.356) | -0.034 | (0.325) | 0.440* | (0.239) | 0.065 | (0.214) | -0.191 | (0.242) |
| Help with Reading | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Once or twice a month | 0.132 | (0.081) | 0.061 | (0.077) | 0.041 | (0.062) | 0.139* | (0.072) | 0.084 | (0.066) |
| Once or twice a week | 0.167* | (0.086) | 0.074 | (0.080) | 0.098 | (0.068) | 0.058 | (0.072) | 0.115 | (0.078) |
| Several Times a Week | 0.381** | (0.169) | 0.282* | (0.171) | 0.600*** | (0.177) | 0.435*** | (0.167) | 0.269 | (0.218) |

## Appendix 5G - Full Regression Output from Table 5.12 and 5.13 (continued)

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Almost Every Day | 0.156 | (0.300) | 0.605** | (0.279) | 1.063*** | (0.270) | 0.553 | (0.430) | 0.309 | (0.314) |
| Every Day | 0.131* | (0.070) | 0.190*** | (0.068) | 0.412*** | (0.061) | 0.270*** | (0.068) | 0.225*** | (0.060) |
| Trips to the Library | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Less than once a week | -0.235** | (0.098) | -0.264*** | (0.093) | -0.131 | (0.081) | -0.107 | (0.074) | -0.091 | (0.069) |
| Once or twice a month | -0.011 | (0.073) | -0.042 | (0.071) | 0.159*** | (0.056) | 0.191*** | (0.062) | 0.099 | (0.061) |
| Once or twice a week | -0.033 | (0.067) | 0.049 | (0.068) | 0.143** | (0.065) | 0.191*** | (0.065) | 0.052 | (0.073) |
| Several Times a Week | -0.097 | (0.096) | 0.041 | (0.095) | 0.390*** | (0.077) | 0.336*** | (0.091) | -0.025 | (0.104) |
| Almost Every Day | -0.177 | (0.297) | -0.197 | (0.266) | 0.327 | (0.212) | 0.190 | (0.225) | 0.492* | (0.255) |
| Every Day | -0.165 | (0.295) | -0.853 | (0.567) | -0.363 | (0.444) | 0.303 | (0.960) | 0.029 | (0.785) |
| Observations | 2379 | | 2379 | | 2379 | | 2379 | | 2379 | |
| R-squared | 0.155 | | 0.195 | | 0.258 | | 0.186 | | 0.166 | |

*Notes:* Full Regression Output from 2SLS regression models. Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

# Appendix 5H - Full Regression Output from Table 5.14 and 5.15

## Table 5H1 - Full regression output from birth order OLS Models (two child family)

| | Internalising | | Externalising | | Reading | | Maths | | Pattern | |
|---|---|---|---|---|---|---|---|---|---|---|
| Average Birth Spacing | 0.024* | (0.013) | 0.007 | (0.013) | -0.011 | (0.012) | -0.015 | (0.013) | -0.007 | (0.013) |
| (Average Birth Spacing)$^2$ | -0.002** | (0.001) | -0.001 | (0.001) | -0.000 | (0.001) | 0.000 | (0.001) | 0.000 | (0.001) |
| Boy | -0.029 | (0.029) | -0.312*** | (0.027) | -0.138*** | (0.027) | 0.105*** | (0.033) | -0.022 | (0.028) |
| London | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| North East | -0.038 | (0.080) | 0.059 | (0.092) | -0.124 | (0.083) | -0.049 | (0.109) | 0.035 | (0.089) |
| North West | 0.022 | (0.064) | 0.026 | (0.063) | -0.114* | (0.061) | 0.013 | (0.103) | 0.052 | (0.086) |
| Yorkshire/Humber | -0.071 | (0.050) | 0.072 | (0.061) | -0.211*** | (0.080) | -0.083 | (0.114) | -0.122 | (0.088) |
| East Midlands | 0.042 | (0.066) | 0.041 | (0.080) | -0.124* | (0.066) | -0.065 | (0.088) | 0.030 | (0.070) |
| West Midlands | -0.004 | (0.067) | -0.061 | (0.068) | -0.114* | (0.066) | -0.049 | (0.090) | -0.091 | (0.081) |
| East England | -0.144** | (0.072) | -0.005 | (0.076) | -0.236*** | (0.065) | -0.170* | (0.100) | -0.004 | (0.077) |
| South East | -0.037 | (0.048) | 0.070 | (0.071) | -0.291*** | (0.056) | -0.176** | (0.088) | -0.002 | (0.072) |
| South West | -0.047 | (0.057) | 0.025 | (0.071) | -0.175** | (0.072) | -0.237*** | (0.087) | -0.068 | (0.078) |
| Wales | 0.042 | (0.044) | 0.049 | (0.062) | -0.410*** | (0.069) | -0.066 | (0.079) | 0.039 | (0.067) |
| Scotland | -0.033 | (0.050) | 0.016 | (0.068) | -0.356*** | (0.059) | -0.276*** | (0.083) | -0.007 | (0.071) |
| Northern Ireland | 0.028 | (0.059) | 0.031 | (0.075) | -0.525*** | (0.075) | -0.001 | (0.096) | 0.099 | (0.089) |
| White | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Indian | -0.172 | (0.140) | -0.129 | (0.089) | 0.278*** | (0.081) | 0.078 | (0.144) | -0.157 | (0.125) |
| Pakistani | -0.144 | (0.100) | 0.105 | (0.107) | 0.196 | (0.175) | -0.284* | (0.146) | -0.503*** | (0.140) |
| Bangladeshi | -0.263 | (0.228) | -0.052 | (0.201) | 0.262 | (0.177) | -0.448*** | (0.092) | -0.319 | (0.248) |
| Black Caribbean | -0.199* | (0.117) | -0.088 | (0.128) | -0.102 | (0.076) | -0.144 | (0.104) | -0.531*** | (0.121) |
| Black African | 0.261** | (0.113) | 0.268** | (0.129) | -0.264** | (0.129) | -0.111 | (0.154) | -0.226 | (0.161) |
| Other | -0.082 | (0.092) | 0.182* | (0.100) | -0.019 | (0.096) | -0.011 | (0.121) | -0.165 | (0.115) |
| Preterm Birth | 0.032 | (0.065) | 0.097 | (0.063) | -0.012 | (0.069) | -0.051 | (0.079) | -0.027 | (0.072) |
| Low Birth Weight | -0.275*** | (0.076) | -0.423*** | (0.075) | -0.164** | (0.076) | -0.240*** | (0.070) | -0.248*** | (0.069) |
| Poor Maternal Health | | | | | | | | | | |
| Excellent Health | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Very Good Health | -0.092*** | (0.031) | -0.103*** | (0.034) | 0.029 | (0.031) | -0.010 | (0.036) | 0.058* | (0.034) |
| Good Health | -0.205*** | (0.036) | -0.191*** | (0.038) | -0.027 | (0.034) | -0.103** | (0.042) | 0.032 | (0.039) |
| Fair Health | -0.286*** | (0.061) | -0.230*** | (0.058) | 0.014 | (0.058) | 0.007 | (0.066) | 0.095 | (0.059) |
| Poor Health | -0.499*** | (0.141) | -0.247** | (0.110) | -0.168 | (0.110) | -0.188* | (0.107) | -0.222* | (0.120) |
| Breastfeeding | | | | | | | | | | |
| Never Breastfed | | | | | | | | | | |
| Under 3 Months | -0.009 | (0.037) | 0.027 | (0.039) | 0.048 | (0.033) | 0.043 | (0.038) | 0.088** | (0.037) |
| 3-6 Months | 0.050 | (0.045) | 0.037 | (0.045) | 0.043 | (0.044) | 0.072 | (0.048) | 0.145*** | (0.051) |
| Over 6 Months | 0.015 | (0.055) | 0.105* | (0.057) | 0.104* | (0.061) | 0.126** | (0.064) | 0.126* | (0.066) |
| Pregnant Smoking | -0.021 | (0.054) | -0.201*** | (0.048) | -0.025 | (0.047) | 0.034 | (0.046) | -0.061 | (0.047) |
| Maternal Age | 0.029 | (0.023) | 0.027 | (0.025) | 0.082*** | (0.023) | 0.062*** | (0.023) | 0.062*** | (0.023) |
| (Maternal Age)$^2$ | -0.000 | (0.000) | -0.000 | (0.000) | -0.001*** | (0.000) | -0.001** | (0.000) | -0.001*** | (0.000) |
| Income | | | | | | | | | | |
| Lowest Quintile | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| 2nd Quintile | -0.009 | (0.068) | 0.005 | (0.057) | 0.024 | (0.054) | -0.011 | (0.063) | 0.065 | (0.057) |
| 3rd Quintile | 0.075 | (0.074) | 0.003 | (0.058) | 0.094* | (0.054) | 0.063 | (0.063) | 0.041 | (0.060) |
| 4th Quintile | 0.042 | (0.072) | 0.007 | (0.058) | 0.095* | (0.055) | 0.091 | (0.066) | 0.154** | (0.063) |
| Top Quintile | 0.128* | (0.073) | 0.083 | (0.062) | 0.187*** | (0.058) | 0.149** | (0.070) | 0.168*** | (0.063) |
| Maternal Education | | | | | | | | | | |

## Table 5H1- Full regression output from birth order OLS models (two child family) (continued)

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| No Formal Qualifications | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| GCSE | 0.141** | (0.059) | 0.045 | (0.056) | 0.120** | (0.055) | 0.069 | (0.057) | 0.096* | (0.053) |
| A-Level/Diploma | 0.189*** | (0.066) | 0.152** | (0.063) | 0.156*** | (0.058) | 0.143** | (0.063) | 0.157*** | (0.059) |
| Degree | 0.122* | (0.070) | 0.145** | (0.073) | 0.297*** | (0.063) | 0.282*** | (0.072) | 0.330*** | (0.067) |
| Maternal Depression | -0.619*** | (0.063) | -0.426*** | (0.051) | -0.063 | (0.053) | -0.066 | (0.049) | -0.057 | (0.044) |
| Parental Occupation | | | | | | | | | | |
| Managerial/Profession | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Intermediate | -0.078 | (0.048) | -0.062 | (0.044) | -0.000 | (0.044) | -0.110** | (0.046) | -0.064 | (0.046) |
| Semi/Self Employed | 0.065 | (0.060) | 0.045 | (0.060) | -0.199*** | (0.058) | -0.156*** | (0.052) | -0.026 | (0.055) |
| Lower Supervisory | -0.088 | (0.070) | -0.093 | (0.069) | -0.126* | (0.065) | -0.156** | (0.068) | -0.124* | (0.064) |
| Semi Routine | -0.140** | (0.066) | -0.216*** | (0.057) | -0.237*** | (0.053) | -0.247*** | (0.058) | -0.283*** | (0.055) |
| Maternal Employment | 0.031 | (0.042) | 0.022 | (0.038) | 0.072* | (0.038) | 0.025 | (0.041) | -0.094** | (0.037) |
| Drawing/Painting | | | | | | | | | | |
| Never | | | | | | | | | | |
| Once or twice a month | -0.031 | (0.166) | -0.109 | (0.137) | -0.073 | (0.144) | 0.056 | (0.160) | -0.445*** | (0.171) |
| Once or twice a week | -0.067 | (0.149) | -0.174 | (0.126) | 0.014 | (0.129) | 0.055 | (0.141) | -0.418*** | (0.157) |
| Several Times a Week | -0.032 | (0.148) | -0.239* | (0.124) | 0.027 | (0.129) | 0.052 | (0.140) | -0.418*** | (0.149) |
| Almost Every Day | -0.090 | (0.151) | -0.267** | (0.126) | 0.079 | (0.129) | 0.035 | (0.141) | -0.514*** | (0.150) |
| Every Day | -0.070 | (0.151) | -0.270** | (0.131) | 0.034 | (0.129) | 0.039 | (0.142) | -0.526*** | (0.151) |
| Help with Reading | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Once or twice a month | 0.032 | (0.042) | -0.107** | (0.042) | -0.008 | (0.042) | 0.020 | (0.043) | -0.020 | (0.046) |
| Once or twice a week | -0.002 | (0.047) | -0.122** | (0.048) | -0.044 | (0.043) | -0.050 | (0.055) | -0.010 | (0.047) |
| Several Times a Week | -0.023 | (0.104) | -0.188 | (0.134) | 0.167 | (0.118) | 0.247** | (0.114) | 0.214* | (0.113) |
| Almost Every Day | 0.185 | (0.191) | 0.138 | (0.184) | 0.068 | (0.266) | 0.266 | (0.188) | 0.277 | (0.178) |
| Every Day | 0.057 | (0.042) | 0.031 | (0.039) | 0.358*** | (0.038) | 0.207*** | (0.040) | 0.157*** | (0.039) |
| Trips to the Library | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Less than once a week | 0.027 | (0.057) | 0.037 | (0.055) | 0.007 | (0.047) | -0.031 | (0.054) | 0.018 | (0.053) |
| Once or twice a month | 0.074* | (0.040) | 0.098** | (0.041) | 0.062 | (0.039) | 0.038 | (0.039) | 0.036 | (0.039) |
| Once or twice a week | 0.038 | (0.042) | 0.145*** | (0.042) | 0.097** | (0.039) | -0.000 | (0.044) | 0.020 | (0.039) |
| Several Times a Week | 0.096 | (0.063) | 0.086 | (0.064) | 0.110* | (0.058) | 0.098 | (0.067) | -0.048 | (0.069) |
| Almost Every Day | 0.041 | (0.175) | 0.124 | (0.175) | 0.158 | (0.136) | 0.074 | (0.138) | -0.052 | (0.150) |
| Every Day | 0.001 | (0.334) | -0.622*** | (0.210) | 0.414* | (0.226) | 0.730*** | (0.249) | -0.031 | (0.204) |
| Observations | 5,506 | | 5,506 | | 5,506 | | 5,506 | | 5,506 | |
| R-squared | 0.151 | | 0.168 | | 0.176 | | 0.107 | | 0.108 | |

