Family income and children's outcomes: evidence for the UK

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I declare that all the material contained in this thesis is my own work. All errors and omissions are solely my responsibility

Olivia Birchall

Abstract

This thesis explores inequalities in educational attainment by family background, focusing on three specific aspects of this important issue.

University participation is one outcome which displays large gaps by family background. I examine the effect of debt aversion on university participation and find firstly, that young people from all family backgrounds who are debt averse are less likely to attend university when they finish school, and secondly, that the size of this effect does not differ substantially by family background. Thus whilst debt aversion poses a barrier to entry into university, it doesn't explain the gap in participation rates by family background. In fact, these gaps open up much earlier and are already apparent when the children are still very young.

The second empirical chapter uses data at ages 5 and 7 to explore this further, and shows that family income itself seems to have a direct impact on children's cognitive test scores at these ages, with other important influential factors including the stability of the child's environment, the presence of the natural father, and parental behaviours such as taking the child to the library regularly. As well as highlighting the importance of these and other factors, this chapter makes a methodological contribution by introducing an augmented random effects model which helps address issues of endogeneity and a lack of within-variation in key variables that have faced similar studies in the past.

Finally, children's test scores demonstrate substantial stochastic variation, with the implication that the development trajectories of groups divided according to ability and family background may demonstrate regression to the mean effects. Dealing with this statistical phenomenon using various methods in order to isolate the substantive effects of family background confirms that bright children from poorer families do drop behind their peers, providing justification for a continued policy focus on this group.

The existence of inequalities in educational outcomes by family background also has implications for social mobility, which further highlights the importance of investing in the cognitive development of young children from disadvantaged backgrounds.

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British longitudinal datasets referred to in the follow chapters:

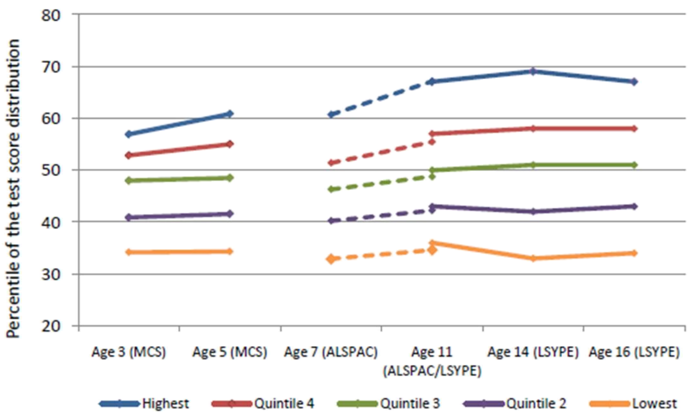
Dataset	Abbreviation	Country	Initial Sample Size	Timespan
National Child Development Study	NCDS	UK	17,000	1958 - present
British Cohort Study	BCS	UK	17,000	1970 - present
Millennium Cohort Study	MCS	UK	19,000	2000 - present
Longitudinal Survey of Young People in England	LSYPE	England	21,000	1994 - 2010

1 Introduction

1.1 Family Income and Children's Outcomes in the UK

This thesis examines the relationship between parental income and certain educational and cognitive outcomes of their children. A long tradition of research has established that there is a clear link between the socio-economic background of one's parents, and the prospects of that individual in regards to their education and other outcomes later in life (e.g. see Hanushek, 1986; Haveman and Wolfe, 1995; Dearden *et al*, 2011b). Examining outcomes for individuals grouped according to their family background demonstrates large gaps between people from the most advantaged and most disadvantaged families. More recent research has attempted to establish when these gaps appear and to trace them throughout an individuals' lifetime. For example, the following figure, using data from three large-scale longitudinal surveys, indicates that although there are already gaps in cognitive achievement by socio-economic background at age 3, these are substantially larger by age 16.

Figure 1-1 Cognitive Achievement outcomes by socio-economic position quintile, across surveys and ages



Notes: *Children in each survey are divided into fifths, ranked according to a constructed measure of socio-economic position based on their parents' income, social class, housing tenure, and a self-reported measure of financial difficulties. The chart plots the average cognitive achievement measures for each group from the ages of 3 through to 16.*

Source: Goodman *et al* (2011), p5. *Longitudinal and Life Course Studies* special edition on "The socio-economic gradient in cognitive and educational achievement"

The effect of family income on children's achievements is complex and works through a large number of economic and social variables – from experiences in the womb, to family structure and the home environment, and to the variations in financial support that it also implies. Various studies have attempted to identify which factors have the greatest impact (e.g. Gregg *et al*, 2007, Violato *et al,* 2011). One important question is the issue of whether family income itself has a causal impact on children's cognitive outcomes or whether it merely reflects other influences (Mayer, 1997). Since family income is strongly correlated with many other aspects of family background and the home environment, this introduces methodological issues which must be addressed in order to reach clear conclusions on the true mechanisms behind the relationship between parent's income and their children's educational and cognitive outcomes.

This thesis will contribute to the current literature on this topic by examining three specific aspects of the relationship between parental income and outcomes.

- In Chapter 3, I undertake an analysis of what determines the university participation decision, with a particular focus on the effect of debt aversion on this decision. Participation in HE is an important avenue for progression for those from poorer families, and it is possible that differential perceptions of debt act as a barrier.
- Chapter 4 then analyses the early years of a child's life, with a focus on differences in the cognitive development of children from different family backgrounds between ages 5 and 7 when the children have just started school. I look at the role played by various factors in explaining this gap, examining the influence of family income *per se*, school related factors as well as a broad range of other individual, family and environmental factors.
- Chapter 5 then revisits the work of Feinstein (2003) in examining trajectories in the development of children from different family income groups. In particular, I use methods that are robust to regression to the mean, given the recent assertion (see for instance, Jerrim and Vignoles,

2013) that this phenomenon has led to a mistaken view of the relative progress of bright children from disadvantaged backgrounds.

The relationship between the income and outcomes of individual parents and children is of course related to the larger issue of intergenerational mobility in society as a whole. This will be discussed in more detail in the following section, with particular emphasis on the role of education as a facilitator or possible hindrance to social mobility.

1.2 The Role of Education in Social Mobility

In recent years, there has been a significant government policy interest in social mobility and the links between the economic success or failure of family members from consecutive generations. One key element of this is education, however, the role of education has been described as “one of the great unsolved debates in our thinking about social mobility” (Major, 2012). On the one hand, there is a general consensus amongst policymakers and academics that education can play a key role in breaking the inter-generational transfer of social disadvantage, and allow each individual (no matter what their background) to reach the level of achievement that reflects their own abilities and talents, rather than their parents’. On the other hand however, it is also the case that research can cast education as a perpetuator of social (dis)advantage, as socio-economic background is highly correlated with educational achievement at various stages of the lifecycle. Put differently, the key question in this debate is whether education functions as “the great social leveller” or rather “enables the privileged to consolidate their position in society” (Major, 2012, pp. 155). Although it is generally assumed that education is the key which provides a way out of inherited disadvantage, much of the empirical literature on this point has actually indicated that, at least in the UK and the US, education has played a strong and even increasing role in perpetuating socio-economic advantage in recent decades and has thus been a force for social immobility.

Possible mechanisms behind the inheritance of inequality in the United States are explored in Bowles and Gintis (2002), examining a heterogeneous collection of mechanisms, including the genetic and cultural transmission of cognitive skills and non-cognitive personality traits in demand by employers, the inheritance of wealth and income-enhancing group memberships, such as race, and the superior education and health status enjoyed by the children of higher status families. They find that education, race and wealth have been the key drivers of income persistence. This is supported by findings from Restuccia and Urrutia (2004) who find that approximately one-half of the intergenerational correlation in earnings in the US is accounted for by parental investment in education, in particular early education. In terms of policy recommendations, they find that the impact of an increase in public resources devoted to early education is greater than that of an increase in college subsidies.

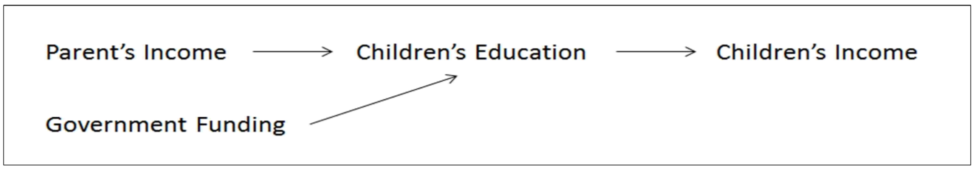
Key factors determining the degree of social mobility in the UK are examined in Blanden *et al* (2007). They focus in particular on non-cognitive traits, cognitive skills, educational attainment and labour market attachment and employ a decomposition approach to evaluate the relative contributions of these factors. By estimating the univariate relationship between parental income and each of these variables individually and then combining these results with the return on each variable from an earnings equation, they find that education is the key transmission mechanism for the persistence in the socio-economic outcomes considered (income and social class), as parent's income affects children's educational outcomes and this in turn affects their own earnings. Non-cognitive variables and cognitive skills are also important contributors, accounting for 0.06 points (19%) and 0.09 points (27%) of the 0.32 intergenerational co-efficient respectively. It should be noted, furthermore, that these factors also have an important indirect role in determining educational attainment. In addition, the authors explore the factors which contributed to the decline in intergenerational income mobility between the 1958 cohort and the 1970 cohort. Of particular significance is the decline in the importance of ability and rise in the importance of parent's income in the determination of children's educational outcomes.

Further evidence which portrays education as a perpetrator of social advantage is provided in Lindley and Machin (2012) which shows that “people from already-rich family backgrounds … are increasingly reaping higher rewards in the labour market from their higher qualifications” (p283). The large increase in university participation, and especially more recently of post-graduate qualifications, has occurred primarily among people from rich backgrounds. Coupled with rising wage differentials for the more educated, this has led to increasing inequality within generations, and since this has reinforced existing inequalities, the end result has been a fall in social mobility. Blanden and Macmillan (2004) describes this as an unintended but nonetheless very real consequence of education policy in the UK.

Education has been targeted as a policy instrument for improving social mobility in many countries and for some time. However, Esping-Anderson (2004) argues that this focus has been misguided. He points out that the Netherlands, for example, has seen a clear increase in mobility despite spending less than the OECD average on education, and argues further that while educational-system characteristics such as tracking or the mix of public and private schools may help account for group-specific mobility patterns, they generally fail to explain overall mobility differences. Through a detailed analysis of education and social mobility in the OECD countries, he concludes that “social inheritance remains as pervasive as ever in large part because education systems largely reproduce pre-existing inequalities” (p309). He argues that the assumption that formal education can completely undo these inequalities has led to a misplaced focus of public policy on education (be it through redistributive investment as in the Becker model or through system reform). Rather than continuing this narrow focus, he recommends a shift to other mechanisms including the early years, “cultural capital”, cognitive ability and parenting.

In the past, the role of education in social mobility may have been conceived of rather simplistically, as in the following model. In this diagram, there is a single arrow from parent’s income to their children’s education, which can also be substituted by public investment such as government grants to higher education. This model implies that the only hindrance to increased educational attainment by young people from disadvantaged families is their inability to invest in their desired level of education (due to credit constraints) and that government funds can be injected to substitute family resources.

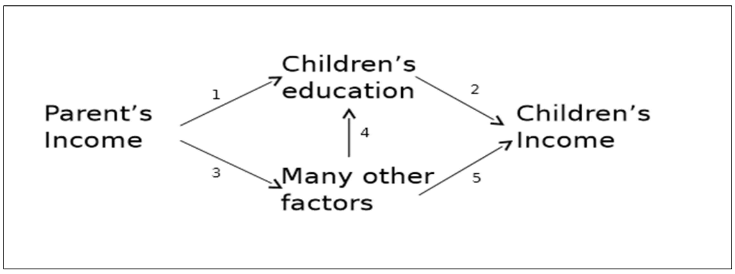
Figure 1-2: Simple model of the role of education in social mobility



Source: own representation

However, there has been a government policy focus on widening participation for some time, and the link between children's education and parental income has actually strengthened despite this. This could in part be related to changes to the education system, such as the decline of grammar schools, for example. More broadly, it also could be because the above model is too simplistic and ignores many other factors that are strongly correlated with parents' income and affect both the children's education and their final outcomes. The influence of parent's income on their children's education is much more complex than the simplistic representation above implies. Parents' income is both correlated directly with children's educational attainment and also with a whole host of other characteristics. These characteristics influence children's educational attainment, and also have a direct impact themselves on the children's later incomes. This can be represented by the following diagram.

Figure 1-3: Extended model of education and other factors affecting social mobility



Source: Own representation

This demonstrates the importance of other factors that are correlated with family income. In particular, arrows 3 and 4 are neglected in the above, more simplistic, conception of this relationship, and will be examined in detail in this thesis.

Education is and remains a key determinant of labour market access and wage levels. For children from disadvantaged backgrounds, it can help them leave their background behind and make a way for themselves according to their own talents and abilities, while for children from advantaged backgrounds, it helps them to maintain this standing and even capitalise on it further. However, looking at the evidence for the UK over the past few decades, the relationship between parent's income and children's education has strengthened, despite widening participation policies which have aimed to reduce the gap in educational attainment between children from more or less advantaged families (Galindo-Rueda and Vignoles, 2005; Blanden and Machin, 2004), such that education has acted as a strong force to perpetuate advantage, rather than being an effective mechanism to increase social mobility.

This thesis will examine the gaps in educational attainment between children and young people from different family backgrounds and explore barriers which exist to improved attainment and increased participation. These issues will be explored within the framework of human capital theory, which will be described in the following section.

1.3 Theoretical Framework: The Human Capital Model

This thesis examines young people's decision regarding whether or not to participate in university and also explores gaps in cognitive ability that open up between children from different family backgrounds very early in life. These are two key points in the educational process where outcomes have a strong influence on the ability of poorer children to progress in the labour market later in life, and where there has been some lack of success of government policy in equalizing outcomes between children from different family backgrounds. Both of these issues can be understood within the theoretical framework of human capital theory.

This theory regards education as more than a consumption good – much more as an investment which makes people more productive and generates a return in the labour market. It also provides insights into the rise and fall of families and the determinants of intergenerational mobility. Following a brief overall introduction to the theory of human capital, two models that have been proposed to explain the university participation decision and intergenerational mobility from this theoretical perspective will be briefly laid out. This will be followed by a brief discussion of some very recent papers giving a modern perspective on human capital.

Human capital theory was first introduced in the late 1950s and early 1960s especially through the work of Jacob Mincer, Theodore Schultz and Gary Becker. These economists discussed the importance of investments in human beings, such as training, education and health services. Starting to view activities such as education as investments in man provided answers to an array of phenomenon for which there had been *ad hoc* theories, or no real answers at all (Becker, 1962). This approach also gave insight into two key paradoxes – the growth of the economy relative to the growth of physical capital (Schultz, 1961); and the skewness of the income distribution relative to the distribution of ability (Mincer, 1958). Human capital theory has continued to develop over the last half-century and has become a core area of analysis within economics.

The key idea is that investments in human beings, such as education, on-the-job-training and so on can be seen as analogous to investments in physical capital such as factories and machines. Activities which “influence future real incomes through the imbedding of resources in people” (Becker, 1962, p9) can be seen as investments in human capital. According to this theory, people will invest in human capital to the point where their marginal cost of investing is equal to the marginal return of this investment. Returns to human capital are most often in the form of higher wages and a faster increase in wages over the lifetime. Young people have a greater incentive to invest in human capital as they will be able to accrue the benefits of this over a longer period, and also because their opportunity cost of taking time away from work to improve their skills and increase their knowledge is lower than for people who have already spent some considerable time in the workforce. In terms of measuring human capital, one common approach is to measure inputs, e.g. years of post-secondary education or months on the job, whilst an alternative approach is to itemize certain achievements, such as degrees attained (Blair, 2011). Both approaches have limitations however, as “human capital takes many forms, including skills and abilities, personality, appearance, reputation, and appropriate credentials” (Becker and Tomes, 1986).

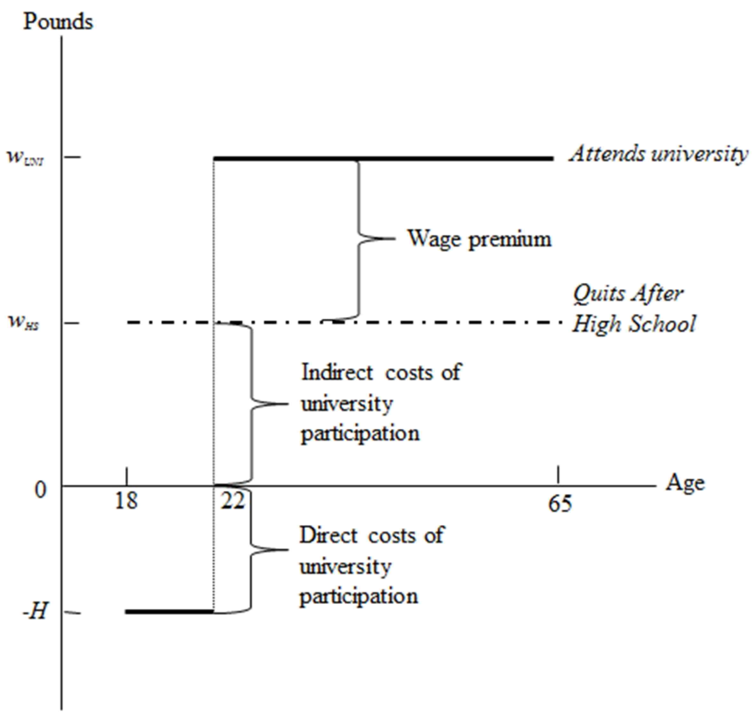
The human capital approach has been applied to a diverse array of phenomena. The following sections describe how it has provided insights into the two main questions of this thesis: the decision concerning whether or not to progress from school to university; and the factors affecting the cognitive outcomes of children in relation to the income of their parents.

1.3.1 The University Participation Decision

Since education can be viewed as an investment good which derives a return in the labour market, it can be assumed that people will decide on an optimal amount of education where the marginal benefit is equal to the marginal cost. Another way to look at this is to consider the present value of lifetime earnings which a person would receive under various scenarios. Education is chosen to maximise the expected present value of the stream of future incomes, up to retirement, net of the costs of education so that at its optimum the present value of the i^{th} year of schooling just equals the cost of the i^{th} year of education. The present value summarises three elements, firstly, the returns to education, which accrue through higher wages, secondly, the costs, including direct costs such as fees and text books as well as opportunity costs i.e. the wages foregone to that person during the time of their studies, and thirdly, the person’s discount rate, which reflects not only the market rate of interest but also the person’s time preferences. Lower costs, higher returns and lower discount rates will lead to additional investment in education.

Figure 1.4 below shows the economic trade-off in a person’s decision to continue in education after they finish school or to enter the labour force at that point. It shows the age-earnings profile associated with each alternative. On the one hand, the worker can enter the workforce immediately after finishing school. Assuming that there is no on-the-job training and the skills learned at school do not depreciate over time, the worker's productivity and real earnings will be constant over the life cycle. They will earn a lower level of wages than what they would have earned had they invested in further education. On the other hand, the person could decide to remain in education and undertake a university qualification. This involves both direct

Figure 1-4 Potential Earnings Streams Faced by a High School Graduate



Source: Own representation, based on Borjas (2010)

and indirect costs initially – direct costs are shown by the negative value *H* while indirect costs are represented by W_{HS} (the earnings of the person who entered the labour force straight after school). However, this model indicates that someone who attends university will earn a higher wage after graduation until retirement. This higher wage is something firms must pay to induce graduates to work for them and is a compensating differential that compensates graduates for their training costs. Individuals will weigh up the present value of the net earnings they could generate from the two paths and make their decision accordingly. Human capital theory suggests that each person's decision will depend on the rate of discount they apply in the calculation of present value. Direct and opportunity costs must be outweighed by the benefits in terms of future discounted returns.

This figure shows flat lines for each income path, however, this is an oversimplifying assumption which implies that wages do not increase over the lifetime, and furthermore that all workers have the same ability. Wages will typically increase over the lifetime since working also increases human capital by giving workers skills and experience and because workers often receive on-the-job training. However, they will increase at a decreasing rate, reflecting diminishing returns to investment in human capital, similar to the case of physical capital. Furthermore, the rate of increase in wages will be positively linked to a person's ability level since more able persons will get relatively more from additional investments in human capital.

Age-earnings profiles using real life data and illustrating the way that the wages of workers with a particular level of schooling change over their lifetimes typically have properties which reflect these theoretical ideas - they show that highly educated workers earn more than less educated workers; they show that earnings rise over time, but at a decreasing rate, and they show that the earnings pathways of groups with different levels of schooling diverge from each other (Mincer, 1958).

An alternative theory of how people make the decision as to how much education to invest in is called signalling theory (Spence, 1973; Arrow 1973; Sitglitz, 1975). Whereas human capital theory is based on the idea that education raises a worker's productivity, signalling is based on the idea that employers cannot directly observe a worker's ability and instead use their education as a signal to determine who will be a productive worker. It can be assumed that the cost of achieving a university education is lower for more able or high-productivity individuals, for example because they will not have to spend as much time studying. For this reason, high-productivity workers will be willing to incur the costs involved in higher education and attain the qualification, which acts as a signal to employers and secures them a higher wage. Although low-productivity workers would also like to earn the higher wage, it is too costly for them to attain the university qualification. In this way, university qualifications act as an effective signal that helps the firm correctly distinguish between high and low productivity workers.

It is very difficult to see which of these theories is “true” using empirical methods as both have the same implications, for example that more educated workers earn higher wages and that people will invest most heavily in human capital when they are young. Whilst various innovative ideas have been used to try to determine which is more accurate (e.g. see Tyler *et al*, 2000, which uses difference-in-difference methodology to ascertain the signalling effect of the GED[1]), the evidence is still divided. In fact, it is likely that both explanations play a role, i.e. that education increases worker’s productivity and also sends a signal as to their ability level.

The third chapter of this thesis explores the university participation decision in the context of human capital theory. The focus is not on the returns to education, but rather on the costs of university and especially the young person’s perception of these costs. Only the path where they attend university involves negative earnings for some period, and the research in this thesis focuses on the issue of debt aversion and the young person’s attitude to this period of negative earnings.

1.3.2 The Rise and Fall of Families

The fourth and fifth chapters of this thesis are concerned with the early years’ cognitive development of children from different family backgrounds. My analysis explores the extent to which children from well-off families perform better than children from disadvantaged families in cognitive assessments up to age 7, focusing on the mechanisms behind this. Furthermore, I examine whether the rate of development differs for children from different family background and ability groups. This is closely linked to the question of intergenerational mobility, since the educational attainment of children is linked to their own future labour market outcomes (e.g. see

[1] The GED, or General Educational Development tests are available for US and Canadian citizens who have not graduated from high-school. The GED is designed to provide an alternative qualification which indicates an equivalent level of academic skills to a high-school diploma.

Blanden and Machin, 2008, which exploits this link to derive current estimates of intergenerational income mobility).

A general framework for understanding intergenerational mobility, presented in Becker and Tomes (1986), relates the rise and fall of families to investments in human capital and other factors. A greatly simplified version of this model is presented below. Although my research is not based directly on this model, some important implications of the model are very relevant for my work and it provides a general framework where the relationship between parent's income and their children's outcomes is directly linked to investments in human capital, along with other factors.