*Notes:* Full Regression Output from OLS regression models. Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

## Table 5H2- Full regression output from birth order OLS models (three child family)

| | Internalising | | Externalising | | Reading | | Maths | | Pattern | |
|---|---|---|---|---|---|---|---|---|---|---|
| Average Birth Spacing | 0.049** | (0.024) | 0.071*** | (0.023) | 0.031 | (0.022) | 0.025 | (0.023) | 0.032 | (0.024) |
| (Average Birth Spacing)$^2$ | -0.004* | (0.002) | -0.004** | (0.002) | -0.002 | (0.002) | -0.003 | (0.002) | -0.003 | (0.002) |
| Boy | -0.046 | (0.036) | -0.312*** | (0.035) | -0.128*** | (0.038) | 0.045 | (0.036) | -0.076** | (0.038) |
| London | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| North East | 0.132 | (0.116) | 0.137 | (0.116) | -0.009 | (0.110) | 0.044 | (0.151) | 0.142 | (0.114) |
| North West | 0.124 | (0.078) | 0.065 | (0.080) | -0.122 | (0.094) | -0.039 | (0.112) | 0.024 | (0.102) |
| Yorkshire/Humber | -0.076 | (0.094) | -0.098 | (0.076) | -0.142 | (0.109) | -0.057 | (0.104) | 0.118 | (0.107) |
| East Midlands | 0.065 | (0.085) | -0.004 | (0.086) | -0.182 | (0.110) | -0.000 | (0.116) | 0.039 | (0.082) |
| West Midlands | -0.062 | (0.105) | -0.105 | (0.084) | -0.085 | (0.097) | 0.057 | (0.101) | 0.124 | (0.088) |
| East England | -0.114 | (0.073) | 0.041 | (0.083) | -0.144 | (0.094) | -0.152 | (0.115) | 0.197** | (0.085) |
| South East | -0.155* | (0.085) | 0.121 | (0.078) | -0.057 | (0.076) | -0.113 | (0.100) | 0.258*** | (0.082) |
| South West | -0.144 | (0.103) | 0.071 | (0.089) | 0.005 | (0.099) | 0.022 | (0.105) | 0.152 | (0.097) |
| Wales | 0.092 | (0.083) | 0.144** | (0.071) | -0.333*** | (0.099) | -0.055 | (0.097) | 0.202** | (0.084) |
| Scotland | 0.097 | (0.072) | 0.066 | (0.065) | -0.163* | (0.084) | -0.258*** | (0.099) | 0.138 | (0.091) |
| Northern Ireland | 0.052 | (0.085) | 0.117 | (0.079) | -0.431*** | (0.084) | 0.061 | (0.108) | 0.195** | (0.091) |
| White | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Indian | 0.078 | (0.113) | 0.279*** | (0.087) | 0.482*** | (0.094) | 0.091 | (0.133) | 0.003 | (0.113) |
| Pakistani | -0.283*** | (0.092) | 0.074 | (0.106) | 0.360*** | (0.094) | -0.392*** | (0.093) | -0.492*** | (0.097) |
| Bangladeshi | -0.451** | (0.219) | 0.492*** | (0.092) | 0.558*** | (0.156) | -0.050 | (0.169) | -0.071 | (0.134) |
| Black Caribbean | -0.192 | (0.127) | -0.071 | (0.162) | 0.057 | (0.124) | -0.401*** | (0.113) | -0.315*** | (0.107) |
| Black African | -0.057 | (0.121) | 0.323* | (0.165) | 0.322** | (0.133) | -0.265** | (0.133) | -0.429*** | (0.103) |
| Other | -0.234 | (0.169) | 0.083 | (0.155) | -0.002 | (0.124) | -0.240* | (0.144) | 0.303* | (0.156) |
| Preterm Birth | -0.113 | (0.095) | -0.080 | (0.102) | -0.172** | (0.087) | -0.033 | (0.112) | -0.154 | (0.099) |
| Low Birth Weight | -0.115 | (0.111) | -0.153 | (0.104) | -0.125 | (0.089) | -0.210** | (0.103) | -0.170* | (0.098) |
| Poor Maternal Health | | | | | | | | | | |
| Excellent Health | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Very Good Health | -0.145*** | (0.048) | -0.141*** | (0.052) | 0.034 | (0.047) | 0.018 | (0.052) | 0.065 | (0.046) |
| Good Health | -0.196*** | (0.055) | -0.214*** | (0.059) | -0.106* | (0.055) | -0.042 | (0.057) | -0.023 | (0.053) |
| Fair Health | -0.303*** | (0.084) | -0.268*** | (0.085) | -0.019 | (0.074) | -0.011 | (0.084) | 0.057 | (0.073) |
| Poor Health | -0.540*** | (0.170) | -0.263 | (0.184) | -0.220 | (0.169) | -0.253* | (0.131) | -0.194 | (0.166) |
| Breastfeeding | | | | | | | | | | |
| Never Breastfed | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Under 3 Months | 0.001 | (0.051) | 0.052 | (0.047) | 0.083* | (0.048) | 0.128*** | (0.048) | -0.002 | (0.048) |
| 3-6 Months | 0.111 | (0.077) | 0.110 | (0.075) | 0.144** | (0.070) | 0.212*** | (0.066) | 0.248*** | (0.071) |
| Over 6 Months | 0.110 | (0.077) | 0.088 | (0.089) | 0.114 | (0.076) | 0.223** | (0.091) | 0.134* | (0.080) |
| Pregnant Smoking | -0.010 | (0.065) | -0.143** | (0.071) | -0.002 | (0.053) | 0.066 | (0.060) | 0.110* | (0.065) |
| Maternal Age | -0.030 | (0.034) | 0.010 | (0.037) | 0.022 | (0.029) | 0.004 | (0.032) | -0.005 | (0.032) |
| (Maternal Age)$^2$ | 0.000 | (0.001) | 0.000 | (0.001) | -0.000 | (0.000) | 0.000 | (0.001) | 0.000 | (0.001) |
| Income | | | | | | | | | | |
| Lowest Quintile | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| 2nd Quintile | -0.034 | (0.070) | -0.072 | (0.074) | -0.040 | (0.065) | -0.050 | (0.069) | -0.035 | (0.067) |
| 3rd Quintile | 0.065 | (0.083) | 0.037 | (0.075) | 0.021 | (0.061) | 0.029 | (0.079) | -0.018 | (0.073) |
| 4th Quintile | 0.102 | (0.084) | 0.109 | (0.089) | 0.002 | (0.067) | 0.025 | (0.078) | 0.009 | (0.072) |
| Top Quintile | 0.209** | (0.088) | 0.151 | (0.094) | 0.127* | (0.073) | 0.227*** | (0.085) | 0.107 | (0.084) |
| Maternal Education | | | | | | | | | | |
| No Formal Qualifications | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| GCSE | 0.153** | (0.077) | 0.213*** | (0.076) | 0.006 | (0.066) | 0.049 | (0.074) | 0.180*** | (0.067) |

## Table 5H2- Full regression output from birth order OLS models (three child family) (continued)

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| A-Level/Diploma | 0.186** | (0.088) | 0.250*** | (0.086) | 0.098 | (0.084) | 0.152* | (0.089) | 0.296*** | (0.088) |
| Degree | 0.202** | (0.096) | 0.398*** | (0.090) | 0.306*** | (0.086) | 0.313*** | (0.088) | 0.446*** | (0.090) |
| Maternal Depression | -0.577*** | (0.076) | -0.329*** | (0.069) | -0.055 | (0.059) | -0.054 | (0.065) | -0.036 | (0.057) |
| Parental Occupation | | | | | | | | | | |
| Managerial/Profession | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Intermediate | 0.131** | (0.061) | 0.109* | (0.064) | -0.072 | (0.053) | -0.036 | (0.063) | -0.103 | (0.071) |
| Semi/Self Employed | -0.071 | (0.080) | -0.015 | (0.070) | -0.129* | (0.070) | 0.030 | (0.076) | 0.120* | (0.072) |
| Lower Supervisory | -0.151 | (0.105) | -0.096 | (0.092) | -0.231*** | (0.081) | -0.094 | (0.084) | -0.011 | (0.091) |
| Semi Routine | -0.044 | (0.085) | -0.101 | (0.070) | -0.269*** | (0.063) | -0.164** | (0.064) | -0.188*** | (0.063) |
| Maternal Employment | 0.040 | (0.046) | -0.027 | (0.046) | 0.023 | (0.045) | -0.002 | (0.040) | -0.072 | (0.047) |
| Drawing/Painting | | | | | | | | | | |
| Never | | | | | | | | | | |
| Once or twice a month | 0.109 | (0.195) | 0.101 | (0.229) | 0.116 | (0.202) | 0.108 | (0.189) | 0.109 | (0.199) |
| Once or twice a week | 0.009 | (0.169) | 0.053 | (0.197) | 0.139 | (0.196) | 0.086 | (0.173) | 0.105 | (0.210) |
| Several Times a Week | -0.055 | (0.163) | -0.044 | (0.200) | 0.231 | (0.199) | 0.109 | (0.175) | 0.035 | (0.201) |
| Almost Every Day | -0.094 | (0.166) | -0.066 | (0.195) | 0.203 | (0.197) | 0.110 | (0.177) | -0.045 | (0.200) |
| Every Day | -0.047 | (0.171) | -0.102 | (0.204) | 0.176 | (0.198) | 0.026 | (0.184) | -0.076 | (0.204) |
| Help with Reading | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Once or twice a month | 0.107 | (0.068) | 0.054 | (0.060) | 0.035 | (0.055) | 0.079 | (0.059) | 0.007 | (0.055) |
| Once or twice a week | 0.121* | (0.067) | 0.090 | (0.065) | 0.034 | (0.062) | 0.076 | (0.069) | 0.170** | (0.069) |
| Several Times a Week | 0.261* | (0.134) | 0.078 | (0.145) | 0.432*** | (0.131) | 0.379*** | (0.137) | 0.191 | (0.178) |
| Almost Every Day | 0.220 | (0.165) | 0.267 | (0.279) | 0.499** | (0.243) | 0.051 | (0.301) | 0.348 | (0.252) |
| Every Day | 0.110* | (0.060) | 0.222*** | (0.058) | 0.430*** | (0.053) | 0.282*** | (0.058) | 0.195*** | (0.055) |
| Trips to the Library | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Less than once a week | -0.131 | (0.079) | -0.182** | (0.080) | -0.093 | (0.068) | -0.075 | (0.067) | -0.146** | (0.065) |
| Once or twice a month | 0.054 | (0.059) | -0.023 | (0.057) | 0.174*** | (0.048) | 0.141*** | (0.049) | 0.070 | (0.052) |
| Once or twice a week | -0.017 | (0.050) | 0.062 | (0.049) | 0.111** | (0.054) | 0.120** | (0.052) | 0.031 | (0.055) |
| Several Times a Week | 0.025 | (0.078) | 0.133 | (0.086) | 0.333*** | (0.069) | 0.254*** | (0.076) | 0.013 | (0.090) |
| Almost Every Day | -0.049 | (0.204) | -0.059 | (0.195) | 0.116 | (0.183) | 0.142 | (0.207) | 0.294 | (0.208) |
| Every Day | 0.002 | (0.432) | -0.131 | (0.262) | -0.271 | (0.769) | -0.728 | (0.469) | -0.653 | (0.638) |
| Observations | 3229 | | 3229 | | 3229 | | 3229 | | 3229 | |
| R-squared | 0.151 | | 0.191 | | 0.230 | | 0.150 | | 0.135 | |

*Notes:* Full Regression Output from OLS regression models. Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