Becker and Tomes' (1986) model starts with a simple Markov equation expressing the relationship between the incomes of parents and children, such as

$$I_{t+1} = a + bI_t + \varepsilon_{t+1} \tag{1.1}$$

where I_{t+1} is the income of the second generation (the children), and I_t is the parents' income. This equation can refer to the change in overall inequality in a society over time and also the relationship between the incomes of different generations of a family. If b were exactly equal to 1, it would imply that parents and their children enjoy the same incomes. On the other hand, a value of the parameter b of less than one implies that the correlation between the incomes of parents and children is less than perfect, i.e. children of rich parents are less rich than their parents whilst children of poor parents are better off than their parents. A relationship like this would lead to a constant (or declining) level of inequality, whereas a value of b larger than unity would imply a growing level of inequality in the society, with the children of rich parents becoming even richer and the children of poor parents becoming even poorer.

What are the determinants of the incomes of children compared to the incomes of their parents? In Becker and Tomes' model, the degree of intergenerational mobility, or the rise and fall of families, is determined by the interaction of utility maximizing behaviour with investment and consumption opportunities in different generations and with different kinds of luck. A child's human capital is determined by their endowments and the investments of their parents and society. Their human capital in turn influences their earnings, which are the main determinant of their total income (together with bequests received from their parents). These factors will now be described in more detail.

Endowments can entail both cultural and genetic components, and it is assumed that both are automatically transferred from parents to children, according to some degree of "inheritability". As a first approximation, it is assumed that both are transmitted by a stochastic-linear or Markov equation:

$$E_t^i = \alpha_t + hE_{t-1}^i + v_t^i \quad (1.2)$$

where E_t^i is the endowment (or vector of endowments) of the ith family in the tth generation, h is the degree (or vector of degrees) of "inheritability" of these endowments, and v_t^i measures unsystematic components or luck in the transmission process.

The model is developed further through the inclusion of investments in human capital. Human capital depends not only on endowments but also on investments by parents (x) and the society (s). Much research (both before and after Becker and Tomes (1986) was published) shows that investments during childhood are imperative for later developments. On this basis, the model makes the assumption that the total amount of human capital accumulated throughout a person's life, including on-the-job training, is proportional to the amount accumulated during childhood. As such, total human capital accumulated is a function of endowments, parental investment and public expenditures, i.e.

$$H_t = \psi(x_{t-1}, s_{t-1}, E_t), \quad with\, \psi_j > 0, \quad j = x, s, E \quad (1.3)$$

Endowments including ability, early learning, and other aspects of a family's cultural and genetic "infrastructure", in general raise the marginal effect of family and public expenditures on the production of human capital, such that

$$\frac{\delta^2 H_t}{\delta j_{t-1}\delta E_t} = \psi_{jE} > 0, \quad j = x, s \tag{1.4}$$

This is similar to the idea of dynamic complementarity introduced in Cunha and Heckman (2007). Indeed, several of the ideas contained in their later model appear to have their roots in this early work of Becker and Tomes.

The parents' influence on their children's human capital is thus (at least) twofold, working through the endowments and also through their investment. Under the assumption of perfect capital markets where funds can be borrowed for investment in human capital, parents can decide on the optimal amount of investment in the human capital of a child by equating the marginal rate of return and the interest rate.

The marginal rate of return on parental expenditures (r_m) is defined by the equation

$$\frac{\delta Y_t}{\delta x_{t-1}} = \frac{\delta H_t}{\delta x_{t-1}} = \psi_x = 1 + r_m(x_{t-1}, s_{t-1}, E_t) \tag{1.5}$$

where $\frac{\delta r_m}{\delta E} > 0$ by inequality (1.4). As the marginal rate of return is positively linked with endowments, better endowed children will accumulate more human capital. This point has important implications as inequalities would be increased if both ability and resources are transmitted from parents to children.

Earnings are defined as

$$Y_t = \gamma(T_t, f_t)H_t\alpha + l_t \tag{1.6}$$

where the earnings of one unit of human capital (γ) are determined by equilibrium in factor markets and depends positively on technological knowledge (T) and negatively on the ratio of the amount of human capital to nonhuman capital in the economy (f); and where l represents market luck. As such, children who accumulate more human capital will therefore have higher earnings. The positive relationship between endowments and expenditures raises the total effect of endowments on earnings, and the inequality and skewness in earnings relative to that in endowments. Although the research in chapters four and five relates to children's cognitive outcomes in the early years, when they are still far from entering the labour market themselves, the skewness and inequality in the distribution is already very marked.

Under the assumption of perfect capital markets, children's earnings would not be affected directly by their parent's income because parents would be able to borrow to finance investment in their children's human capital. There would be an indirect effect on children's human capital and earnings however, working through the inheritability of endowments. The higher the degree of inheritability, the more closely correlated the human capital and earnings of parents and children would be. Furthermore, children's income would be affected by parents' earnings and wealth because of gifts and bequests.

Under the more realistic assumption that parents have difficulties borrowing for investments in human capital (because it is poor collateral), such investments would have to be self-financed. While rich families would have no difficulties with this, poor families would only be able to invest in their children's human capital to the extent that they were able and willing to limit their own or their children's consumption. Capital market restrictions would therefore lower investments in children from poorer families. A small redistribution of human capital away from rich families and towards poor families would raise the average marginal rate of return across families. Importantly, there would be no conflict between equity, as measured by inequality, and efficiency because this redistribution is equivalent to an improvement in the efficiency of capital markets. The fact that investing in the human capital of children from poor families does not present a trade-off between efficiency and equity is one of the key points made in Cunha and Heckman (2007).

Other factors covered in Becker and Tomes (1986) include decisions regarding the number of children and the influence of family size, marriage decisions and the effect of imperfect assortative mating, and parental altruism regarding gifts and bequests. If wealth is positively related to fertility, family size can increase regression to the mean in wealth by diluting the assets of rich families who make bequests. Imperfect positive assortative mating also tends to cause consumption and wealth to regress towards the mean. As such, their analysis indicates that these factors work to decrease intergenerational mobility, although these effects are complex and not unambiguous.

This model presents a framework to interpret findings on intergenerational mobility. It is based on utility-maximising behaviour by all participants, equilibrium in different markets and stochastic forces (notably luck) with unequal incidence among participants. It shows how parents income is related to the income of their children and indicates the key mechanisms for this, in particular the endowments that are passed on to the children, parents' investment in children's further human capital accumulation, and the effect of this on children's earnings. The key implications arising from this model which have relevance for the empirical work in chapters four and five are:

1) the positive relationship between endowments and investment raises the marginal return on investments and causes these children to accumulate more human capital;
2) children's earnings would depend indirectly on their parent's earnings through the inheritability of endowments even if there were perfect capital markets which facilitated an optimal investment in children's human capital; and
3) in regards to policy, there is no trade-off between equity and efficiency in redistributing human capital from rich families to poorer families.

1.3.3 Selected Recent Work

One recent, highly influential, paper within the area of human capital theory is Cunha and Heckman (2007), which presents a technology of skill formation featuring self-productivity, dynamic complementarity and skill multipliers. Their framework explains a variety of findings from literature not just within empirical economics but also child development and cognitive science. Their model centres on the formation of human capital, estimating for example which periods of a child's life are most productive in ensuring a return to investments in the development of human capital. One clear difference to the early human capital literature, however, is that they state that “the sharp distinction between acquired skills and ability featured in the early human capital literature is no longer tenable” and as such make a clear departure from traditional, “additive” nature and nurture models. In terms of policy recommendations, they argue that a balanced investment strategy that “optimally distributes the resources spent over the full life cycle of the child” is most efficient in achieving reductions in income inequality. This implies the importance of early and continued investments in children’s human capital formation.

Currie and Almond’s chapter in the 2011 Handbook of Labor Economics (Currie and Almond, 2011) reports that a growing concern in the empirical economics literature has been the early years of a child’s life, and in particular how children’s human capital accumulation responds to their environment before age five. Building on the idea of complementarity as discussed in Cunha and Heckman (2007), they develop a model which makes it possible to assess the impact of negative shocks and the extent to which this can be remediated. They find such shocks have a large influence on later outcomes, explaining as much variation in income (for example) as more traditionally examined factors such as years of education. However, they also find that damage can be remediated, although the question of which programs are most effective in doing this remains open. They demonstrate that using a production function approach to human capital development is a useful analytical tool, but that the actual estimation of such a function is difficult due to data constraints that are unlikely to be overcome in practice.

Furthermore, the ability of families to invest in their children’s human capital development is investigated in Caucutt and Lochner (2012). They find that capital constraints do bind for some families (especially young parents at the start of their careers), restricting their ability to invest optimally in their children’s human capital development; and also find evidence of dynamic complementarity of investments, which means that later investments build on earlier investments. These two factors together imply that early interventions tend to be more successful than later interventions at improving human capital outcomes.

These three papers demonstrate that a focus on the early years is a current theme in the human capital literature. Regarding the responsiveness of human capital accumulation to a child's early environment, Currie and Almond (2011) report that although there were no papers on this topic in the top economics journals in 2000, there have been a steady stream of them since 2005 and following. This area is of growing interest in the academic arena and equally so among policy makers. This thesis will contribute further to this body of research, using the human capital framework as described above.

1.3.4 Summary

Human capital theory has become a core theory within economics and has implications for many important empirical questions. As has been discussed above, it demonstrates where people's motivation comes from to invest in education; both their own (university) and their children's. The link between investment in education and later returns via higher wages is analogous to the returns in the form of profits to investments in physical capital such as machinery. The decision mechanism for how much to invest is also equivalent, as this theory postulates that people will invest in human capital to the point where the marginal benefit is equal to the marginal return. This has important implications for an individual's decision regarding whether to progress to university education after completing school, and also affects the transmission of earnings and wealth between generations of a family since investments in human capital are a key element of this relationship. Investments in human capital in the early years of a child's life have become an important theme in recent empirical literature in this area.

The theory of human capital provides the broad framework and theoretical perspective for the following chapters. Chapter 3 of this thesis extends the analysis of the university participation decision to include debt aversion, while chapters 4 and 5 examine the relationship between family income and children's cognitive development up to age 7. Some important implications of the basic human capital model for the following analysis have been highlighted above.

1.4 Policy Context: Recent Relevant Policy Changes and Initiatives

The existence of gaps in educational attainment between children from different family backgrounds has been recognised as a serious social issue. The current government has various policies in place to address educational inequalities at various stages of childhood into adulthood. In order to provide a context for the research contained in this thesis, this section provides a brief overview of certain relevant policy changes and initiatives.

1.4.1 Policies Relating to the Early Years

The current government has continued support for Sure Start Children's Centres, which are an initiative that was initially introduced by the previous labour government. Sure Start children's centres offer universally accessible services but focus in particular on those in greatest need. They work to make sure all children are properly prepared for school, address health and other developmental issues, and also offer support to parents. However, although Sure Start is supported officially, the programme has reportedly seen substantial budget cuts, leading to the closure of an estimated 400 centres (Butler, 2013). On the other hand, certain policies introduced by the current government indicate an increased emphasis on the early years. This includes, for example, increasing the status of early years education professionals to be equal to teachers in primary schools and introducing initiatives to encourage more high-quality graduates to work in the sector (DfE, 2013a).

1.4.2 The Pupil Premium

The pupil premium provides schools with extra funding to raise the attainment of disadvantaged pupils. It is designed to address the current inequalities in educational attainment by attaching greater funding for pupils with disadvantaged backgrounds. In this context, disadvantaged children are defined as those children who have been eligible for free school meals at any point in the past 6 years, as well as children who have been looked after for 6 months or longer. It is in place from reception to year 11 and in the 2013-14 financial year, funding for the pupil premium increased to

£1.875 billion, such that schools receive £900 per pupil, plus an additional £53 for primary school pupils (DfE, 2013b).

The pupil premium is paid to schools and there are no requirements for how it is to be spent. However, there is an emphasis on the achievement of results, as Ofsted inspections report on how schools' use of the funding affects the attainment of their disadvantaged pupils and new measures on the attainment of pupils attracting the Pupil Premium have been included in the performance tables (*ibid*.). An Ofsted report describing how schools view the Pupil Premium has reported that schools for which the total amount received was not large often did not disaggregate it from the rest of their budgets. School leaders reported that the funds were often used to maintain or enhance existing provision rather than investing in new initiatives and that the most common usage was to pay for teaching assistants (Ofsted, 2012).

More recently, certain resources have become available to help schools direct the funding towards practices which will be most effective for raising the attainment of disadvantaged pupils in particular, such as the 'Education Endowment Foundation toolkit' developed by the Sutton Trust and Durham University. This is a tool which ranks various educational approaches according to their effectiveness, cost, and the strength of the evidence relating specifically to that practice (Education Endowment Foundation, 2014). The Pupil Premium has been praised as having the potential to be very effective in facilitating social mobility, although with the caveat that this will require 'more training, frameworks and parental engagement' (Sobel, 2013).

1.4.3 The Removal of Education Maintenance Allowance

The Education Maintenance Allowance was previously available to people aged 16 to 18 years of age and enrolled in either a full-time further education course at a school or college, a course leading to an apprenticeship or a Foundation Learning Programme. The maximum amount of £30 per week was available to young people whose families had an annual income below £20, 817. Young people from families earning up to £25,521 were eligible to receive £20 per week while young people from families earning up to £30,810 were eligible to receive £10 per week. These funds were paid directly to the young person and could be used at their discretion, for example to fund travel, lunches or other requirements.

The EMA has now been removed and replaced by the 16 to 19 Bursary Fund. Under the current scheme, the most vulnerable young people are eligible to receive a bursary of £1,200 per year (equivalent to £23 per week), whilst any remaining funds can be disbursed at the discretion of the local authorities, schools, colleges and other education providers (DfE, 2013c). The major difference is in terms of funding levels, as whilst the EMA amounted to £564 million in 2010/11, the new Bursaries Fund totalled only as much as £180 million at its introduction (Coughlan, 2011). Regarding the bursary scheme now operated by further education and Sixth form providers in the city of Manchester, Manchester city council has reported that "because of limited funding, neither the scheme itself nor the reach is as extensive as the EMA …. For example, the Manchester College is supporting circa 250 young people with its bursary scheme, as opposed to the circa 1,000 supported with Educational Maintenance Allowance" (Manchester City Council Economic Scrutiny Committee, 2012).

The government's stated aim was indeed to reduce the deadweight loss of the program and make it more targeted to those who were most in need. Whilst this cut came alongside the raft of heavy cuts made in response to the financial crisis, it was justified based on reports that 88% of young people receiving the grant would have participated in post-compulsory education anyway, even without the financial support the EMA provided. This finding came from a report which documented that 12% of respondents who received EMA agreed with the statement 'I would not have done a course or training, if I had not received an EMA.' (Spielhofer *et al*, 2010) However, the IFS has pointed out that many public policies have a high deadweight cost and that EMAs could have other benefits such as improving attendance or allowing students to spend more time studying and less on part-time work. They have also said that the benefits of EMA in terms of higher wages 'completely offset' the costs, based on earlier research on the impact of EMA on participation (Chowdury *et al*, 2007; Chowdury and Emmerson, 2010). In any case, the effect of this type of funding on the 16 – 18 participation rate is soon to become a non-issue, as the statutory participation rate is being raised in England to 18 as of 2015. This is discussed in the following sub-section.

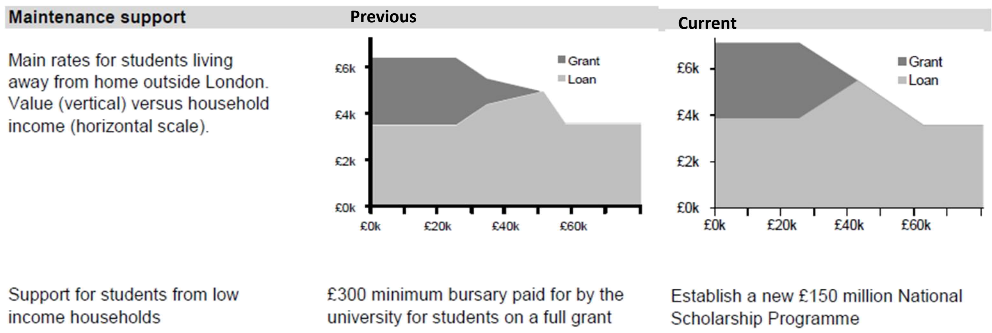
1.4.4 Raising of the Participation Age to 18

Although currently most 17 and 18 year old participate in post-compulsory education (88% and 76% respectively), legislation is being introduced which will make it a statutory requirement for 17 and 18 year olds to engage in either full-time education at a school or college, an apprenticeship or alternatively part-time education or training together with employment, self-employment or voluntary work of at least 20 hours a week. This is partly based on the decline in unskilled jobs available and the need for young people to be equipped for modern day employment. This will most likely benefit young people from disadvantaged backgrounds, as they are the most likely to be NEET (not in employment, education, or training) or in JWT (jobs without training). However, concerns have already been raised highlighting the need to provide suitable post-16 pathways, and high-quality guidance and support. It is expected that the young people affected by the change are likely to undertake jobs with training, vocational courses or courses leading to low-level qualifications, and that the main benefit will be in terms of increased future earnings. Although the changes will make participation compulsory by law, it is unclear how effective sanctions will be, and there is a strong wish to encourage voluntary participation (Spielhofer, 2007).

1.4.5 Change to University Funding Arrangements

In 2012/13, the Government raised the cap on tuition fees to £9,000 and cut most ongoing direct public funding for tuition. It also changed loan repayment terms by increasing the repayment threshold to £21,000, charging a real rate of interest on loans for those making repayment, and extending the maximum duration of loans from 25 to 30 years. A further major change was that fee loans are now available to part-time students. Institutions charging annual fees of over £6,000 have to spend some of this additional income on widening participation. Most universities decided to charge the maximum £9000 fee. Changes to maintenance loans and grants have also been introduced as per the below, with an increase in the total available to those on the lowest incomes and some simplifications to the system.

Figure 1-5: Changes to Maintenance Grants and Loans



Source: Bolton (2011)

1.4.6 Summary

These are some of the policies which are currently applicable or indicate recent changes. They all deal with issues of educational inequality, although at various stages of the educational journey. There are two main themes which come out of this brief overview – firstly the intense pressure on government budgets after the financial crisis which resulted in heavy cuts, and on the other hand, an ambition to provide support for pupils from disadvantaged backgrounds. This aims to reduce and even remove the attainment gap between these students and the remaining cohort. The policies discussed above have been described in order to provide a policy context for the following research, which focuses on differences in educational outcomes according to family background and socio-economic status and seeks to provide further insights, leading to more effective support for young people from disadvantaged backgrounds.

1.5 Outline of Research

This thesis examines various aspects of the relationship between family background and children's outcomes. Three separate, empirical chapters contribute to the existing literature on the relationship between parent's income and their children's cognitive and educational outcomes by examining three specific aspects of this relationship. By expanding the traditional view of the role of education to a more complex picture of a broad range of forces with various impacts on education and further outcomes, it provides scope for potentially more effective policies to meet the specific needs of disadvantaged children, in particular in the early years of their lives when gaps in educational attainment are starting to open up. Further detail on each chapter is provided below.

1.5.1 Debt Aversion and University Participation

The first empirical chapter examines debt aversion as a possible factor behind the substantial gap in university participation rates between young people from rich and poor families. One measure puts this gap at 38 percentage points, with 19% of young people from the most disadvantaged neighbourhoods participating in university at ages 18/19, compared to 57% from the most advantaged neighbourhoods[2]. The analysis is based on the idea that concerns about getting into debt may lead young people to choose not to participate in university, and the hypothesis that this effect may be more severe for young people from disadvantaged backgrounds.

The increase in undergraduate fees up to £9,000 *per annum* as of 2013 further increases the potential impact of this factor, since it means that large debts are becoming an inescapable aspect of obtaining a university education. There is substantial anecdotal evidence that concerns about debt pose a far greater barrier to university participation for young people from lower income families (e.g. Burdmann, 2005), however, it has been difficult to attain robust quantitative estimates of this effect due to data limitations. To date, the only paper to address this question directly (Callendar and Jackson, 2005) focused on a small sample of young people pursuing a HE entrance qualification and could only report on their participation intention, since the young people were only interviewed in one period.

[2] HEFCE Trends in Young Participation, 2010

In chapter three, I take the opportunity provided by the LSYPE dataset to examine this important issue in a more robust way than has been possible to date. This dataset has several advantages, in that it is based on a nationally representative sample of young people (including weights that align it more fully with the total population), rather than a sample made up of students or young people pursuing HE entrance qualifications, and furthermore follows these young people over time allowing us to observe actual university participation (or not) as opposed to participation intention. The richness of the data also makes it possible to control for a wide range of personal and family characteristics. In particular, the fact that the dataset is linked to the National Pupil Database provides test statistics that can be used as proxies for innate ability in order to address the potential endogeneity of the family income variable.

The main method employed in this chapter is logistic regression. This is supplemented by various other techniques in order to examine whether the effects of debt aversion are more severe for poorer families. This chapter makes an important contribution in measuring the effect of one factor which may pose a substantial barrier to university participation, and potentially more so for young people from poor families, but has not been estimated using robust econometric methods in the past.

1.5.2 Factors Affecting Cognitive Development in the Early Years

Some economists have argued strongly that investments in education that are made early in a child's life make sense in terms of both equity and efficiency (Becker and Tomes, 1986; Cunha and Heckman, 2007). By the time a child is of university age, their family background has already strongly influenced their educational outcomes, and it may in fact be too late for government policies to be effective in opening up options for them in regards to higher education. This chapter focuses on the first few years of school (between the ages of 5 and 7) and explores factors that contribute to children's cognitive development in this important period of their lives.

There are three sets of factors explored in this chapter. Firstly, family income is examined to explore whether or not this has a direct, independent effect on children's outcomes. The second set of factors examined are school related factors, such as whether or not the school charges fees and is co-educational, and the years of experience of the child's teacher. To my knowledge, this is the first analysis of the impact of family background on children's outcomes to use the fourth wave of data from the Millennium Cohort Study, and as such the first study of school effects that is able to control for such a vast array of potential correlates. And finally, an extensive list of other factors is also tested, including factors relating to the child's own characteristics, the family structure, parental behaviours and attitudes, the home environment, the neighbourhood, and money related factors such as car usage and home ownership amongst others.

This chapter uses panel data methods to address the endogeneity of key variables arising from unobserved individual heterogeneity correlated with family income and other factors. Other authors using panel techniques with this dataset (e.g. see Violato *et al*, 2011) encountered an issue of limited within-subject variation in the key variables. In this chapter, I introduce an augmented random effects model which addresses this issue whilst maintaining the consistency achieved through a fixed effects framework.

As well as this methodological contribution, this chapter makes a further contribution to the current literature by identifying key factors, alongside family income, which impact on children's development between ages 5 and 7 and can potentially be targeted for government policy interventions. It takes a broad view of the impact of family background on educational attainment and attempts to identify important contributing factors.

1.5.3 Trajectories of Development and Regression to the Mean

The third empirical chapter examines differences in the trajectories of cognitive development of young children from different family income groups. It has been found that if children are divided into groups based on their family background and an early test score, change measured from this point shows a sharp increase in the performance of low ability children from well-off families and a sharp decrease in the performance of high ability children from poor families (Feinstein, 2003). However, a pattern such as this often merely reflects regression to the mean, which is a statistical artefact occurring for individual data measured at more than one point in time and containing random variation. Jerrim and Vignoles (2011) suggest that this differing pattern for children from rich and poor families no longer occurs once RTM is accounted for. Blanden (2012) has called for further research to be carried out on this issue.

Early years test scores are a prime candidate for RTM effects because of the high variability in children's performance between tests. I employ two techniques to deal with the RTM effect and isolate the true effect of family income on the children's rates of cognitive development at these ages. Both techniques have their roots in epidemiology, where this issue is often discussed in studies examining relative change over time in a certain outcome. The first technique is discussed and briefly applied to the MCS data in Jerrim and Vignoles (2013). This chapter provides much greater detail on the various effects operating in that data set, quantifies the RTM effect for different groups, and employs an extra wave of data which makes it possible to use an alternative cognitive ability test. The second technique involves using a value-added functional form and I show how this can be effective in dealing with RTM.