## Table 5H3- Full regression output from birth order OLS models (three child family, last born excluded)

| | Internalising | | Externalising | | Reading | | Maths | | Pattern | |
|---|---|---|---|---|---|---|---|---|---|---|
| Average Birth Spacing | 0.046 | (0.066) | 0.095 | (0.063) | -0.003 | (0.070) | 0.100 | (0.076) | 0.108* | (0.065) |
| (Average Birth Spacing)$^2$ | -0.003 | (0.009) | -0.011 | (0.009) | 0.004 | (0.010) | -0.019* | (0.011) | -0.017* | (0.009) |
| Boy | -0.082 | (0.050) | -0.311*** | (0.051) | -0.122** | (0.047) | 0.052 | (0.047) | -0.075 | (0.050) |
| London | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| North East | 0.107 | (0.160) | 0.077 | (0.152) | -0.199 | (0.139) | -0.110 | (0.143) | 0.105 | (0.151) |
| North West | 0.100 | (0.112) | 0.072 | (0.116) | -0.191* | (0.110) | -0.060 | (0.122) | 0.082 | (0.116) |
| Yorkshire/Humber | -0.135 | (0.122) | -0.216* | (0.115) | -0.217* | (0.115) | -0.066 | (0.106) | 0.204* | (0.122) |
| East Midlands | 0.000 | (0.121) | 0.066 | (0.145) | -0.148 | (0.146) | 0.058 | (0.139) | 0.182 | (0.115) |
| West Midlands | -0.088 | (0.138) | -0.117 | (0.108) | -0.067 | (0.111) | 0.083 | (0.090) | 0.141 | (0.102) |
| East England | -0.194* | (0.105) | 0.057 | (0.114) | -0.252** | (0.102) | -0.183* | (0.109) | 0.235** | (0.102) |
| South East | -0.201* | (0.117) | 0.129 | (0.111) | -0.054 | (0.096) | -0.095 | (0.093) | 0.348*** | (0.091) |
| South West | -0.224* | (0.130) | 0.026 | (0.119) | -0.031 | (0.115) | -0.064 | (0.100) | 0.216** | (0.107) |
| Wales | -0.030 | (0.116) | 0.056 | (0.102) | -0.389*** | (0.125) | -0.045 | (0.096) | 0.217** | (0.102) |
| Scotland | 0.144 | (0.097) | 0.085 | (0.094) | -0.182* | (0.105) | -0.282*** | (0.106) | 0.213** | (0.101) |
| Northern Ireland | 0.049 | (0.105) | 0.138 | (0.101) | -0.435*** | (0.103) | 0.077 | (0.105) | 0.326*** | (0.109) |
| White | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Indian | 0.100 | (0.149) | 0.141 | (0.134) | 0.553*** | (0.126) | 0.169 | (0.161) | -0.089 | (0.156) |
| Pakistani | -0.366*** | (0.120) | 0.074 | (0.133) | 0.326*** | (0.089) | -0.416*** | (0.112) | -0.454*** | (0.121) |
| Bangladeshi | -0.576** | (0.254) | 0.391*** | (0.124) | 0.503** | (0.207) | 0.056 | (0.169) | 0.013 | (0.160) |
| Black Caribbean | -0.198 | (0.176) | -0.117 | (0.249) | 0.105 | (0.166) | -0.359** | (0.139) | -0.189 | (0.147) |
| Black African | 0.039 | (0.175) | 0.359** | (0.161) | 0.323 | (0.196) | -0.245 | (0.190) | -0.382*** | (0.142) |
| Other | -0.283 | (0.197) | -0.113 | (0.205) | -0.034 | (0.188) | -0.012 | (0.170) | 0.370* | (0.220) |
| Preterm Birth | -0.247** | (0.121) | -0.111 | (0.119) | -0.174 | (0.117) | -0.058 | (0.130) | -0.140 | (0.120) |
| Low Birth Weight | -0.015 | (0.121) | -0.033 | (0.118) | -0.075 | (0.110) | -0.165 | (0.112) | -0.166 | (0.111) |
| Poor Maternal Health | | | | | | | | | | |
| Excellent Health | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Very Good Health | -0.140** | (0.067) | -0.171** | (0.068) | 0.005 | (0.061) | 0.002 | (0.054) | 0.055 | (0.058) |
| Good Health | -0.147** | (0.072) | -0.207*** | (0.075) | -0.090 | (0.068) | 0.008 | (0.062) | -0.015 | (0.063) |
| Fair Health | -0.200* | (0.104) | -0.241** | (0.102) | -0.011 | (0.096) | 0.151 | (0.103) | 0.060 | (0.095) |
| Poor Health | -0.673** | (0.281) | -0.285 | (0.250) | -0.201 | (0.252) | -0.126 | (0.213) | -0.072 | (0.236) |
| Breastfeeding | | | | | | | | | | |
| Never Breastfed | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Under 3 Months | 0.044 | (0.072) | 0.056 | (0.063) | 0.164** | (0.066) | 0.191*** | (0.062) | 0.023 | (0.060) |
| 3-6 Months | 0.122 | (0.104) | 0.100 | (0.092) | 0.205** | (0.092) | 0.319*** | (0.078) | 0.244*** | (0.082) |
| Over 6 Months | 0.142 | (0.109) | 0.153 | (0.116) | 0.191* | (0.110) | 0.222* | (0.113) | 0.199* | (0.103) |
| Pregnant Smoking | -0.100 | (0.090) | -0.181** | (0.088) | -0.021 | (0.068) | 0.111 | (0.076) | 0.169** | (0.085) |
| Maternal Age | -0.033 | (0.051) | 0.038 | (0.051) | 0.024 | (0.043) | 0.005 | (0.044) | -0.060 | (0.043) |
| (Maternal Age)$^2$ | 0.001 | (0.001) | -0.000 | (0.001) | -0.000 | (0.001) | -0.000 | (0.001) | 0.001 | (0.001) |
| Income | | | | | | | | | | |
| Lowest Quintile | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| 2nd Quintile | -0.101 | (0.089) | -0.112 | (0.101) | -0.053 | (0.077) | -0.057 | (0.085) | -0.010 | (0.089) |
| 3rd Quintile | -0.071 | (0.108) | 0.026 | (0.091) | 0.083 | (0.076) | 0.128 | (0.099) | 0.009 | (0.102) |
| 4th Quintile | 0.056 | (0.111) | 0.037 | (0.118) | -0.002 | (0.085) | 0.099 | (0.108) | 0.034 | (0.102) |
| Top Quintile | 0.228** | (0.112) | 0.103 | (0.120) | 0.126 | (0.088) | 0.351*** | (0.105) | 0.211* | (0.111) |
| Maternal Education | | | | | | | | | | |
| No Formal Qualifications | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| GCSE | 0.212** | (0.104) | 0.192** | (0.095) | -0.005 | (0.081) | 0.034 | (0.090) | 0.135 | (0.083) |
| A-Level/Diploma | 0.133 | (0.119) | 0.248** | (0.116) | 0.116 | (0.107) | 0.108 | (0.109) | 0.244** | (0.115) |
| Degree | 0.151 | (0.123) | 0.341*** | (0.110) | 0.296*** | (0.105) | 0.280** | (0.112) | 0.378*** | (0.109) |
| Maternal Depression | -0.630*** | (0.086) | -0.326*** | (0.086) | -0.020 | (0.077) | -0.060 | (0.081) | -0.022 | (0.074) |
| Parental Occupation | | | | | | | | | | |
| Managerial/Profession | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |

## Table 5H3- Full regression output from birth order OLS models (three child family, last born excluded) (continued)

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Intermediate | 0.149* | (0.086) | 0.032 | (0.085) | -0.154** | (0.069) | -0.155* | (0.092) | -0.171* | (0.089) |
| Semi/Self Employed | -0.054 | (0.101) | -0.050 | (0.095) | -0.167** | (0.085) | 0.019 | (0.090) | 0.004 | (0.087) |
| Lower Supervisory | -0.071 | (0.115) | -0.128 | (0.121) | -0.248** | (0.102) | -0.084 | (0.103) | -0.106 | (0.110) |
| Semi Routine | -0.093 | (0.110) | -0.225** | (0.089) | -0.296*** | (0.080) | -0.179** | (0.083) | -0.326*** | (0.079) |
| Maternal Employment | 0.043 | (0.063) | -0.126* | (0.068) | -0.022 | (0.057) | 0.033 | (0.064) | -0.074 | (0.062) |
| Drawing/Painting | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Once or twice a month | 0.048 | (0.232) | -0.006 | (0.253) | 0.097 | (0.207) | -0.098 | (0.257) | 0.101 | (0.290) |
| Once or twice a week | 0.072 | (0.203) | 0.021 | (0.209) | 0.110 | (0.184) | -0.047 | (0.240) | 0.103 | (0.302) |
| Several Times a Week | -0.010 | (0.202) | -0.144 | (0.215) | 0.194 | (0.204) | -0.008 | (0.260) | 0.046 | (0.302) |
| Almost Every Day | -0.124 | (0.204) | -0.111 | (0.209) | 0.149 | (0.199) | -0.045 | (0.256) | -0.037 | (0.295) |
| Every Day | -0.073 | (0.210) | -0.208 | (0.218) | 0.156 | (0.200) | -0.104 | (0.260) | -0.055 | (0.302) |
| Help with Reading | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Once or twice a month | 0.145* | (0.077) | 0.019 | (0.074) | 0.036 | (0.068) | 0.071 | (0.073) | 0.016 | (0.069) |
| Once or twice a week | 0.163* | (0.092) | 0.060 | (0.082) | 0.108 | (0.075) | 0.048 | (0.079) | 0.146* | (0.080) |
| Several Times a Week | 0.388** | (0.181) | 0.346* | (0.178) | 0.624*** | (0.184) | 0.464*** | (0.164) | 0.227 | (0.230) |
| Almost Every Day | 0.345 | (0.209) | 0.653** | (0.293) | 0.955*** | (0.294) | 0.491 | (0.439) | 0.126 | (0.275) |
| Every Day | 0.141* | (0.078) | 0.179** | (0.073) | 0.430*** | (0.066) | 0.255*** | (0.072) | 0.203*** | (0.064) |
| Trips to the Library | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Less than once a week | -0.198* | (0.103) | -0.266** | (0.105) | -0.111 | (0.089) | -0.117 | (0.081) | -0.143* | (0.079) |
| Once or twice a month | -0.024 | (0.076) | -0.026 | (0.069) | 0.205*** | (0.064) | 0.219*** | (0.064) | 0.101 | (0.065) |
| Once or twice a week | -0.044 | (0.064) | 0.077 | (0.063) | 0.172** | (0.070) | 0.224*** | (0.070) | 0.062 | (0.081) |
| Several Times a Week | -0.133 | (0.106) | 0.081 | (0.104) | 0.385*** | (0.082) | 0.357*** | (0.098) | -0.044 | (0.119) |
| Almost Every Day | -0.014 | (0.309) | -0.087 | (0.280) | 0.319 | (0.225) | 0.193 | (0.237) | 0.469* | (0.276) |
| Every Day | -0.671*** | (0.183) | -0.520* | (0.308) | -1.340*** | (0.304) | -1.383*** | (0.156) | -1.662*** | (0.256) |
| Observations | 1994 | | 1994 | | 1994 | | 1994 | | 1994 | |
| R-squared | 0.157 | | 0.196 | | 0.257 | | 0.195 | | 0.163 | |

*Notes:* Full Regression Output from OLS regression models. Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

## Table 5H4- Full regression output from birth order OLS models (four child family)

| | Internalising | | Externalising | | Reading | | Maths | | Pattern | |
|---|---|---|---|---|---|---|---|---|---|---|
| Average Birth Spacing | 0.127*** | (0.046) | 0.114** | (0.047) | 0.045 | (0.035) | -0.005 | (0.037) | 0.015 | (0.040) |
| (Average Birth Spacing)$^2$ | -0.012*** | (0.004) | -0.008** | (0.004) | -0.004 | (0.003) | -0.001 | (0.003) | -0.004 | (0.003) |
| Boy | -0.101 | (0.068) | -0.312*** | (0.070) | -0.212*** | (0.059) | -0.010 | (0.062) | -0.149** | (0.071) |
| London | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| North East | -0.244 | (0.280) | -0.158 | (0.339) | 0.211 | (0.224) | -0.035 | (0.332) | -0.125 | (0.203) |
| North West | 0.085 | (0.139) | 0.083 | (0.165) | -0.253* | (0.134) | -0.034 | (0.169) | -0.079 | (0.132) |
| Yorkshire/Humber | -0.273* | (0.154) | -0.230 | (0.224) | -0.306* | (0.171) | -0.433** | (0.181) | 0.054 | (0.184) |
| East Midlands | -0.261 | (0.218) | 0.043 | (0.201) | -0.166 | (0.175) | -0.080 | (0.200) | -0.152 | (0.173) |
| West Midlands | -0.161 | (0.143) | -0.114 | (0.150) | -0.371*** | (0.127) | -0.139 | (0.190) | 0.020 | (0.168) |
| East England | -0.323** | (0.153) | -0.023 | (0.153) | -0.500*** | (0.128) | -0.437*** | (0.160) | -0.081 | (0.136) |
| South East | -0.347** | (0.152) | -0.124 | (0.195) | -0.112 | (0.132) | -0.208 | (0.158) | 0.174 | (0.151) |
| South West | -0.166 | (0.142) | 0.175 | (0.141) | -0.353** | (0.143) | -0.426** | (0.214) | -0.076 | (0.187) |
| Wales | -0.284 | (0.202) | 0.009 | (0.188) | -0.420*** | (0.124) | -0.134 | (0.158) | 0.230 | (0.143) |
| Scotland | -0.105 | (0.139) | -0.002 | (0.159) | -0.294** | (0.143) | -0.434*** | (0.165) | 0.033 | (0.144) |
| Northern Ireland | -0.043 | (0.118) | -0.041 | (0.152) | -0.559*** | (0.123) | -0.132 | (0.152) | 0.059 | (0.125) |
| White | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Indian | 0.208 | (0.194) | 0.187 | (0.310) | 0.492*** | (0.162) | 0.345 | (0.309) | 0.105 | (0.169) |
| Pakistani | -0.139 | (0.158) | 0.212 | (0.135) | 0.759*** | (0.144) | 0.122 | (0.144) | -0.132 | (0.156) |
| Bangladeshi | -0.386 | (0.235) | 0.118 | (0.169) | 0.592*** | (0.176) | -0.041 | (0.186) | -0.127 | (0.144) |
| Black Caribbean | -0.123 | (0.258) | -0.076 | (0.299) | 0.108 | (0.200) | -0.271 | (0.184) | -0.459*** | (0.152) |
| Black African | -0.083 | (0.176) | 0.050 | (0.250) | 0.116 | (0.194) | -0.416 | (0.257) | -0.460** | (0.214) |
| Other | -0.123 | (0.210) | 0.608*** | (0.202) | 0.585** | (0.230) | 0.089 | (0.253) | 0.092 | (0.210) |
| Preterm Birth | -0.128 | (0.176) | -0.067 | (0.169) | -0.323** | (0.157) | -0.217 | (0.154) | -0.189 | (0.125) |
| Low Birth Weight | -0.042 | (0.197) | -0.139 | (0.175) | 0.341* | (0.201) | 0.217 | (0.168) | 0.191 | (0.138) |
| Poor Maternal Health | | | | | | | | | | |
| Excellent Health | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Very Good Health | -0.142 | (0.101) | -0.255*** | (0.095) | -0.049 | (0.078) | 0.032 | (0.096) | 0.100 | (0.094) |
| Good Health | -0.309*** | (0.117) | -0.368*** | (0.095) | -0.253*** | (0.081) | -0.108 | (0.094) | -0.013 | (0.090) |
| Fair Health | -0.006 | (0.136) | -0.178 | (0.121) | -0.241** | (0.109) | 0.000 | (0.124) | 0.217* | (0.128) |
| Poor Health | -0.074 | (0.232) | -0.222 | (0.192) | -0.249 | (0.185) | -0.111 | (0.187) | 0.094 | (0.207) |
| Breastfeeding | | | | | | | | | | |
| Never Breastfed | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Under 3 Months | 0.118 | (0.091) | 0.011 | (0.087) | -0.015 | (0.077) | -0.075 | (0.088) | 0.097 | (0.087) |
| 3-6 Months | 0.262** | (0.109) | 0.013 | (0.117) | -0.097 | (0.108) | -0.065 | (0.113) | 0.128 | (0.131) |
| Over 6 Months | 0.214* | (0.126) | 0.283** | (0.135) | 0.035 | (0.140) | 0.010 | (0.146) | 0.124 | (0.148) |
| Pregnant Smoking | 0.117 | (0.109) | -0.056 | (0.115) | -0.087 | (0.095) | 0.019 | (0.092) | -0.001 | (0.101) |
| Maternal Age | 0.118* | (0.065) | 0.228*** | (0.070) | 0.042 | (0.046) | 0.042 | (0.055) | 0.043 | (0.053) |
| (Maternal Age)$^2$ | -0.002* | (0.001) | -0.004*** | (0.001) | -0.001 | (0.001) | -0.001 | (0.001) | -0.001 | (0.001) |
| Income | | | | | | | | | | |
| Lowest Quintile | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| 2$^{nd}$ Quintile | 0.213 | (0.131) | 0.080 | (0.118) | 0.078 | (0.095) | 0.102 | (0.093) | 0.007 | (0.092) |
| 3$^{rd}$ Quintile | 0.327** | (0.131) | -0.024 | (0.123) | 0.108 | (0.101) | 0.030 | (0.103) | -0.062 | (0.099) |
| 4$^{th}$ Quintile | 0.292* | (0.153) | 0.228* | (0.137) | 0.412*** | (0.116) | 0.188 | (0.130) | 0.009 | (0.112) |
| Top Quintile | 0.364** | (0.184) | 0.258* | (0.151) | 0.578*** | (0.138) | 0.451*** | (0.142) | 0.093 | (0.166) |
| Maternal Education | | | | | | | | | | |
| No Formal Qualifications | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| GCSE | -0.007 | (0.106) | 0.265** | (0.108) | 0.182** | (0.089) | 0.163* | (0.089) | 0.000 | (0.092) |
| A-Level/Diploma | 0.115 | (0.131) | 0.225 | (0.138) | 0.444*** | (0.109) | 0.300** | (0.141) | 0.122 | (0.128) |
| Degree | 0.095 | (0.153) | 0.181 | (0.161) | 0.489*** | (0.129) | 0.319** | (0.158) | 0.134 | (0.205) |
| Maternal Depression | -0.435*** | (0.133) | -0.426*** | (0.110) | -0.017 | (0.090) | -0.102 | (0.090) | -0.038 | (0.104) |