The chapter contributes to the existing literature on the relationship between family income and children's cognitive outcomes by clarifying the relative effects of random statistical variation and real substantive benefits accruing from additional family income. I provide a detailed analysis of these trends using data from the Millennium Cohort Study, with the aim of attaining estimates of the relative rates of cognitive development of children from different family backgrounds, which are robust to the phenomenon of RTM. The development of bright children from disadvantaged backgrounds is an important economic and societal issue, and accurate measures of the development of different ability and family income groups is an important foundation for the discussion of this issue and policies relating to this group.

1.6 Aims and Objectives

This thesis examines the influence of family income on children's educational and cognitive outcomes in their early years and at the point of entry to university. The aim is to investigate two key points in the educational process where (i) there is general agreement that outcomes are key in determining the ability of poorer children to progress in the labour market and (ii) there has been some lack of success of government policy (and therefore some need for additional insight). University participation is one outcome where the gap between young people from rich and poor backgrounds is still very substantial despite having been a government policy focus for some time. Social and environmental factors in the early years of a child's life are seen as essential in explaining subsequent success in the education system and thus the labour market. As the discussions in this introduction underline, various government programmes have failed to narrow the gap in performance between those from more and less affluent backgrounds in these early years. To shed light on this issue, we need to view through a clear lens and I therefore examine whether children from different backgrounds show different rates of development or whether these patterns merely reflect random variation within individuals over time.

The aims of the thesis can therefore be summarised as:

- To examine the effect of debt aversion on university participation and whether this effect differentially impacts on children from different family income groups
- To explore which factors are the key determinants of children's cognitive development in the first few years of school
- To test if children from different family income groups have different trajectories of development (in terms of the change in their cognitive test scores over time) or whether observed differences are merely a statistical artefact

The results of these three questions, taken together, help to focus attention on the key issues relating to family income and children's cognitive and educational outcomes. In particular, they show that a broad view of the influence of family background and a focus on the early years of a child's life are justified and furthermore point to specific areas that can be targeted in order to reduce inequalities in children's academic outcomes.

The availability of high quality longitudinal datasets on children and young people in the UK makes it possible to examine these issues in great detail. For the first empirical chapter, I use data from the Longitudinal Study of Young People in England (LSYPE), which is the first dataset I am aware of with a large nationally representative sample and data on debt aversion, family income and university participation. For the final two chapters, I use the Millennium Cohort Study (MCS), a very rich dataset with multiple tests of cognitive ability at ages 3, 5 and 7 as well as data on a vast array of other factors related to the child, their family, their neighbourhood, their school and so on. Each chapter uses various methodological techniques to answer the questions of interest. Methodologically, one issue that affects all empirical work in this area is the endogeneity of family income in the sense that it is not possible to control for all individual heterogeneity that is correlated with the outcome measure and with family income. I take a variety of approaches to dealing with this issue in this research, such as including a wide range of control variables including proxies for unobserved ability, and applying panel data techniques to difference out any time-invariant individual effect, in particular an innovative augmented random effects model.

This thesis is structured as follows. In chapter 2, I review some of the existing literature on the determinants of children's development and educational success, focusing on family income. Chapter 3 starts with the gap in university participation between children from rich and poor families and examines the influence of debt aversion on the university participation decision. Given the evidence that this gap actually opens up much earlier in life, chapter 4 examines a wide range of factors that influence children's development in the first few years of school. Chapter 5 focuses on differential trajectories of development in the early years and the potential for regression to the mean effects to wrongly influence the measurement of these changes. Chapter 6 concludes with a summary and suggestions for how government policies can be most effective in encouraging the success of young children from disadvantaged families.

2 Literature Review

The previous chapter introduced the key themes of this thesis, focusing on the relationship between family background and educational outcomes, and the implications this has for social mobility. A large body of work has contributed to understanding the determinants of children's educational and cognitive outcomes. This chapter will start by reviewing some important contributions to the literature on the determinants of children's outcomes more generally, before focusing on the role of family income. The discussion of the role of family income will be divided according to various themes.

2.1 Factors Affecting Child Development and Educational Attainment

The question of which factors are most important in facilitating children's development has been addressed by well-known economists for some time. Hanushek (1986), on the economics of schooling, provides a thorough review of research on the determinants of educational success. He writes that educational attainment depends on a broad array of individual, family, peer and school related factors. Family factors most frequently include parents' education and wealth, as well as more specific issues such as the influence of parental divorce or the number of siblings, whilst the school related inputs include teacher salaries and pupil/teacher ratios. His paper furthermore discusses various methodological issues related to the estimation of an education production function, such as difficulties in specifying and measuring what the output should be. He reviews 147 papers published between 1966 and 1986 and reports that findings on school and teacher quality as well as expenditure on schools are somewhat ambiguous, but that family background has a clear and important role in explaining differences in achievement.

A further review of current literature on the determinants of children's attainments was given in Haveman and Wolfe (1995). They briefly describe the econometric framework introduced by Gary Becker as well as approaches from other disciplines. They suggest that a complete framework would consider the influence of the society first (as expressed in government policy which determines the "social investment in children"), the choices parents make in regards to the quality and quantity of family resources devoted to the children, and finally the choices and opportunities of children themselves. In terms of particular determinants of children's attainments, they find a strong consensus regarding poverty and growing up in a low-income family. In particular, it is clear that lower educational and labour market attainment is associated with parental choices or attributes which result in reduced access by children to economic resources or opportunities.

Other determinants they consider include whether or not the mother works, and when in the child's development she (re)enters the labour market; family structure such as single-parenthood and the number of siblings; and stressful events during childhood such as moving home. They find that single-parenthood, stressful events and the mother working all have negative effects in the studies surveyed, although if the mother works when the child is already a teenager there appears to be a positive effect due to the extra income and the positive role-modelling. Growing up in a neighbourhood with "good" characteristics such as lower unemployment and where the residents are more educated is also found to have a positive effect on the children's outcomes.

A further important finding of the paper is that earlier studies may have overestimated the degree of intergenerational mobility in the society. Two key changes relate, on the one hand, to improvements in the data used (in particular the use of panel data which made it possible to use longer-term measures of income and reduced measurement error by removing the need to rely on proxy reports by adult children of their parents incomes), and furthermore to the use of more sophisticated methodologies. These two developments have led to more recent estimates of intergenerational mobility which are much lower than the early findings and in fact call into question the idea that society is highly mobile.

2.2 Family Background and Child Outcomes

One factor which is consistently highlighted in papers on the determinants of child development is family background. Without exception, it can be seen that children with richer and more educated parents achieve better outcomes across a broad range of education related measures. The next section will review the literature on the relationship between family background and children's outcomes, from various angles. I first explore the effect on various outcomes from the early years into adulthood. Secondly, I review papers that have tried to establish whether there is a causal impact of income in itself or whether the effect of income actually works through other channels. The third section explores one of these mediating factors in more detail, namely the intergenerational transfer of cognitive ability. Finally, I look into the literature on social mobility over generations.

2.2.1 From Birth into Employment

A large number of papers have been written on the relationship between family background and children's outcomes. Some use longitudinal datasets to look at how outcomes progress over time, while many focus on an outcome at a single point in time. Blanden *et al* (2007), for example, discusses the fact that children from well-off families have better non-cognitive traits and perform better in all cognitive tests; achieve more at all levels of education as they grow up; and have greater labour market attachment in their teens and 20s. Reviewing the literature in general, it is clear that family income has a substantial and continued effect on a wide range of outcomes from birth into adulthood. In this section, I will briefly discuss this evidence starting with gaps in cognitive test scores and academic achievement between young children from different backgrounds. I then move on to looking at school related outcomes, such as GSCE attainment and choices about staying on in post-compulsory schooling and the type of qualifications to pursue (i.e. academic or vocational qualifications). There is also a great deal of evidence linking family background to university related outcomes such as participation, graduation, degree class and university quality. Finally, family income is also related to adult labour market outcomes such as the return to education.

The literature on cognitive achievement in the early years shows a clear consensus that there is a significant gap between the test scores of children from high and low income groups. For example, Feinstein (2003) uses data from the BCS and illustrates clear differences by family socio-economic status (SES) in an ability index at 22 months. Dearden *et al* (2011) shows with data from the MCS that cognitive test scores at age 3 and age 5 are strongly correlated with family income, as are a wide range of other family and child characteristics and the child's home learning environment. They show that children from poor families are not only more likely to be in the bottom quintile of achievement at age 3, they are also less likely to escape from this category by age 5. There is thus a very early gap in achievement and a widening of this gap as children grow up.

This gap continues to widen during the school years. The empirical evidence has focused in particular on GCSE attainment, the staying on decision and the choice of academic or vocational tracks and shows that these factors are also highly correlated with the child's family background. Mickelwright (1988) uses data from the NCDS to explore the determinants of staying on in post-compulsory education. Looking firstly at the effect of parents' education and social class, he finds there is both a direct effect and a secondary effect working through school type and ability. Focusing on family income however (with a reduced sample for whom this is available), he finds that it has no direct effect for boys, above and beyond the effects of social class and parents education and the child's ability and school type.

Conlon (2005), also using data from the NCDS, finds that family background[3] is an important determinant of the type of post-compulsory qualification pursued (i.e. academic or vocational). Although prior ability is key in determining the level of qualification attained (for both tracks), he finds that the choice of track is more related to parents' background and local labour market opportunities than to prior ability. Lenton (2005) also finds that socioeconomic background is an important determinant of young people's choices at age 16, and in particular that having a father or mother in a professional or managerial occupation greatly increases the likelihood of tacking an academic track. Gregg *et al* (2012) attempt to estimate the

[3] Defined in this paper as a vector of family background characteristics including number of siblings, father's social class and parent's interest in the child's education (among others).

causal impact of father's income on children's GCSE attainment by focusing on the recession of the 1980s and isolating the effect of job loss associated with major industry contractions, mainly in manufacturing. They map data on industry-level employment change into the BCS which contains data on father's industry and employment and their children's outcomes and find that a child with a displaced father obtained, on average, 18 grade points lower or half a GCSE at grades A*-C less than their otherwise-identical counterparts.

Feinstein and Symonds (1999) examine performance at secondary school and find that parental inputs, including parental expectations, are among the most important factors that determine this. They also find that peer effects have an important role to play, whilst schooling inputs (such as the pupil/teacher ratio) are not found to have a significant impact. In terms of A-level results, Bekhradnia (2003) shows that the majority of students attaining zero to 12 A level points are from the lower socio-economic classes, while the majority of students attaining 27 to 30 A level points are from the higher socio-economic classes. These studies all demonstrate clear links between family background and children's outcomes in regards to their choices at age 16 and other outcomes at school.

Another key area examined in the empirical literature is university participation. For example Dearden *et al* (2011) describes a 28% point gap in university participation by family background, with 12.2% of 18-19 year olds from low-income families studying for a degree compared to 30.4% from high-income backgrounds. Blanden and Machin (2004) show that the relationship between family income and both participation in full time education at age 19 and degree attainment at age 23 strengthened as university participation expanded in the 1980s and 1990s.

Furthermore, Galindo-Rueda and Vignoles (2005) also found that the influence of family background is growing and show how the decline in the importance of ability in explaining university participation (relative to the influence of family background) is partly due to the fact that low ability children with high economic status have experienced the largest increases in educational attainment in recent years.

The literature on other university related outcomes is reviewed by Adnett and Slack (2007) who show that these outcomes also vary by family background. For example, Johnes and McNabb (2004) find that students from poorer backgrounds are more likely to drop out of university (for women this is predominantly for non-academic reasons); Smith and Naylor (2001) find that social class has a strong effect on degree performance and Smith, McKnight and Naylor (2000) find that graduates from poorer backgrounds have a lower probability of finding employment in graduate occupations.