## Table 5H4- Full regression output from birth order OLS models (four child family) (continued)

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Parental Occupation | | | | | | | | | | |
| Managerial/Profession | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Intermediate | -0.051 | (0.107) | 0.008 | (0.110) | 0.051 | (0.095) | -0.155 | (0.098) | -0.205* | (0.120) |
| Semi/Self Employed | -0.031 | (0.140) | -0.084 | (0.119) | -0.221** | (0.111) | -0.265** | (0.134) | -0.232** | (0.112) |
| Lower Supervisory | 0.086 | (0.171) | -0.006 | (0.159) | -0.074 | (0.130) | -0.305** | (0.124) | -0.209* | (0.116) |
| Semi Routine | -0.018 | (0.151) | -0.195* | (0.116) | -0.152* | (0.091) | -0.317*** | (0.114) | -0.404*** | (0.108) |
| Maternal Employment | 0.041 | (0.083) | 0.127* | (0.074) | 0.124* | (0.065) | 0.144** | (0.068) | 0.129* | (0.075) |
| Drawing/Painting | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Once or twice a month | 0.773 | (0.556) | 0.496 | (0.419) | 0.577** | (0.241) | 0.337 | (0.227) | -0.103 | (0.291) |
| Once or twice a week | 1.057* | (0.540) | 0.689* | (0.408) | 0.593*** | (0.199) | 0.432** | (0.219) | 0.042 | (0.259) |
| Several Times a Week | 0.953* | (0.544) | 0.569 | (0.394) | 0.665*** | (0.213) | 0.357 | (0.221) | -0.121 | (0.261) |
| Almost Every Day | 0.887 | (0.549) | 0.571 | (0.401) | 0.724*** | (0.198) | 0.234 | (0.220) | -0.125 | (0.263) |
| Every Day | 0.854 | (0.537) | 0.510 | (0.406) | 0.603*** | (0.198) | 0.193 | (0.216) | -0.066 | (0.265) |
| Help with Reading | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Once or twice a month | -0.145 | (0.122) | 0.122 | (0.118) | 0.049 | (0.087) | -0.073 | (0.098) | -0.015 | (0.099) |
| Once or twice a week | -0.108 | (0.124) | -0.035 | (0.125) | -0.091 | (0.095) | -0.096 | (0.117) | -0.163 | (0.112) |
| Several Times a Week | 0.152 | (0.207) | -0.398* | (0.220) | 0.256 | (0.199) | -0.001 | (0.222) | 0.210 | (0.231) |
| Almost Every Day | -0.427 | (1.100) | 0.612* | (0.320) | 0.175 | (0.576) | 1.025** | (0.489) | 1.763*** | (0.307) |
| Every Day | -0.002 | (0.095) | 0.234** | (0.105) | 0.465*** | (0.085) | 0.174* | (0.092) | 0.078 | (0.104) |
| Trips to the Library | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Less than once a week | -0.171 | (0.124) | -0.001 | (0.115) | -0.122 | (0.118) | -0.071 | (0.132) | 0.065 | (0.119) |
| Once or twice a month | -0.073 | (0.110) | -0.085 | (0.116) | 0.010 | (0.090) | -0.010 | (0.097) | 0.240** | (0.099) |
| Once or twice a week | 0.029 | (0.103) | 0.013 | (0.097) | 0.013 | (0.079) | 0.104 | (0.083) | 0.111 | (0.087) |
| Several Times a Week | -0.099 | (0.123) | -0.017 | (0.129) | 0.192 | (0.129) | 0.231* | (0.128) | 0.220* | (0.122) |
| Almost Every Day | -1.795** | (0.828) | -1.735*** | (0.451) | -0.384 | (0.402) | -0.561 | (0.399) | -1.123 | (0.703) |
| Every Day | 0.372 | (0.441) | -1.033* | (0.559) | 0.179 | (0.497) | 0.222 | (0.802) | 0.090 | (0.474) |
| Observations | 1167 | | 1167 | | 1167 | | 1167 | | 1167 | |
| R-squared | 0.191 | | 0.225 | | 0.319 | | 0.181 | | 0.148 | |

*Notes:* Full Regression Output from OLS regression models. Taylor-Linearized standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

## Table 5H5- Full regression output from birth order OLS models (four child Family, last borns excluded)

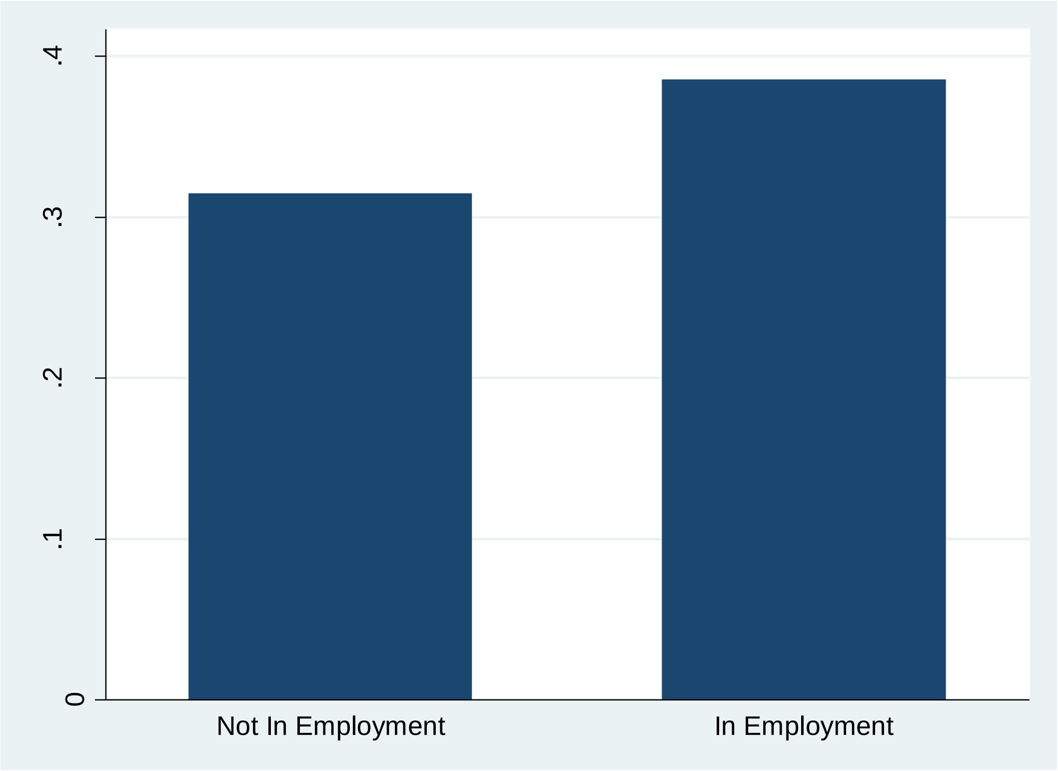
| | Internalising | | Externalising | | Reading | | Maths | | Pattern | |
|---|---|---|---|---|---|---|---|---|---|---|
| Average Birth Spacing | 0.228** | (0.109) | 0.308*** | (0.097) | 0.107* | (0.064) | -0.069 | (0.074) | -0.088 | (0.070) |
| (Average Birth Spacing)$^2$ | -0.026* | (0.014) | -0.034*** | (0.011) | -0.012 | (0.008) | 0.004 | (0.009) | 0.011 | (0.008) |
| Boy | -0.139 | (0.085) | -0.387*** | (0.088) | -0.126* | (0.072) | -0.042 | (0.073) | -0.176** | (0.084) |
| London | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| North East | -0.447 | (0.330) | -0.345 | (0.334) | 0.252 | (0.260) | 0.161 | (0.318) | -0.017 | (0.222) |
| North West | 0.146 | (0.159) | 0.016 | (0.200) | -0.123 | (0.151) | 0.089 | (0.204) | 0.054 | (0.151) |
| Yorkshire/Humber | -0.271 | (0.188) | -0.379 | (0.263) | -0.229 | (0.196) | -0.377* | (0.227) | 0.072 | (0.222) |
| East Midlands | -0.483 | (0.297) | -0.298 | (0.234) | -0.018 | (0.221) | 0.005 | (0.216) | 0.029 | (0.148) |
| West Midlands | -0.085 | (0.177) | -0.181 | (0.197) | -0.300* | (0.155) | 0.012 | (0.194) | 0.099 | (0.206) |
| East England | -0.450** | (0.185) | -0.216 | (0.202) | -0.503*** | (0.130) | -0.466*** | (0.173) | -0.090 | (0.166) |
| South East | -0.510** | (0.199) | -0.270 | (0.238) | -0.238* | (0.143) | -0.149 | (0.180) | 0.307* | (0.185) |
| South West | -0.158 | (0.169) | 0.212 | (0.186) | -0.417** | (0.184) | -0.487* | (0.250) | -0.050 | (0.209) |
| Wales | -0.216 | (0.211) | 0.006 | (0.203) | -0.396*** | (0.139) | 0.019 | (0.188) | 0.386** | (0.183) |
| Scotland | -0.215 | (0.157) | -0.193 | (0.181) | -0.267 | (0.168) | -0.417** | (0.190) | 0.179 | (0.158) |
| Northern Ireland | -0.171 | (0.140) | -0.109 | (0.177) | -0.571*** | (0.133) | -0.252 | (0.176) | 0.102 | (0.154) |
| White | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Indian | 0.638*** | (0.218) | 0.199 | (0.552) | 0.782*** | (0.251) | 0.597 | (0.474) | 0.112 | (0.172) |
| Pakistani | -0.145 | (0.202) | 0.357** | (0.166) | 0.733*** | (0.174) | 0.210 | (0.170) | -0.175 | (0.198) |
| Bangladeshi | -0.419* | (0.220) | 0.247 | (0.258) | 0.577** | (0.264) | -0.110 | (0.224) | -0.202 | (0.207) |
| Black Caribbean | -0.488 | (0.314) | -0.214 | (0.309) | -0.114 | (0.209) | -0.569*** | (0.200) | -0.282 | (0.193) |
| Black African | -0.306 | (0.231) | 0.067 | (0.228) | 0.086 | (0.208) | -0.524* | (0.291) | -0.587** | (0.262) |
| Other | 0.036 | (0.268) | 0.585* | (0.306) | 0.695*** | (0.250) | 0.203 | (0.326) | 0.354 | (0.250) |
| Preterm Birth | -0.056 | (0.212) | -0.146 | (0.196) | -0.291 | (0.194) | -0.240 | (0.193) | -0.302** | (0.142) |
| Low Birth Weight | -0.173 | (0.237) | -0.104 | (0.200) | 0.256 | (0.239) | 0.206 | (0.200) | 0.250 | (0.167) |
| Poor Maternal Health | | | | | | | | | | |
| Excellent Health | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Very Good Health | -0.102 | (0.132) | -0.245** | (0.118) | -0.020 | (0.098) | 0.069 | (0.102) | 0.156 | (0.113) |
| Good Health | -0.371** | (0.157) | -0.347*** | (0.124) | -0.209** | (0.097) | -0.118 | (0.110) | 0.059 | (0.107) |
| Fair Health | 0.127 | (0.191) | -0.160 | (0.153) | -0.169 | (0.135) | -0.048 | (0.151) | 0.286* | (0.162) |
| Poor Health | -0.136 | (0.295) | -0.228 | (0.238) | -0.477*** | (0.180) | -0.432** | (0.181) | -0.045 | (0.240) |
| Breastfeeding | | | | | | | | | | |
| Never Breastfed | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Under 3 Months | 0.195* | (0.117) | 0.002 | (0.120) | 0.063 | (0.092) | -0.058 | (0.101) | 0.028 | (0.097) |
| 3-6 Months | 0.288** | (0.142) | 0.044 | (0.140) | 0.037 | (0.132) | 0.080 | (0.131) | 0.105 | (0.154) |
| Over 6 Months | 0.379** | (0.147) | 0.109 | (0.190) | 0.179 | (0.156) | 0.261* | (0.157) | 0.410*** | (0.146) |
| Pregnant Smoking | 0.212 | (0.138) | 0.092 | (0.134) | -0.025 | (0.109) | 0.134 | (0.104) | 0.021 | (0.121) |
| Maternal Age | 0.112 | (0.084) | 0.208** | (0.087) | -0.016 | (0.065) | 0.078 | (0.063) | 0.122 | (0.075) |
| (Maternal Age)$^2$ | -0.002 | (0.001) | -0.004** | (0.001) | 0.000 | (0.001) | -0.001 | (0.001) | -0.002 | (0.001) |
| Income | | | | | | | | | | |
| Lowest Quintile | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| 2nd Quintile | 0.171 | (0.161) | 0.083 | (0.139) | 0.030 | (0.107) | 0.065 | (0.113) | -0.016 | (0.119) |
| 3rd Quintile | 0.344** | (0.170) | -0.206 | (0.160) | 0.129 | (0.120) | 0.111 | (0.128) | 0.006 | (0.127) |
| 4th Quintile | 0.368* | (0.193) | 0.283 | (0.177) | 0.382*** | (0.141) | 0.177 | (0.151) | -0.020 | (0.159) |
| Top Quintile | 0.282 | (0.222) | 0.099 | (0.203) | 0.602*** | (0.175) | 0.498*** | (0.172) | 0.123 | (0.211) |
| Maternal Education | | | | | | | | | | |
| No Formal Qualifications | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| GCSE | -0.066 | (0.136) | 0.188 | (0.138) | 0.171 | (0.108) | 0.179* | (0.107) | 0.039 | (0.111) |
| A-Level/Diploma | 0.156 | (0.164) | 0.233 | (0.170) | 0.559*** | (0.141) | 0.317* | (0.165) | 0.237 | (0.147) |
| Degree | 0.066 | (0.188) | 0.218 | (0.184) | 0.474*** | (0.142) | 0.195 | (0.157) | 0.156 | (0.235) |