In terms of the returns to education, there is some evidence that these are also related to family background. Dearden *et al* (2004a) use data from the 1970 British Cohort Study to estimate the returns to a "marginal learner" and find in regards to father's social class that returns to staying on in post-compulsory education are higher for men from a high socio-economic background (at 13-14%) than for men from a low socio-economic background (8-11%), although this difference is not statistically significant. For women, they find returns of 17-19% and 15-16% for higher and lower socio-economic classes respectively. On the other hand, they also estimate returns to achieving a higher education qualification (compared to a level 2 qualification) and find that the returns to males from a low income family are actually higher than for males from a higher income family (at 23-24% verses 9-11%). However, it should be noted that the returns are measured as the percentage gain from the baseline 'counterfactual' and the comparison groups in each case are quite different, with low income males earning around 20% lower hourly wages as a baseline. For females, the returns to higher education are found to be similar across family income and social class groups.

A different line of inquiry is pursued in Adnett and Slack (2007) which takes as their starting point the substantial gap in university participation rates between young people from more or less advantaged backgrounds and proposes that insufficient monetary returns to a degree for young people from disadvantaged backgrounds may be the reason for their decision not to participate. By comparing returns to entrants from a disadvantaged background with non-entrants from a similar background, they find there are in fact significant incentives to undertaking higher education for disadvantaged young people, although they acknowledge that data and methodological issues put a caveat on the robustness of this finding.

An alternative approach would be to compare returns for HE participants from advantaged and disadvantaged backgrounds. This is the approach undertaken in Altonji and Dunn (1996), who use sibling pairs from the Panel Study of Income Dynamics and the National Longitudinal Surveys of Labor Market Experience of Young Men and Young Women to explore the question of whether parental education raises the return to education. Their results are mixed, as some specifications indicate there is a significant positive interaction effect between parent's income and children's returns to an additional year of education, especially in the models that include family fixed effects, however, the authors express concern that these results are biased upwards. Other specifications, without fixed effects, return insignificant results indicating the returns may in fact be constant across different levels of parental education.

On the other hand, Dale and Krueger (2002) explore the payoff to attending a more selective college and find that there is a negative interaction between parental income and school-average SAT, which means that students from poor backgrounds benefit more from attending a more selective college. Since there is no clear pattern of lower returns to higher educational qualifications for young people from disadvantaged backgrounds, it appears that the mechanism of inequality is the fact that young people from these backgrounds are less likely to pursue these qualifications in the first place, for example because they didn't achieve high A level scores.

2.2.2 A Causal Influence?

One important question addressed in the literature is whether income in itself causally influences children's outcomes. The key methodological issue is being unable to control satisfactorily for unobserved heterogeneity among children and families i.e. the endogeneity of family income. Parents' incomes are not random, but are determined by their own characteristics, which they pass genetically to their children and which affect the way they raise them and the home and learning environment they provide for them. Shea (2000) writes that intergenerational transmission of ability, either genetically or through culture, will lead to intergenerational persistence in income, 'even if parents' income *per se* doesn't matter'. It is therefore an important empirical issue. Various strategies have been employed to try to identify the causal effect of income on children's cognitive and educational outcomes, although this remains a very difficult task.

Mayer (1997) is a very thorough study which employs five strategies to separate out the effect of parent's income *per se* and their other characteristics. Firstly, she looks at income from different sources, i.e. welfare, earned income and "other" income. Secondly, the effect of parental income before and after an outcome is examined. If earnings after the outcome strongly affect the outcome, this implies it is the traits associated with permanent income that affected the outcome, rather than the income itself. Thirdly, she explores parents' specific purchases and activities and the relationship between parent's income and their psychological well-being and therefore their parenting behaviours. The fourth method is to examine trends in parental income and children's outcomes since the 1950s. Finally, she uses exogenous sources of variation such as different benefits across states. While none of these approaches is conclusive in itself, taken together, they provide a strong impression that it is not money itself that is driving the test score gap, but rather the factors correlated with income including parental characteristics and behaviours.

One paper which tries to identify the causal effect by using a quasi-experiment is Copeland and Costello (2010). They demonstrate how the opening of a casino on tribal land in North Carolina exogenously increased incomes of American Indian families, and that this had significant effects on the years of educational attainment and crime rates of the children in these families. The authors use data from the Great Smoky Mountains Study of Youth, a longitudinal study including American Indian and non-Indian children in North Carolina. Their identification strategy centres on the fact that after a casino was opened on the Eastern Cherokee reservation, a portion of the profits was distributed regularly based purely on pre-existing American Indian status and independent of potential recipients employment status, income or other household characteristics. The authors use two estimation strategies, a difference-in-differences approach and a fixed effects estimation and show that the transfer, which is relatively large and also considered to be a permanent increase in incomes, had positive and statistically significant effects on education and crime related outcomes. They furthermore show there is some indication that the mechanism mediating this effect was an improvement in parenting quality.

A very similar approach is adopted in Loken (2007), which treats the Norwegian oil boom of the 1970s and 80s as a natural experiment that exogenously increased the incomes of families living in certain parts of Norway. However, they find that income has no causal effect on educational attainment. This finding may be quite specific to Norway, however, due to institutional factors such as the availability of student grants and maintenance.

Other papers which also use an instrumental variables approach to identify the causal effect of income *per se* on children's outcomes include, for example, Shea (2000), which focuses on influences on father's income that are due to "luck" such as his union membership status, the industry he works in and any job loss due to plant closure or the death of the business. His identifying assumption is that these instruments are all uncorrelated to that father's own ability, making it possible to abstract from inherited ability and estimate the effect of income *per se*. Nonetheless, he himself admits that any wage premia accruing to the father through his union status and industry may indeed be partly related to ability. He finds that changes in parents' income due to luck have no significant effect on children's wages, earnings, years of schooling, and total family income. This finding is stable when using all three instruments together or each one at a time.

Chevalier *et al* (2011) also use union membership as an instrument to identify the causal effect of parents' income, in this case on post-compulsory schooling. They instrument both parents' education (using the raising of the school leaving age in 1952) and parents' income (using union membership) and find that maternal education has a causal impact but that the other variables (including parents' income) become insignificant. Finally, Dahl and Lochner (2005) used large, non-linear changes in the Earned Income Tax Credit over two decades in the United States as their instrument for family income. They find that a $1,000 increase in income raises combined math and reading test scores by 6% of a standard deviation in the short-run and that test gains are larger for children from disadvantaged families.

In general, it is very difficult to find a plausible instrument for family income that is not subject to criticism or highly dependent on a particular set of circumstances (e.g. the potential relationship of union status and ability; or the difficulties in applying the circumstances of the Norwegian oil boom more generally). Another popular approach to dealing with the endogeneity of family income is to use fixed effects models. Possibly the most famous paper to take this approach is Blau (1999) which uses matched mother–child data from the National Longitudinal Survey of Youth (NLSY) to examine the relationship between parents' income and children's test scores. Her results indicate a small positive effect of income on test scores in OLS regressions controlling for parental characteristics, but no effect in regressions controlling for child fixed effects. These fixed effects models identify the effect of income by comparing test results in years of high parental income to results for the same child in years of low income, which has been criticised (see Shea, 2000) for focusing attention on short-run variation in parents' income which could have less impact on children than cross section variation in long-run income for several reasons, i.e. because parents can borrow and save, because income may be measured with error, and because children's outcomes may depend on lagged as well as current income.

Dooley and Stewart (2004 and 2007) also adopt a fixed effects approach to address the question of whether the link between family income and child outcomes constitutes a causal relationship rather than simply being due to unobserved heterogeneity. Using Canadian data, they in fact implement a series of empirical strategies starting with simple OLS, then using a fixed effects model, going on to compare parameters on variables measured before and after an outcome and finally including indicators of the family's consumption pattern. Their 2004 paper focuses on cognitive outcomes, and they find a positive but small direct effect of income, while their 2007 paper, focusing on behavioural-emotional outcomes, finds no effect for income but an important role for parenting style.

The literature also contains various examples of ingenious though possibly less robust or reliable methods for estimating the causal effect of family income on children's educational outcomes. Ermisch and Francesconi (2001), for example, provides mathematical models of the effects on educational attainment of parents' education, experience of a single parent family and family income in a more restricted sense and makes the argument that such associations can be given a causal interpretation wherever parents are 'too poor' to make financial transfers to their children, or if their preferences have earnings separable from financial transfers.

Chevalier and Lanot (2002) explore the relative importance of family characteristics and financial constraints on schooling attainment, firstly using the NCDS and BCS, and follow this up by using the Family Expenditure Survey (FES) to simulate the effect of a financial transfer similar to the EMA. By adding £30 per week to the father's weekly earnings while keeping the other family characteristics constant, they attempt to separate the effects of family characteristics from financial constraints. They find that the effect of the transfer are minimal across the board and conclude therefore that children's schooling achievement is dominated by the effect of family characteristics.

Finally, Aughenbaugh and Gittleman (2003) compares and contrasts the effect of income on child development in the United States and the United Kingdom and finds that for both countries, income generally has an effect on child development that is positive and significant, but whose size is small relative to other family background variables. Although they discuss extensively and attempt to deal with the endogeneity of family income, all they can really do is to restrict the covariates to a "core" set that are arguably exogenous. They argue this is partly due to data limitations in the dataset they use (i.e. siblings are interviewed but on the same day so there is no within-family variation in income and they cannot use sibling fixed effects as per Shea 2000), however, it also demonstrates the difficulties in estimating the causal effect of income more generally.

2.2.3 Intergenerational Transfer of Ability

Family income and children's achievement may also be joint outcomes of parents own characteristics, such as cognitive ability. What parents earn is determined to a large extent by their personal characteristics, which are also strong determinants of who their children are. That means that there would most likely be a strong link between parents' income and variables that describe their children (e.g. early years test scores), even if money did not exert an independent influence. Recent papers linking parents IQ or other measures of cognitive ability to their children's include Anger and Heineck (2010), who find that individuals' cognitive skills are positively related to their parents' abilities, despite controlling for educational attainment and family background and Brown *et al* (2011), who find that how the parent performs in reading and mathematics during their childhood is positively related to the corresponding test scores of their offspring as measured at a similar age. Since higher IQ is generally associated with higher income (e.g. see Feinstein and Bynner, 2004), one reason for the link between parent's income and children's cognitive ability is thus the genetic transfer of this innate ability from parents to children.

Evidence regarding the genetic transfer of ability does not preclude the importance of the home environment however, as several papers find that both nature and nurture contribute significantly to their children's outcomes. For example, Bjorklund *et al* (2010) compares intergenerational correlations in IQ with correlations between siblings and finds that siblings, who share both parental factors and neighbourhood influences, show a stronger correlation – as much as 50%, while the intergenerational correlation is around one third. De Coulon *et al* (2011) includes reading and numeracy skills of the parents measured when they are adults and also from when they themselves where still children and find that both have a significant impact on their children's reading and numeracy outcomes. This implies it is not only genetically transferred ability that affects the children's outcomes but that parents adult skills also matter. Furthermore, Bjorklund *et al* (2007) uses data on the rearing and bearing parents of children in different family situations (looking at six family types including the child being raised by both biological parents, by the biological mother / father with or without a partner, and by two adoptive parents) and finds a significant role for both pre-birth and post-birth influences.

Crawford, Goodman and Joyce (2010) explores the intergenerational transmission of cognitive skills as a possible explanatory factor determining the socio-economic gradient in child outcomes. They use data from the BCS70 which contains ability measures and other important information for two generations of the same family as the children of cohort members were also surveyed and tested. They find that parental cognitive ability accounts for 50 per cent of the raw gap in cognitive test scores between children from rich and poor families and 16 per cent of the gap after controlling for a wide range of mechanisms through which ability may be transmitted across generations (such as differences in the home learning environment). However, inclusion of the parental ability variables does not substantively change the results for the other covariates, such as family structure, the child's social skills, and attitudes of both the child and the parent towards education.