**Table 5H5- Full regression output from birth order OLS models (four child family, last borns excluded) (continued)**

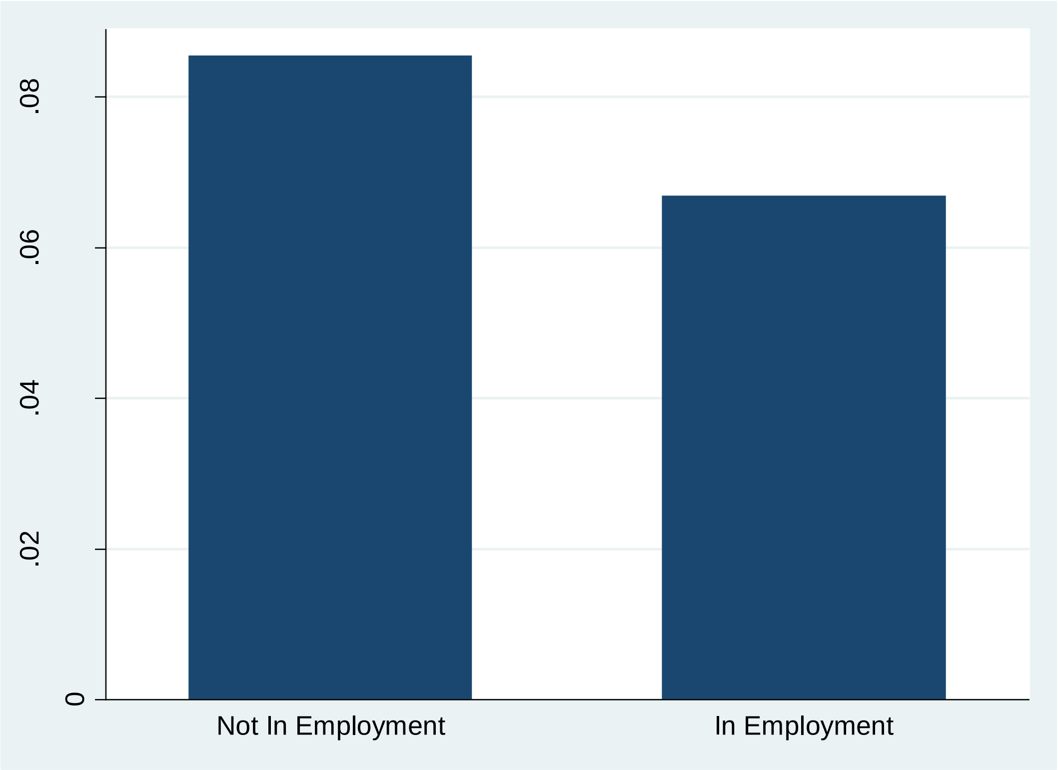
| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Maternal Depression | -0.634*** | (0.178) | -0.496*** | (0.143) | 0.050 | (0.105) | -0.074 | (0.104) | 0.021 | (0.118) |
| Parental Occupation | | | | | | | | | | |
| Managerial/Profession | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Intermediate | 0.021 | (0.142) | -0.030 | (0.154) | 0.021 | (0.126) | -0.129 | (0.133) | -0.134 | (0.168) |
| Semi/Self Employed | -0.001 | (0.186) | -0.206 | (0.157) | -0.230 | (0.147) | -0.298* | (0.165) | -0.191 | (0.141) |
| Lower Supervisory | 0.283 | (0.195) | -0.010 | (0.181) | 0.022 | (0.149) | -0.342** | (0.159) | -0.295** | (0.148) |
| Semi Routine | -0.016 | (0.198) | -0.317** | (0.148) | -0.153 | (0.102) | -0.388*** | (0.140) | -0.469*** | (0.126) |
| Maternal Employment | 0.127 | (0.119) | 0.239** | (0.098) | 0.104 | (0.075) | 0.162** | (0.080) | 0.088 | (0.094) |
| Drawing/Painting | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Once or twice a month | 0.720 | (0.733) | 0.535 | (0.516) | 0.506* | (0.286) | 0.138 | (0.290) | -0.230 | (0.330) |
| Once or twice a week | 1.078 | (0.695) | 0.691 | (0.503) | 0.518** | (0.242) | 0.293 | (0.268) | 0.001 | (0.305) |
| Several Times a Week | 0.838 | (0.702) | 0.464 | (0.481) | 0.584** | (0.228) | 0.167 | (0.266) | -0.218 | (0.310) |
| Almost Every Day | 0.749 | (0.710) | 0.504 | (0.486) | 0.599** | (0.232) | 0.058 | (0.275) | -0.296 | (0.310) |
| Every Day | 0.905 | (0.694) | 0.511 | (0.490) | 0.523** | (0.227) | 0.006 | (0.275) | -0.154 | (0.314) |
| Help with Reading | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Once or twice a month | -0.032 | (0.137) | 0.210 | (0.136) | 0.152 | (0.104) | -0.034 | (0.119) | 0.100 | (0.121) |
| Once or twice a week | -0.032 | (0.164) | 0.125 | (0.154) | 0.013 | (0.119) | -0.010 | (0.134) | -0.140 | (0.137) |
| Several Times a Week | 0.011 | (0.316) | -0.454 | (0.411) | 0.324 | (0.365) | 0.129 | (0.349) | 0.248 | (0.170) |
| Almost Every Day | -2.870*** | (0.278) | 0.046 | (0.322) | 1.378*** | (0.240) | 0.936*** | (0.264) | 2.269*** | (0.302) |
| Every Day | 0.101 | (0.125) | 0.341*** | (0.131) | 0.543*** | (0.103) | 0.260** | (0.119) | 0.140 | (0.123) |
| Trips to the Library | | | | | | | | | | |
| Never | (omitted) | | (omitted) | | (omitted) | | (omitted) | | (omitted) | |
| Less than once a week | -0.147 | (0.165) | 0.002 | (0.139) | -0.170 | (0.131) | -0.022 | (0.134) | 0.125 | (0.138) |
| Once or twice a month | -0.007 | (0.133) | -0.078 | (0.141) | -0.049 | (0.095) | -0.018 | (0.108) | 0.270** | (0.129) |
| Once or twice a week | 0.118 | (0.122) | 0.016 | (0.122) | 0.014 | (0.098) | 0.135 | (0.108) | 0.169 | (0.112) |
| Several Times a Week | -0.095 | (0.154) | -0.101 | (0.184) | 0.342** | (0.145) | 0.379** | (0.148) | 0.282* | (0.146) |
| Almost Every Day | -1.067 | (1.038) | -1.542** | (0.644) | 0.148 | (0.290) | -0.163 | (0.387) | -0.753 | (0.802) |
| Every Day | 0.578 | (0.411) | -0.991** | (0.467) | 0.258 | (0.473) | 0.222 | (0.716) | 0.181 | (0.480) |
| Observations | 759 | | 759 | | 759 | | 759 | | 759 | |
| R-squared | 0.246 | | 0.270 | | 0.362 | | 0.248 | | 0.189 | |

## Appendix 6A - Descriptive relationships

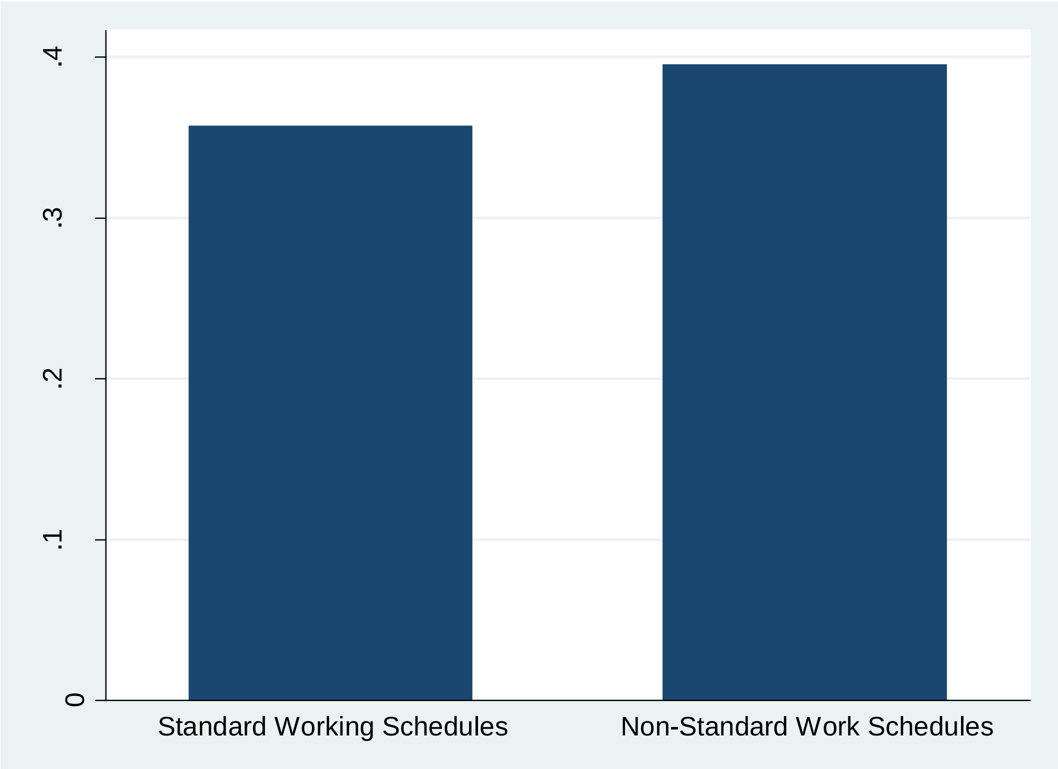
Maternal Employment and Adolescent Drinking