Several authors have used adoption as an identification strategy to quantify the relative contribution of nature and nurture to children's outcomes. Since adopted children experience the benefits of higher family income that are expressed in the family environment and parenting practices but do not share the same genes as their adoptive parents, adoption provides an effective way of estimating how much of the effect of family income on educational and other outcomes is due to each of these factors respectively. Das and Sjogren (2002) presented the first of these using a small sample of families from Minnesota and found that the genetic transmission of ability is important for future incomes. Other papers which use data on adoptees include Bjorklund *et al* (2007), who use Swedish data and find that both nature and nurture are important and that there is also an interaction effect and Plug and Vijverberg (2003), who use US data and find that 55-60 per cent of parental ability is genetically transmitted.

Two interesting papers by Bruce Sacerdote use data from an adoption agency in the US who assign families to children in a first-come, first-served basis, thereby ensuring a random allocation of children to families, which would remove any potential bias caused by families selecting children based on certain characteristics. Sacerdote (2002) examines the effect of being adopted into a high-socioeconomic-status (SES) family versus a lower-SES family on a range of outcomes including test scores, educational attainment, the selectivity of college attended and marital status and finds that the SES of the adoptive family is strongly associated with college attendance and the selectivity of the college. This paper also uses the British NCDS, and argues that children were randomly assigned to adoptive parents in this dataset too as adoptive-family SES is uncorrelated with birth mother's SES, birth mother's smoking status or child's birthweight. His results from the two datasets highlight the importance of the environment a family provides for children, quite separate from any transfer of genetic ability.

Sacerdote (2007) uses a larger and more robust dataset from the same adoption agency as the previous paper. His results in this paper reemphasise the shared role of nature and nurture on children's outcomes. He shows that of the variation in educational attainment, shared family environment explains 16 per cent and genetic factors explain 44 per cent; of variation in the adoptees family income, shared environment explains 14 per cent, and genetic factors 33 per cent. Thus there is a strong role for genetic factors in determining these outcomes. By contrast, other outcomes such as drinking, smoking, the selectivity of college attended and marital status appear to be more nurture based. He also finds that parental education and family size are much more influential than family income, which suggests the quality and quantity of parental attention may be two important underlying factors explaining the importance of family environment on child outcomes. In general, papers using data on adopted children to overcome the endogeneity of the family income variable all find that the family environment and the child's genetic makeup both make an important and statistically significant contribution to the children's future outcomes.

The intergenerational transfer of ability is just one mechanism which may be mediating the relationship between parent's income and children's cognitive development. Other possible mechanisms include parental behaviours and attitudes, educational resources and investment in a stimulating home environment, parent's psychological functioning, neighbourhoods and schools etc. The literature on the various factors mediating the relationship between family income and children's cognitive and educational outcomes will be reviewed in more detail (in particular in regards to the early years) in chapter five.

2.2.4 Social Mobility and Intergenerational Transfer

The relationship between the income and ability of the parents and their children's outcomes on an individual level is of course also related to the broader question of intergenerational mobility in the society as a whole. A strong correlation between inequality in the income distribution and immobility in terms of incomes and occupations has been documented (e.g. Ermisch *et al*, 2012). Furthermore, many of the mechanisms appear to be the same in both cases, notably education and cognitive ability.

Early measures of intergenerational mobility were included in work on human capital theory. Becker and Tomes (1986), for example, calculated an intergenerational income coefficient of 0.15 for the United States. It was thus thought that the US was a highly mobile society, where 'almost all earnings advantages and disadvantages are wiped out within three generations' (*ibid*, p1). However, later developments showed that measurement error was artificially reducing this figure and that the true value was actually much higher. There is now somewhat of a general consensus that the intergenerational income coefficient lies around 0.4 (Esping-Andersen, 2004), which can be interpreted as saying that 40% of the gap in incomes in the parent's generation is passed down to the children's generation.

Looking at data for the UK, Dearden *et al* (1997) use two methods to estimate the degree of intergenerational mobility in Britain using data from the 1958 NCDS. Their paper includes a discussion of the difficulties involved in accurately measuring the intergenerational transmission coefficient including the bias introduced by using transitory rather than permanent income, for example, and the fact that parents have children at different ages, introducing the need to control for age effects. They find that intergenerational mobility in Britain is limited, with clear intergenerational correlations between fathers and both sons and daughters regarding labour market earnings and years of schooling. Depending on the methodology used, they estimate an intergenerational mobility parameter of between 0.4 and 0.6 for men and 0.45 and 0.7 for women. They also uncover a further interesting feature, namely that upward mobility from the bottom of the earnings distribution is much more likely than downward mobility from the top.

Although this already indicates a highly immobile society, Blanden *et al* (2004) documents a further fall in mobility between 1958 and 1970. Using data from two of the large British longitudinal surveys - the National Child Development Study (NCDS), where the children were born in March 1958, and the British Cohort Study (BCS), where the children were born in April 1970 – they show that the economic status of the 1970 cohort was much more strongly connected to parental economic status than the 1958 cohort. This fall in intergenerational income mobility is confirmed by both regression and transition matrices approaches. They found, furthermore, that the increased educational attainment of the younger birth cohort is a large contributor to this, due to the fact that a greater share of the rapid educational upgrading of the British population has taken place among people with rich parents.

Whilst the existence of the two longitudinal cohort surveys for 1958 and 1970 make it possible to estimate intergenerational earnings mobility for these years, Nicoletti and Ermisch (2007) supplement this finding by estimating intergenerational mobility for the period 1950 – 1972. Although there is no dataset available for this period which contains information on earnings for two generations, the authors are able to overcome this by using a two sample two stage least squares estimator to impute father's earnings using the information that is available on their education and occupation. They also use various techniques to deal with potential age bias arising from the way earnings change over the life cycle and the fact that fathers have children at different ages. They find that earnings mobility didn't change substantially over the period 1950 to 1960, but that it declined between 1961 and 1972.

Blanden *et al* (2013) provided further detail on these trends by contrasting the decline in earnings mobility for these cohorts with the steady figures for mobility relating to social class, where the degree of intergenerational mobility was found to be unchanged between the two cohorts. They test various hypotheses regarding this and find evidence that the permanent component of income that is unrelated to social class is a key driver of this result. The distinction between income mobility and social class mobility permeates the literature, with papers from a more sociological slant often focusing on social class whist from an economics perspective income seems to be the main variable, although there is also overlap between the two areas. The effect of class concepts on mobility was highlighted specifically by Deputy Prime Minister Nick Clegg in a recent speech (in September 2012) where he identified class as a real barrier to mobility (Clegg, 2012).

Looking ahead to future trends in social mobility, Blanden and Machin (2008) predict that mobility is likely to remain close to the low level observed for the 1970 birth cohort. They examine the relationships between parent's incomes, intermediate outcomes (such as degree attainment, test scores and non-cognitive abilities) and children's later earnings in the 1958 and 1970 cohorts and note that the decline in mobility between these cohorts was accompanied by a strengthening of the relationship between parent's income and intermediate outcomes. The earnings of children in the Millennium Cohort are not yet available (as these children are still too young to have entered the labour force). However, since examining the relationship between parents' income and intermediate outcomes shows no further strengthening between the 1970 and 2000 birth cohorts, the authors predict that the social mobility coefficient is also likely to have remained steady.

More recent evidence on this is provided in Blanden and Macmillan (2012) which discusses the effects of policies that have been introduced specifically to encourage social mobility in recent years. Policies focusing on the early years, such as Sure Start, have yet to demonstrate a concrete contribution to mobility. For example, whilst results from the National Evaluation of Sure Start (NESS) show some effects on behavioural variables they show no effects on language skills. There has been no overall change in the correlation between early years test scores and family income across the children of the NCDS and BCS cohort members and the MCS cohort, which suggests that society is yet to see the returns, in terms of reducing inequality in outcomes, of the increased investment in Early Years.

Regarding schooling, policies such as increased expenditure in schools, reduced class-sizes and other interventions such as the literacy hour do appear to be reducing educational differences across family backgrounds at age 16 (Gregg and Macmillan, 2010). However, there is no improvement as yet for post-16 attainments - for example, there is no evidence so far of an increase in lower social class groups attaining a degree. AimHigher, a program designed to ensure fair access and support the progression onto Higher Education for young people from non-traditional backgrounds, has shown mixed evidence (qualitative research indicates positive results but there are difficulties in identifying this in quantitative studies), and in any case AimHigher has now been closed down (Passy and Morris, 2010, Emmerson *et al*, 2006).

Finally, in regards to access to top professions, evidence had shown that when comparing the 1958 and 1970 cohorts, those entering the top professions looked less like the average in terms of family incomes, but more like the average in terms of ability. This was true especially for doctors, lawyers, bankers and accountants. Partly in answer to this evidence, a Social Mobility and Child Poverty commission was established, chaired by Alan Milburn MP and addressing fair access to the professions, among other things. Recommendations included moves towards more transparency regarding internships to address the nepotism that is rife within this practice (Blanden and Macmillan, 2012). To date there are no indications of how effective such policies may be in improving social mobility. Blanden and Macmillan (2012) argues that the picture is mixed– with positive change around age 16, but less clarity in the early years, for post-16 qualifications and in access to the professions. The impact improvements in age-16 outcomes will have on future mobility levels depends partly on how the returns to GCSEs change over time and whether or not this improvement feeds through to A-levels results and university access.

2.2.5 Summary

The literature reviewed in this section has shown that there is clear evidence of differences in children's outcomes when measured according to their family background. This applies from outcomes in the very early years of life, throughout school, and even in the labour market. Literature on two key mechanisms behind this have been explored: the money itself (although evidence on this is still divided); and the intergenerational transfer of ability. Examining trends in social mobility shows that the UK is quite an immobile society and that this is unlikely to change in the near future. In summary, the literature reviewed in this section shows that children's outcomes are determined to a large extent by their background. The research that follows explores three more specific angles of this relationship. Literature relevant to each of these aspects is included, along with the methodology, results and discussion, in the following chapters.

3 The Contribution of Debt Aversion to Lower University Participation Rates among Poorer Families

3.1 Introduction

Many countries have experienced a long term trend away from a model of fully state funded university education to more privately funded models, with students or their families contributing an increasing proportion of the costs through fees. Higher Education financing in England has certainly moved along these lines, moving from fee-free education until 1998 to increasing fee levels and greater dependency on loans for students' living and accommodation expenses (Adnett, 2006; Blanden *et al*., 2003). After being introduced at a level of £1000 *per annum* in 1998, fees were allowed to increase in 2006 to a maximum of £3000 *per annum*. This figure increased in line with inflation, up to £3375 in 2011/12. However, following the publication of the findings of Brown Review in 2010, it was decided to increase undergraduate fees to a cap of £9000 from October 2012 (Wilkins *et al*, 2013). One main reason for this shift in funding is that many studies have shown high positive returns to education (e.g. Blundell *et al*, 2000; Walker and Zhu, 2011) such that there is an argument for students to bear more of the fee burden themselves on equity grounds. These changes are also a consequence of increased participation, due to the need for increased funding as student numbers continue to grow.

This raises the question of the role that fees play as a determinant of participation, especially for young people from disadvantaged family backgrounds. There is a substantial gap between the university participation rates of young people in the highest and lowest family income groups / socio-economic backgrounds. This can be seen from Table 3.1 below which draws on two sources. The BIS statistics show the estimated percentage of maintained school pupils aged 15 who had entered higher education by age 19. It shows a participation rate gap of around 18 percentage points between pupils who did and did not receive Free School Meals (a commonly used proxy measure for family background), which has remained steady since 2007/8. Participation rates are higher for students at independent schools, but this data has not been made available by FSM status. The HEFCE Trends in Young Participation is based on characteristics of the neighbourhood where the young people live[4].

Table 3-1 HE Participation Rates

	2006/07	2007/08	2008/09	2009/10	2010/11
Progression to HE by FSM status					
Source: BIS					
FSM	14%	15%	17%	18%	20%
Non-FSM	33%	33%	35%	36%	38%
Gap (pp)	19	18	18	18	18
Trends in Young Participation					
Source: HEFCE					
Low Part. (Q1)	16%	17%	18%	19%	..
High Part. (Q5)	55%	56%	58%	57%	
Gap (pp)	39	39	40	38	..