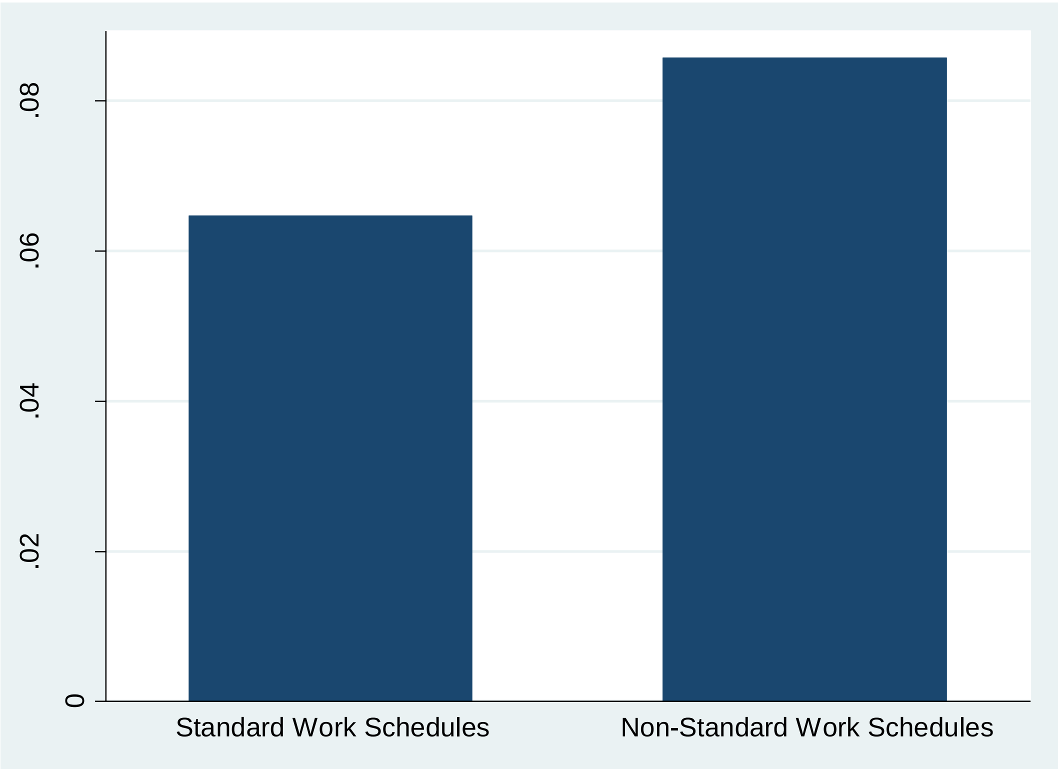

Maternal Employment and Adolescent Smoking



Maternal Non-Standard Work Schedules and Adolescent Drinking




Maternal Non-Standard Work Schedules and Adolescent Smoking



## Appendix 6B - Full regression output from LPM, GLS and FE-LPM specifications for adolescent drinking in Table 6.7

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | LPM | | GLS | | FE-LPM | |
| Child Age | | | | | | |
| 10 | (Omitted) | | (Omitted) | | (Omitted) | |
| 11 | 0.071*** | (0.009) | 0.076*** | (0.007) | 0.067*** | (0.010) |
| 12 | 0.134*** | (0.010) | 0.142*** | (0.009) | 0.118*** | (0.017) |
| 13 | 0.268*** | (0.010) | 0.275*** | (0.010) | 0.230*** | (0.021) |
| 14 | 0.425*** | (0.010) | 0.434*** | (0.010) | 0.397*** | (0.027) |
| 15 | 0.556*** | (0.010) | 0.567*** | (0.010) | 0.533*** | (0.033) |
| Maternal Age | -0.028*** | (0.006) | -0.027*** | (0.007) | -0.005 | (0.019) |
| (Maternal Age)$^2$ | 0.000*** | (0.000) | 0.000*** | (0.000) | 0.000 | (0.000) |
| Number of Children | -0.020*** | (0.003) | -0.019*** | (0.004) | -0.004 | (0.012) |
| Single Household | 0.028*** | (0.007) | 0.023*** | (0.008) | 0.003 | (0.020) |
| Self Employed | 0.017 | (0.013) | 0.016 | (0.015) | 0.041 | (0.028) |
| Girl | -0.011* | (0.006) | -0.013 | (0.008) | (Omitted) | |
| Region | | | | | | |
| North East | (Omitted) | | (Omitted) | | (Omitted) | |
| North West | -0.063*** | (0.019) | -0.059** | (0.024) | -0.510*** | (0.028) |
| Yorkshire/Humber | -0.007 | (0.020) | -0.015 | (0.025) | -0.515** | (0.215) |
| East Midlands | -0.022 | (0.020) | -0.032 | (0.025) | -0.990*** | (0.278) |
| West Midlands | -0.068*** | (0.020) | -0.072*** | (0.025) | -1.277*** | (0.191) |
| East of England | -0.023 | (0.020) | -0.024 | (0.025) | -0.696*** | (0.208) |
| London | -0.159*** | (0.019) | -0.174*** | (0.023) | -0.867*** | (0.186) |
| South East | -0.065*** | (0.019) | -0.060** | (0.024) | -0.816*** | (0.200) |
| South West | -0.040** | (0.020) | -0.038 | (0.026) | -0.509* | (0.265) |
| Wales | -0.015 | (0.021) | -0.026 | (0.026) | -0.840*** | (0.137) |
| Scotland | -0.090*** | (0.019) | -0.091*** | (0.024) | -0.753*** | (0.250) |
| Northern Ireland | -0.147*** | (0.020) | -0.157*** | (0.025) | (Omitted) | |
| Urban | -0.034*** | (0.008) | -0.037*** | (0.010) | 0.010 | (0.061) |
| Out After 9pm | 0.175*** | (0.009) | 0.140*** | (0.009) | 0.074*** | (0.012) |
| Meals With Family | | | | | | |
| Never | (Omitted) | | (Omitted) | | (Omitted) | |
| 1-2 | -0.023 | (0.014) | -0.017 | (0.014) | -0.023 | (0.019) |
| 3-5 | -0.035*** | (0.013) | -0.032** | (0.013) | -0.032* | (0.019) |
| 6-7 | -0.056*** | (0.013) | -0.051*** | (0.013) | -0.043** | (0.020) |
| Mat Mental Health | | | | | | |
| Top Quintile | (Omitted) | | (Omitted) | | (Omitted) | |
| 2nd Quintile | -0.004 | (0.010) | -0.002 | (0.009) | 0.001 | (0.012) |
| 3rd Quintile | -0.011 | (0.010) | -0.009 | (0.010) | -0.001 | (0.013) |
| 4th Quintile | -0.028*** | (0.010) | -0.021** | (0.010) | -0.007 | (0.013) |
| Bottom Quintile | -0.034*** | (0.010) | -0.019* | (0.010) | 0.017 | (0.015) |
| Alcohol Spending | 0.001*** | (0.000) | 0.001*** | (0.000) | 0.000 | (0.000) |
| Maternal Education | | | | | | |
| Degree Level | (Omitted) | | (Omitted) | | (Omitted) | |
| Other Higher | 0.029*** | (0.010) | 0.029** | (0.013) | -0.053 | (0.069) |
| A-Level | 0.021** | (0.010) | 0.018 | (0.012) | -0.087 | (0.061) |
| GCSE/O-Level | 0.025*** | (0.009) | 0.025** | (0.011) | 0.012 | (0.080) |
| Other Qualifications | 0.028** | (0.013) | 0.019 | (0.016) | -0.108 | (0.101) |
| No Qualifications | -0.033** | (0.013) | -0.043*** | (0.016) | -0.019 | (0.105) |
| Own House | -0.066*** | (0.008) | -0.056*** | (0.010) | 0.012 | (0.041) |
| Individuals | 8861 | | 8861 | | 8861 | |
| Observations | 18946 | | 18946 | | 18946 | |
| R-Squared | 0.230 | | 0.228 | | 0.240 | |

*Notes:* Clustered standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

## Appendix 6C - Full regression output from LPM, GLS and FE-LPM specifications for adolescent smoking in Table 6.7

| | (1) LPM | | (2) GLS | | (3) FE-LPM | |
|---|---|---|---|---|---|---|
| Child Age | | | | | | |
| 10 | (Omitted) | | (Omitted) | | (Omitted) | |
| 11 | 0.006* | (0.003) | 0.007** | (0.003) | 0.010* | (0.006) |
| 12 | 0.026*** | (0.004) | 0.029*** | (0.004) | 0.036*** | (0.009) |
| 13 | 0.055*** | (0.005) | 0.057*** | (0.005) | 0.065*** | (0.013) |
| 14 | 0.113*** | (0.006) | 0.112*** | (0.006) | 0.118*** | (0.017) |
| 15 | 0.175*** | (0.007) | 0.177*** | (0.007) | 0.196*** | (0.022) |
| Maternal Age | -0.008** | (0.004) | -0.004 | (0.004) | 0.048*** | (0.012) |
| (Maternal Age)$^2$ | 0.000* | (0.000) | 0.000 | (0.000) | -0.001*** | (0.000) |
| Number of Children | -0.006*** | (0.002) | -0.006*** | (0.002) | -0.002 | (0.007) |
| Single Household | 0.020*** | (0.004) | 0.018*** | (0.005) | 0.012 | (0.013) |
| Self Employed | 0.003 | (0.007) | 0.007 | (0.009) | 0.020 | (0.019) |
| Girl | 0.001 | (0.004) | 0.003 | (0.004) | (Omitted) | |
| Region | | | | | | |
| North East | (Omitted) | | (Omitted) | | (Omitted) | |
| North West | 0.003 | (0.012) | 0.002 | (0.015) | 0.130*** | (0.018) |
| Yorkshire/Humber | 0.007 | (0.012) | 0.004 | (0.015) | 0.057 | (0.133) |
| East Midlands | 0.003 | (0.012) | 0.001 | (0.015) | 0.027 | (0.156) |
| West Midlands | -0.023** | (0.011) | -0.024* | (0.014) | -0.061 | (0.128) |
| East of England | 0.020 | (0.012) | 0.017 | (0.015) | -0.174 | (0.152) |
| London | -0.010 | (0.011) | -0.015 | (0.014) | -0.008 | (0.125) |
| South East | -0.008 | (0.011) | -0.010 | (0.014) | -0.000 | (0.114) |
| South West | 0.011 | (0.012) | 0.012 | (0.016) | 0.119 | (0.148) |
| Wales | -0.008 | (0.013) | -0.010 | (0.016) | 0.322** | (0.135) |
| Scotland | -0.010 | (0.012) | -0.009 | (0.015) | -0.054 | (0.141) |
| Northern Ireland | -0.003 | (0.012) | -0.006 | (0.016) | (Omitted) | |
| Urban | 0.001 | (0.005) | 0.003 | (0.006) | -0.013 | (0.040) |
| Out After 9pm | 0.137*** | (0.008) | 0.112*** | (0.008) | 0.061*** | (0.010) |
| Meals With Family | | | | | | |
| Never | (Omitted) | | (Omitted) | | (Omitted) | |
| 1-2 | -0.026** | (0.010) | -0.022** | (0.010) | -0.007 | (0.012) |
| 3-5 | -0.033*** | (0.010) | -0.030*** | (0.010) | -0.017 | (0.013) |
| 6-7 | -0.048*** | (0.009) | -0.047*** | (0.010) | -0.033** | (0.013) |
| Mat Mental Health | | | | | | |
| Top Quintile | (Omitted) | | (Omitted) | | (Omitted) | |
| 2$^{nd}$ Quintile | -0.005 | (0.006) | -0.010 | (0.006) | -0.022*** | (0.008) |
| 3$^{rd}$ Quintile | -0.018*** | (0.006) | -0.019*** | (0.006) | -0.023*** | (0.008) |
| 4$^{th}$ Quintile | -0.017*** | (0.006) | -0.018*** | (0.006) | -0.025*** | (0.008) |
| Bottom Quintile | -0.027*** | (0.006) | -0.024*** | (0.006) | -0.019** | (0.009) |
| Alcohol Spending | 0.000*** | (0.000) | 0.000*** | (0.000) | 0.000 | (0.000) |
| Maternal Education | | | | | | |
| Degree Level | (Omitted) | | (Omitted) | | (Omitted) | |
| Other Higher | -0.007 | (0.006) | -0.008 | (0.007) | -0.100* | (0.055) |
| A-Level | -0.013** | (0.005) | -0.010 | (0.007) | -0.050 | (0.049) |
| GCSE/O-Level | 0.003 | (0.005) | 0.005 | (0.006) | -0.043 | (0.049) |
| Other Qualifications | 0.008 | (0.008) | 0.008 | (0.010) | -0.061 | (0.066) |
| No Qualifications | -0.005 | (0.009) | -0.003 | (0.010) | 0.003 | (0.063) |
| Own House | -0.034*** | (0.005) | -0.034*** | (0.006) | -0.006 | (0.023) |
| Individuals | 8861 | | 8861 | | 8861 | |
| Observations | 18946 | | 18946 | | 18946 | |
| R-Squared | 0.072 | | 0.072 | | 0.057 | |

*Notes:* Clustered standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

## Appendix 6D - Applying inverse probability weighting to check the robustness of the empirical estimates to missing data

**Table 6D1- Regression output from logit model**

| | |
|---|---|
| Mother Employed | 0.760*** |
| | (0.221) |
| Single Household | 0.116** |
| | (0.059) |
| Managerial/Profession | (Omitted) |
| Intermediate | -0.228** |
| | (0.114) |
| Semi/Self Employed | -0.237 |
| | (0.156) |
| Lower Supervisory | -0.545*** |
| | (0.184) |
| Semi Routine | -0.501*** |
| | (0.098) |
| Degree Level Education | (Omitted) |
| Other Higher | 0.305 |
| | 0.108 |
| A-Level | 0.138 |
| | 0.100 |
| GCSE/O-Level | 0.180 |
| | 0.093 |
| Other Qualifications | -0.435 |
| | 0.108 |
| No Qualifications | -0.877 |
| | 0.100 |
| Maternal Age | -0.080 |
| | (0.053) |
| (Maternal Age)$^2$ | 0.001 |
| | (0.001) |
| Observations | 20329 |
| Pseudo R-Squared | 0.038 |

*Notes:* Coefficients from a logit regression model. Clustered standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%

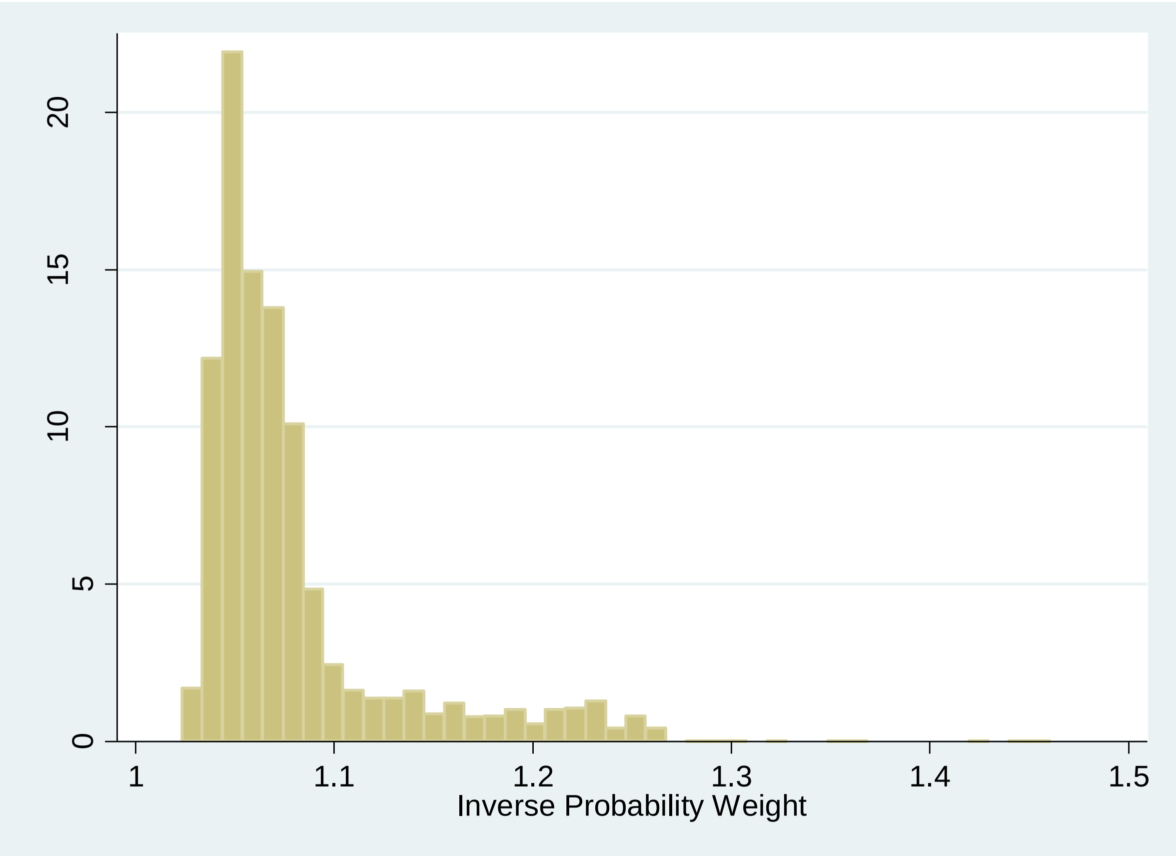



*Figure 6D1- Distribution of IPWs*

**Table 6D2- Regression output from LPM specifications with and without the implementation of inverse probability weights**

| | (1)<br>Drinking<br>Unweighted | (2)<br>Drinking<br>Weighted | (3)<br>Smoking<br>Unweighted | (4)<br>Smoking<br>Weighted |
|---|---|---|---|---|
| Employed | 0.048*** | 0.049*** | -0.010** | -0.010** |
| | (0.008) | (0.008) | (0.005) | (0.005) |
| Observations | 18946 | 18946 | 18946 | 18946 |
| R-squared | 0.230 | 0.229 | 0.072 | 0.073 |

*Notes:* Results from LPM specification. Clustered standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

## Appendix 6E - Full regression output from the 2SLS specifications in Table 6.16 and 6.17

| | Younger Siblings IV Strategy | | | | Local Labour Market Conditions IV Strategy | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | | (4) | |
| | Drinking | | Smoking | | Drinking | | Smoking | |
| Child Age | | | | | | | | |
| 10 | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| 11 | 0.073*** | (0.010) | 0.007** | (0.003) | 0.029** | (0.014) | 0.009 | (0.006) |
| 12 | 0.134*** | (0.011) | 0.024*** | (0.004) | 0.119*** | (0.015) | 0.023*** | (0.007) |
| 13 | 0.264*** | (0.012) | 0.048*** | (0.005) | 0.263*** | (0.016) | 0.061*** | (0.009) |
| 14 | 0.403*** | (0.012) | 0.097*** | (0.006) | 0.382*** | (0.016) | 0.112*** | (0.010) |
| 15 | 0.532*** | (0.012) | 0.152*** | (0.007) | 0.491*** | (0.016) | 0.169*** | (0.012) |
| Maternal Age | -0.006 | (0.008) | -0.007* | (0.004) | -0.033** | (0.014) | 0.000 | (0.009) |
| (Maternal Age)$^2$ | 0.000 | (0.000) | 0.000 | (0.000) | 0.000** | (0.000) | -0.000 | (0.000) |
| Number of Children | -0.062*** | (0.011) | -0.004 | (0.005) | -0.011 | (0.020) | -0.022* | (0.013) |
| Single Household | 0.028*** | (0.008) | 0.015*** | (0.004) | 0.016 | (0.011) | 0.017** | (0.007) |
| Self Employed | 0.140*** | (0.029) | 0.008 | (0.015) | 0.005 | (0.050) | 0.061* | (0.032) |
| Girl | 0.004 | (0.007) | 0.010*** | (0.004) | -0.000 | (0.009) | 0.009 | (0.006) |
| Region | | | | | | | | |
| North East | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| North West | -0.051** | (0.021) | 0.004 | (0.012) | -0.088*** | (0.026) | -0.007 | (0.018) |
| Yorkshire/Humber | 0.018 | (0.023) | 0.007 | (0.012) | -0.029 | (0.029) | 0.003 | (0.019) |
| East Midlands | -0.012 | (0.023) | 0.009 | (0.012) | -0.035 | (0.027) | -0.011 | (0.018) |
| West Midlands | -0.039* | (0.022) | -0.014 | (0.012) | -0.090*** | (0.029) | -0.017 | (0.019) |
| East of England | 0.014 | (0.022) | 0.027** | (0.012) | -0.022 | (0.029) | 0.039** | (0.020) |
| London | -0.169*** | (0.021) | -0.006 | (0.011) | -0.186*** | (0.027) | -0.023 | (0.018) |
| South East | -0.051** | (0.021) | 0.001 | (0.011) | -0.062** | (0.026) | -0.005 | (0.017) |
| South West | -0.007 | (0.023) | 0.018 | (0.013) | -0.060** | (0.028) | 0.015 | (0.019) |
| Wales | -0.009 | (0.023) | -0.003 | (0.013) | -0.041*** | (0.013) | -0.011 | (0.008) |
| Scotland | -0.067*** | (0.022) | -0.009 | (0.012) | -0.088*** | (0.026) | -0.007 | (0.018) |
| Northern Ireland | -0.149*** | (0.023) | -0.003 | (0.012) | -0.029 | (0.029) | 0.003 | (0.019) |
| Urban | -0.040*** | (0.009) | -0.002 | (0.005) | -0.035 | (0.027) | -0.011 | (0.018) |
| Mat Mental Health | | | | | | | | |
| Top Quintile | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| 2nd Quintile | 0.046*** | (0.016) | -0.005 | (0.009) | 0.004 | (0.025) | 0.042** | (0.017) |
| 3rd Quintile | 0.066*** | (0.020) | -0.015 | (0.010) | 0.000 | (0.033) | 0.028 | (0.021) |
| 4th Quintile | 0.051** | (0.021) | -0.014 | (0.011) | -0.023 | (0.034) | 0.027 | (0.022) |
| Bottom Quintile | 0.031 | (0.019) | -0.025** | (0.010) | -0.040 | (0.033) | 0.007 | (0.021) |
| Alcohol Spending | 0.001*** | (0.000) | 0.000*** | (0.000) | 0.001*** | (0.000) | 0.000*** | (0.000) |
| Out After 9pm | 0.177*** | (0.010) | 0.136*** | (0.008) | 0.179*** | (0.013) | 0.153*** | (0.012) |
| Meals With Family | | | | | | | | |
| Never | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| 1-2 | -0.033** | (0.016) | -0.026** | (0.010) | -0.014 | (0.021) | -0.009 | (0.016) |
| 3-5 | -0.050*** | (0.015) | -0.032*** | (0.010) | -0.031 | (0.020) | -0.022 | (0.015) |
| 6-7 | -0.082*** | (0.015) | -0.048*** | (0.010) | -0.046** | (0.020) | -0.051*** | (0.015) |
| Maternal Education | | | | | | | | |
| Degree Level | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| Other Higher | 0.026** | (0.011) | -0.012** | (0.006) | 0.036** | (0.016) | -0.002 | (0.010) |
| A-Level | 0.002 | (0.011) | -0.016*** | (0.006) | 0.043*** | (0.016) | -0.014 | (0.010) |
| GCSE/O-Level | -0.033** | (0.016) | -0.002 | (0.008) | 0.041 | (0.026) | -0.015 | (0.017) |
| Other Qualifications | -0.081*** | (0.026) | -0.002 | (0.014) | 0.056 | (0.042) | -0.041 | (0.027) |
| No Qualifications | -0.229*** | (0.042) | -0.017 | (0.021) | -0.022 | (0.073) | -0.092* | (0.048) |
| Own House | 0.040* | (0.023) | -0.025** | (0.012) | -0.067* | (0.040) | 0.018 | (0.026) |
| Individuals | 8861 | | 8861 | | 5123 | | 5123 | |
| Observations | 18946 | | 18946 | | 8267 | | 8267 | |
| R-Squared | 0.075 | | 0.072 | | 0.241 | | 0.069 | |

*Notes:* Full regression output from LPM specifications. Robust standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

## Appendix 6F - Full regression output from LPM, GLS and FE-LPM specifications for adolescent drinking in Table 6.18

| | (1) LPM | | (2) GLS | | (3) FE-LPM | |
|---|---|---|---|---|---|---|
| Child Age | | | | | | |
| 10 | (Omitted) | | (Omitted) | | (Omitted) | |
| 11 | 0.071*** | (0.009) | 0.076*** | (0.007) | 0.065*** | (0.010) |
| 12 | 0.132*** | (0.010) | 0.142*** | (0.009) | 0.113*** | (0.017) |
| 13 | 0.266*** | (0.010) | 0.275*** | (0.010) | 0.224*** | (0.022) |
| 14 | 0.423*** | (0.010) | 0.434*** | (0.010) | 0.389*** | (0.027) |
| 15 | 0.552*** | (0.010) | 0.567*** | (0.010) | 0.523*** | (0.034) |
| Maternal Age | -0.027*** | (0.006) | -0.027*** | (0.007) | 0.006 | (0.019) |
| (Maternal Age)$^2$ | 0.000*** | (0.000) | 0.000*** | (0.000) | 0.000 | (0.000) |
| Number of Children | -0.021*** | (0.004) | -0.019*** | (0.004) | -0.004 | (0.012) |
| Single Household | 0.027*** | (0.007) | 0.023*** | (0.008) | 0.003 | (0.020) |
| Self Employed | 0.023* | (0.013) | 0.016 | (0.015) | 0.041 | (0.028) |
| Girl | -0.010* | (0.006) | -0.013 | (0.008) | (Omitted) | |
| Region | | | | | | |
| North East | (Omitted) | | (Omitted) | | (Omitted) | |
| North West | -0.063*** | (0.019) | -0.059** | (0.024) | -0.510*** | (0.028) |
| Yorkshire/Humber | -0.006 | (0.020) | -0.015 | (0.025) | -0.515** | (0.215) |
| East Midlands | -0.021 | (0.020) | -0.032 | (0.025) | -0.990*** | (0.278) |
| West Midlands | -0.064*** | (0.020) | -0.072*** | (0.025) | -1.277*** | (0.191) |
| East of England | -0.020 | (0.020) | -0.024 | (0.025) | -0.696*** | (0.208) |
| London | -0.159*** | (0.019) | -0.174*** | (0.023) | -0.867*** | (0.186) |
| South East | -0.064*** | (0.019) | -0.060** | (0.024) | -0.816*** | (0.200) |
| South West | -0.037* | (0.020) | -0.038 | (0.026) | -0.509* | (0.265) |
| Wales | -0.015 | (0.021) | -0.026 | (0.026) | -0.840*** | (0.137) |
| Scotland | -0.088*** | (0.019) | -0.091*** | (0.024) | -0.753*** | (0.250) |
| Northern Ireland | -0.145*** | (0.020) | -0.157*** | (0.025) | (Omitted) | |
| Urban | -0.034*** | (0.008) | -0.037*** | (0.010) | 0.010 | (0.061) |
| Out After 9pm | 0.175*** | (0.009) | 0.140*** | (0.009) | 0.075*** | (0.012) |
| Meals With Family | | | | | | |
| Never | (Omitted) | | (Omitted) | | (Omitted) | |
| 1-2 | -0.023* | (0.014) | -0.018 | (0.014) | -0.023 | (0.018) |
| 3-5 | -0.035*** | (0.013) | -0.032** | (0.013) | -0.031* | (0.019) |
| 6-7 | -0.055*** | (0.013) | -0.051*** | (0.013) | -0.043** | (0.019) |
| Mat Mental Health | | | | | | |
| Top Quintile | (Omitted) | | (Omitted) | | (Omitted) | |
| 2nd Quintile | -0.002 | (0.010) | -0.002 | (0.009) | 0.001 | (0.012) |
| 3rd Quintile | -0.009 | (0.010) | -0.009 | (0.010) | -0.001 | (0.013) |
| 4th Quintile | -0.025** | (0.010) | -0.021** | (0.010) | -0.007 | (0.013) |
| Bottom Quintile | -0.032*** | (0.010) | -0.019* | (0.010) | 0.017 | (0.015) |
| Alcohol Spending | 0.001*** | (0.000) | 0.001*** | (0.000) | 0.000 | (0.000) |
| Maternal Education | | | | | | |
| Degree Level | (Omitted) | | (Omitted) | | (Omitted) | |
| Other Higher | 0.029*** | (0.010) | 0.029** | (0.013) | -0.053 | (0.069) |
| A-Level | 0.021** | (0.010) | 0.018 | (0.012) | -0.087 | (0.061) |
| GCSE/O-Level | 0.025*** | (0.009) | 0.025** | (0.011) | 0.012 | (0.080) |
| Other Qualifications | 0.028** | (0.013) | 0.019 | (0.016) | -0.108 | (0.101) |
| No Qualifications | -0.033** | (0.013) | -0.043*** | (0.016) | -0.019 | (0.105) |
| Own House | -0.066*** | (0.008) | -0.056*** | (0.010) | 0.012 | (0.041) |
| Individuals | 8861 | | 8861 | | 8861 | |
| Observations | 18946 | | 18946 | | 18946 | |
| R-Squared | 0.247 | | 0.240 | | 0.251 | |

*Notes:* Full regression output from columns 1- 3 in Table 6.15 Clustered standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

## Appendix 6G - Full regression output from LPM, GLS and FE-LPM specifications for adolescent smoking in Table 6.18

| | (1) LPM | | (2) GLS | | (3) FE-LPM | |
|---|---|---|---|---|---|---|
| Child Age | | | | | | |
| 10 | (Omitted) | | (Omitted) | | (Omitted) | |
| 11 | 0.006* | (0.003) | 0.007** | (0.003) | 0.011* | (0.006) |
| 12 | 0.026*** | (0.004) | 0.029*** | (0.004) | 0.037*** | (0.009) |
| 13 | 0.055*** | (0.005) | 0.057*** | (0.005) | 0.066*** | (0.013) |
| 14 | 0.113*** | (0.006) | 0.112*** | (0.006) | 0.120*** | (0.017) |
| 15 | 0.175*** | (0.007) | 0.177*** | (0.007) | 0.199*** | (0.022) |
| Maternal Age | -0.008** | (0.004) | -0.004 | (0.004) | 0.045*** | (0.012) |
| (Maternal Age)$^2$ | 0.000* | (0.000) | 0.000 | (0.000) | -0.001*** | (0.000) |
| Number of Children | -0.006*** | (0.002) | -0.006*** | (0.002) | -0.002 | (0.007) |
| Single Household | 0.020*** | (0.004) | 0.018*** | (0.005) | 0.012 | (0.013) |
| Self Employed | 0.003 | (0.007) | 0.007 | (0.009) | 0.020 | (0.019) |
| Girl | 0.001 | (0.004) | 0.003 | (0.004) | (Omitted) | |
| Region | | | | | | |
| North East | (Omitted) | | (Omitted) | | (Omitted) | |
| North West | 0.003 | (0.012) | 0.002 | (0.015) | 0.130*** | (0.018) |
| Yorkshire/Humber | 0.007 | (0.012) | 0.004 | (0.015) | 0.057 | (0.133) |
| East Midlands | 0.003 | (0.012) | 0.001 | (0.015) | 0.027 | (0.156) |
| West Midlands | -0.023** | (0.011) | -0.024* | (0.014) | -0.061 | (0.128) |
| East of England | 0.020 | (0.012) | 0.017 | (0.015) | -0.174 | (0.152) |
| London | -0.010 | (0.011) | -0.015 | (0.014) | -0.008 | (0.125) |
| South East | -0.008 | (0.011) | -0.010 | (0.014) | -0.000 | (0.114) |
| South West | 0.011 | (0.012) | 0.012 | (0.016) | 0.119 | (0.148) |
| Wales | -0.008 | (0.013) | -0.010 | (0.016) | 0.322** | (0.135) |
| Scotland | -0.010 | (0.012) | -0.009 | (0.015) | -0.054 | (0.141) |
| Northern Ireland | -0.003 | (0.012) | -0.006 | (0.016) | (Omitted) | |
| Urban | 0.001 | (0.005) | 0.003 | (0.006) | -0.013 | (0.040) |
| Out After 9pm | 0.138*** | (0.008) | 0.112*** | (0.008) | 0.061*** | (0.010) |
| Meals With Family | | | | | | |
| Never | (Omitted) | | (Omitted) | | (Omitted) | |
| 1-2 | -0.026** | (0.010) | -0.021** | (0.010) | -0.007 | (0.012) |
| 3-5 | -0.033*** | (0.010) | -0.030*** | (0.010) | -0.017 | (0.013) |
| 6-7 | -0.048*** | (0.009) | -0.047*** | (0.010) | -0.033** | (0.013) |
| Mat Mental Health | | | | | | |
| Top Quintile | (Omitted) | | (Omitted) | | (Omitted) | |
| 2nd Quintile | -0.005 | (0.006) | -0.010 | (0.006) | -0.022*** | (0.008) |
| 3rd Quintile | -0.018*** | (0.006) | -0.019*** | (0.006) | -0.023*** | (0.008) |
| 4th Quintile | -0.017*** | (0.006) | -0.018*** | (0.006) | -0.025*** | (0.008) |
| Bottom Quintile | -0.027*** | (0.006) | -0.024*** | (0.006) | -0.019** | (0.009) |
| Alcohol Spending | 0.000*** | (0.000) | 0.000*** | (0.000) | 0.000 | (0.000) |
| Maternal Education | | | | | | |
| Degree Level | (Omitted) | | (Omitted) | | (Omitted) | |
| Other Higher | -0.007 | (0.006) | -0.008 | (0.007) | -0.100* | (0.055) |
| A-Level | -0.013** | (0.005) | -0.010 | (0.007) | -0.050 | (0.049) |
| GCSE/O-Level | 0.003 | (0.005) | 0.005 | (0.006) | -0.043 | (0.049) |
| Other Qualifications | 0.008 | (0.008) | 0.008 | (0.010) | -0.061 | (0.066) |
| No Qualifications | -0.005 | (0.009) | -0.003 | (0.010) | 0.003 | (0.063) |
| Own House | -0.034*** | (0.005) | -0.034*** | (0.006) | -0.006 | (0.023) |
| Individuals | 8861 | | 8861 | | 8861 | |
| Observations | 18946 | | 18946 | | 18946 | |
| R-Squared | 0.072 | | 0.071 | | 0.058 | |

*Notes:* Full regression output from columns 4- 6 in Table 6.15. Clustered standard errors in parentheses. *** sig at 1%, ** at 5%, * at 10%.

# Appendix 6H - Full regression output for LPM and GLS specifications in Table 6.23

| | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| | Drinking | | | | Smoking | | | |
| | LPM | | GLS | | LPM | | GLS | |
| Mat Work Hrs | 0.004 | (0.037) | 0.007 | (0.037) | 0.003 | (0.020) | -0.002 | (0.020) |
| (Mat Work Hrs)$^2$ | 0.004 | (0.011) | 0.003 | (0.011) | 0.003 | (0.006) | 0.004 | (0.006) |
| Wage | 0.009 | (0.014) | 0.012 | (0.014) | 0.005 | (0.008) | 0.007 | (0.008) |
| Child Age | | | | | | | | |
| 10 | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| 11 | 0.160*** | (0.015) | 0.165*** | (0.015) | 0.009* | (0.006) | 0.017** | (0.007) |
| 12 | 0.184*** | (0.015) | 0.188*** | (0.015) | 0.011* | (0.006) | 0.022*** | (0.007) |
| 13 | 0.341*** | (0.017) | 0.344*** | (0.017) | 0.046*** | (0.008) | 0.056*** | (0.009) |
| 14 | 0.544*** | (0.017) | 0.546*** | (0.017) | 0.113*** | (0.011) | 0.115*** | (0.011) |
| 15 | 0.652*** | (0.017) | 0.660*** | (0.017) | 0.159*** | (0.013) | 0.163*** | (0.013) |
| Maternal Age | -0.029** | (0.013) | -0.031** | (0.013) | -0.017** | (0.007) | -0.014* | (0.008) |
| (Maternal Age)$^2$ | 0.000** | (0.000) | 0.000** | (0.000) | 0.000** | (0.000) | 0.000* | (0.000) |
| Number of Children | -0.021*** | (0.008) | -0.021*** | (0.008) | -0.005 | (0.005) | -0.002 | (0.005) |
| Single Household | 0.036*** | (0.014) | 0.033** | (0.014) | 0.023*** | (0.008) | 0.027*** | (0.009) |
| Girl | -0.001 | (0.012) | -0.001 | (0.012) | -0.002 | (0.007) | -0.001 | (0.007) |
| Region | | | | | | | | |
| North East | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| North West | -0.070** | (0.035) | -0.065* | (0.035) | -0.010 | (0.023) | -0.010 | (0.025) |
| Yorkshire/Humber | 0.038 | (0.037) | 0.041 | (0.037) | -0.028 | (0.023) | -0.032 | (0.025) |
| East Midlands | -0.002 | (0.037) | -0.003 | (0.037) | -0.019 | (0.024) | -0.015 | (0.026) |
| West Midlands | -0.023 | (0.037) | -0.019 | (0.036) | -0.043* | (0.022) | -0.046* | (0.024) |
| East of England | -0.053 | (0.036) | -0.047 | (0.036) | -0.030 | (0.023) | -0.034 | (0.024) |
| London | -0.156*** | (0.035) | -0.155*** | (0.035) | -0.046** | (0.022) | -0.050** | (0.024) |
| South East | -0.044 | (0.035) | -0.045 | (0.034) | -0.030 | (0.022) | -0.031 | (0.023) |
| South West | -0.055 | (0.037) | -0.050 | (0.037) | -0.030 | (0.022) | -0.032 | (0.024) |
| Wales | -0.016 | (0.039) | -0.015 | (0.038) | -0.045* | (0.024) | -0.045* | (0.025) |
| Scotland | -0.090*** | (0.035) | -0.088** | (0.034) | -0.035 | (0.022) | -0.035 | (0.024) |
| Northern Ireland | -0.157*** | (0.037) | -0.155*** | (0.036) | -0.031 | (0.023) | -0.038 | (0.024) |
| Urban | -0.024* | (0.014) | -0.026* | (0.014) | 0.009 | (0.008) | 0.011 | (0.008) |
| Out After 9pm | 0.167*** | (0.017) | 0.159*** | (0.017) | 0.149*** | (0.016) | 0.133*** | (0.015) |
| Meals With Family | | | | | | | | |
| Never | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| 1-2 | 0.002 | (0.026) | 0.008 | (0.026) | -0.033* | (0.019) | -0.027 | (0.018) |
| 3-5 | -0.008 | (0.025) | -0.005 | (0.025) | -0.033* | (0.019) | -0.029 | (0.018) |
| 6-7 | -0.034 | (0.025) | -0.031 | (0.024) | -0.058*** | (0.018) | -0.054*** | (0.017) |
| Mat Mental Health | | | | | | | | |
| Top Quintile | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| 2nd Quintile | 0.016 | (0.019) | 0.014 | (0.019) | -0.028** | (0.012) | -0.031*** | (0.012) |
| 3rd Quintile | 0.005 | (0.019) | 0.002 | (0.018) | -0.026** | (0.012) | -0.034*** | (0.012) |
| 4th Quintile | -0.008 | (0.018) | -0.012 | (0.018) | -0.030*** | (0.012) | -0.032*** | (0.012) |
| Bottom Quintile | -0.003 | (0.020) | -0.008 | (0.019) | -0.029** | (0.013) | -0.032** | (0.013) |
| Alcohol Spending | 0.001*** | (0.000) | 0.001*** | (0.000) | 0.000 | (0.000) | 0.000*** | (0.000) |
| Maternal Education | | | | | | | | |
| Degree Level | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| Other Higher | 0.035* | (0.018) | 0.038** | (0.018) | 0.009 | (0.010) | 0.009 | (0.011) |
| A-Level | 0.028 | (0.019) | 0.027 | (0.019) | -0.011 | (0.010) | -0.007 | (0.011) |
| GCSE/O-Level | 0.052*** | (0.019) | 0.055*** | (0.018) | 0.014 | (0.011) | 0.017 | (0.012) |
| Other Qualifications | 0.043 | (0.030) | 0.039 | (0.029) | 0.025 | (0.020) | 0.020 | (0.021) |
| No Qualifications | -0.027 | (0.037) | -0.028 | (0.037) | -0.001 | (0.023) | 0.003 | (0.024) |
| Own House | -0.031* | (0.017) | -0.031* | (0.017) | -0.028*** | (0.011) | -0.030*** | (0.011) |
| Maternal Occupation | | | | | | | | |
| Management/ Professional | (Omitted) | | (Omitted) | | (Omitted) | | (Omitted) | |
| Intermediate | -0.012 | (0.017) | -0.010 | (0.017) | 0.004 | (0.010) | 0.002 | (0.010) |
| Small Employers | -0.006 | (0.158) | 0.004 | (0.153) | 0.003 | (0.025) | -0.010 | (0.024) |

## Appendix 6H- Full regression output for LPM and GLS specifications in Table 6.20 (continued)

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Lower Supervisory | -0.003 | (0.031) | 0.000 | (0.031) | 0.003 | (0.019) | -0.003 | (0.019) |
| Semi Routine/Routine | -0.005 | (0.018) | -0.005 | (0.018) | 0.015 | (0.011) | 0.013 | (0.011) |
| Individuals | 3,983 | | 3,983 | | 3,983 | | 3,983 | |
| Observations | 5,566 | | 5,566 | | 5,566 | | 5,566 | |
| R-Squared | 0.269 | | 0.267 | | 0.078 | | 0.077 | |

*Notes:* Full regression output from LPM, GLS and FE-LPM specifications. Clustered standard errors in parentheses. *** significant at 1%, ** at 5%, * at 10%.

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