FSM: Free School Meal status. .. Not available

It is clear that there are large differences in the proportion of young people entering HE by neighbourhood. Whilst fewer than one in five young people from the most disadvantaged areas enter higher education, more than one in two young people in the most advantaged areas do so, making them nearly three times more likely to enter higher education. Nonetheless, since the 2004/05 cohort the most disadvantaged quintile has shown a larger participation rate increase compared to the most advantaged areas, of 4.7 percentage points compared with 2.4 percentage points. Both the large gap in participation rates and the slightly faster increase among young people from disadvantaged backgrounds are visible if the areas are classified according to participation rates, parental education, parental occupation or family income.

There are many factors which contribute to this gap, and many of them take effect in early childhood or in the first few years of school. Much research (e.g. see Chowdry *et al.*, 2010) shows that children from poorer backgrounds achieve less well throughout their schooling and are much

[4] The above figures use POLAR2, where participation rates themselves are used to classify areas into quintiles, removing the need to impose assumptions as to the underlying factors behind the participation rates. The figures have been adjusted to deal with distortions arising from regression to the mean.

less likely to continue into post-compulsory schooling and to achieve good A-levels. In fact, participation rates of A-level students from different backgrounds do not display large gaps (Corver, 2010). The decision whether or not to participate in university does not therefore simply occur when someone is 17, but is determined much earlier on in life. Carneiro and Heckman (2002) provides a review of empirical work which indicates that family income influences university participation primarily through long run factors rather than through introducing short run credit constraints at the point of entry. The long-term influence of family socio-economic background and family income on a person's educational path is related to factors such as the parents' own levels of educational attainment, their expectations for the child, their ability to pay for extra tuition or public schooling and the learning environment in the home (Blanden and Gregg, 2004).

Apart from these formative aspects and the issue of credit constraints, a family's income may still have a direct effect at the point of decision to enrol in university once the child has completed secondary education. The current model in the UK is that fees that are paid through government loans and repaid to the government by the student after graduation depending on their earnings. In this context, family income could have an effect on participation through

1) affecting the level of debt the young person incurs at university (as access to credit is more limited and thus possibly more expensive and there is less possibility of depending on family resources)
2) influencing their attitude towards debt - if young people from poorer families are more concerned about accumulating debt, this may act as a barrier to participation (Callender and Jackson, 2005).
3) affecting their expected earnings on graduation (Altonji and Dunn, 1996)
4) influencing their time preferences (if poorer families tended to prefer short-term gains) and thereby making them more likely to opt for positive income in the short run, despite total life-time income generally being lower for workers without a university qualification

Debt aversion is the factor I am primarily interested in exploring in this chapter, as there has been little econometric analysis of this in the UK to date and it is likely to be of growing importance in the coming years given the increases in undergraduate fee levels that have been introduced. There is anecdotal evidence that concerns about debt pose a far greater barrier to university participation for young people from lower income families (Burdmann, 2005) and surveys of students have shown that students from poorer backgrounds are more averse to debt than students from higher income backgrounds (Callender *et al,* 2003). While the possibility of taking out a student loan to cover fees and (at least partly) living expenses reduces the financial risks and barriers involved in completing a degree, it provides little comfort for someone who is debt averse rather than risk-shy or liquidity constrained.

Under the legislation that took effect in 2012/13, some estimates put expected student debt at the completion of a three year undergraduate degree at as much as £40,000. It has also been shown that currently, students from lower income backgrounds graduate with higher debt levels than students from wealthier backgrounds, despite being eligible to receive maintenance grants which do not need to be repaid (Callender *et al,* 2003). The expected debt levels for students from low income families under the new system are thus quite significant, both relative to the income levels of their parents and their own expected income on graduation. This chapter seeks to measure the impact of greater levels of debt aversion among lower income families on the children's university participation decision.

In the next section, a simple theoretical model will be developed which extends the traditional model of university choice in human capital theory to include debt aversion. Debt aversion is defined as associating greater negative utility to negative assets than the positive utility associated with positive assets of the same absolute value. Family income affects almost every parameter of the model, demonstrating how intrinsically it is linked to the university participation decision. Following this section, I use a representative dataset of young people in England (the LSYPE) to analyse the effect of debt aversion on the university participation decision. The data set is longitudinal and follows young people who have chosen differing pathways in terms of work/ further education. It also provides an extensive source of information on their family background (including parents' income and SEC), their attitudes towards debt and controls such as key stage 2 test scores, ethnicity, gender, parent's educational attainment etc.

As well as estimating the effect of debt aversion on university participation generally, I explore whether this effect is stronger for young people from disadvantaged backgrounds. Furthermore, in order to account for the intrinsic link between family income and debt attitudes, this chapter will apply decomposition techniques to split out the effect of family income on university participation into its direct effect and the indirect effect coming through debt aversion, and to test if the effect of debt aversion is more severe for lower income families.

3.2 Literature Review

3.2.1 Studies on the Effects of Debt Aversion on Education-related Decisions

This section provides an overview of five key papers on the effects of debt aversion on decision making in regards to education. Oosterbeek and van den Broek (2006) examine factors influencing the apparently myopic tendency of Dutch students to study for longer than the minimum period and finance their studies through part-time work (generally low-paid and unrelated to their studies), rather than using student loans to finish studying earlier and start working full time in better paid positions. Using data from an online survey of students, they find that debt aversion is one of the key factors affecting this decision. A student who scores 1 standard deviation higher on the debt aversion scale is about 14 percentage points less likely to take up a student loan. To separate the causal impact of debt aversion on borrowing behaviour, they suggest parental debt aversion as an exogenous source of variation in students' debt aversion that has no direct impact on the borrowing decision. Using this as an instrument, their estimate of the impact of debt aversion doubles (and remains statistically significant). If this indicates some measurement error in the students own reported debt aversion, as they suggest, the true effect of debt aversion on borrowing may be higher than their initial findings.

Field (2009) uses a quasi-experiment at NYU law school whereby a lottery determined which type of financial aid students received – one form (Public Sector Scholarships) whereby they graduate without debt but have a contractual obligation to pay fees retrospectively if they choose a private sector career, or an alternate form (Loan Repayment Assistance Program) whereby they graduate with significant debt but this is forgiven if they enter public law. Although the two forms were intentionally created to be equivalent in monetary value, Field shows that the enrolment and career choices made by individuals from the two groups are distinct and that this is consistent with a model where individuals are both debt averse and loss averse[5]. In terms of matriculation, she finds that postponing debt made applicants twice as likely to enrol at law school. Regarding career choice, rates of first job placement in public interest law are 35-46% higher for those that enjoyed scholarships rather than loan repayment assistance. This behaviour is consistent with students experiencing negative utility from carrying debt loads.

Eckel *et al* (2007) use experimental methods to explore the effect of debt aversion and debt use on demand for different forms of subsidies of post-secondary education. They present their sample of Canadian adults aged 18 – 55 with a series of choices (one of which is selected at random and actually paid) involving trade-offs between cash payments and grants or loans for full or part-time education. They combine the results of the experiments with answers to a survey covering debt attitudes[6] (among other things) and run various regressions using this data. Interestingly, they report that debt aversion has a significant positive effect on the take-up of loans for post-secondary education, which they interpret as showing that debt-averse subjects see student loans in a different category of debt. Looking only at large amounts of debt ($5000 loans), the debt aversion variable has a negative coefficient, although the statistical significance is not strong. This does provide some evidence, however, that debt aversion

[5] Following Kahneman and Tversky (1984) who define loss aversion as "the disutility of giving up an object being greater than the utility associated with acquiring it."
[6] the debt attitude questions are mostly related to the possession of credit cards and how the respondent would pay for an unexpected expense

may limit people's willingness to take out large student loans. They also find that having high debt loads makes people more likely to take up student loans. Commenting on this paper, Oosterbeck and van den Broek interpret not having high debt loads as an alternative measure of debt aversion, such that these results then fall in line with their own findings.

Linsenmeier, Rosen and Rouse (2006) study the effects of a financial aid policy reform at an elite American university in 1998 whereby loans were replaced by grants for low-income students. They find that the likelihood of matriculation increased by 3 percentage points (though it was not precisely measured) while among minority students, the effect was statistically significant and as large as 8 – 10 percentage points. Rothstein and Rouse (2011) use data from the same university from a further policy change in the early 2000s where the "no-loans" policy was extended to all students. Exploring the issue of debt loads and career choice, they find that debt on graduation significantly affects career choices, with a noticeable shift among aid recipients into non-profit, government and education ("low-salary") sectors. They present credit constraints and debt aversion as two possible explanations, and find credit constraints to be the more likely cause. However, the behaviour is also consistent with debt aversion as graduates with high debt levels seek to be debt free as quickly as possible by choosing high-salary positions straight out of university. Mincozzi (2005) also finds that high levels of student debt on graduation significantly influence graduates' job decisions as they are associated with a higher initial wage rate the year after finishing school and lower wage growth over the next 4 years. This would also be consistent with debt aversion among graduates although that is not mentioned explicitly in her paper.

Finally, Callender and Jackson (2005) look directly at the question of debt aversion and university participation using a sample of young people in the UK pursuing HE entrance qualifications (A-levels, NVQs, Access courses etc.). Measuring debt aversion through survey responses and including in the regressions a wide range of controls for gender, school results, school type, parent's education, ethnicity and age they find that students from the lower social classes are more debt averse and more likely to be deterred from university participation because of concerns about debt. Although the study provides clear results, it has several weaknesses. Firstly, the cross-sectional nature of their data only allows them to report on potential students' participation intention (rather than actual participation). Secondly, their sample consisted only of young people pursing a higher education entry qualification rather than a sample drawn from the whole population at that age, which introduces sample selection issues given that the decision to continue into post-compulsory schooling is determined by many of the same factors that affect HE participation decisions. Furthermore, their results are based on a survey carried out in 2002 before the introduction of variable, deferred fees in 2006. This was a substantial change to the system and is likely to have had implications for the relationship between debt aversion and participation for the various social class groups. The data I will be using in this chapter addresses these issues as it covers a representative sample of young people (drawn in year 9 when they were in compulsory education) and follows them year by year, thus being able to report on their actual commencement (or not) of university studies at age 18/19 in 2009.

These papers show that young people's attitudes towards debts can have a significant impact on their behaviours regarding enrolment, length of study, take-up of loans and career choice after graduation. This chapter seeks to add to this literature by providing a robust estimate of the impact of debt aversion on the university participation decision in England.

3.2.2 Relationship of Family Income and Debt Aversion

There are very few empirical papers that address the question of whether people from disadvantaged backgrounds are more debt averse on average; however, some relevant articles will be introduced here. The Callender and Jackson (2005) paper discussed above shows a clear relationship between family background and debt aversion. They find social class (based on the occupation of the main earner in the family) to be a statistically significant determinant of debt aversion, controlling for type of school, gender, ethnicity and age, with students from the lower social class group being more debt averse than students from the middle and upper classes. Furthermore, a survey conducted for Universities UK and HEFCE

(Callender *et al,* 2003) with a sample of 1,500 full-time home undergraduate students at seven UK universities gives detailed information about debt attitudes by social class. In particular, they found that students from managerial/professional family backgrounds had more tolerant views on debt and more positive views on borrowing money than other students. For example, 73% of these students agreed that "It is okay to be in debt if you can pay it off" compared to 61% from lower social classes, and 38% agreed that "I would rather be in debt than change my lifestyle" compared to 27%. Furthermore, 67% compared to 76% were seriously worried about the loans they were accumulating at university, whilst 28% agreed they were not worried about their loans because they knew they would get a well-paid job on graduation, compared to 19% of students from lower occupational social class backgrounds. This descriptive report is corroborated by anecdotal evidence in Burdman (2005) who shows that debt aversion presents a barrier to college participation among low income families through interviews with students, counsellors, outreach professionals, and financial aid directors. She also describes how familiarity with credit can play a large role in young people's attitudes towards debt.

Related to debt aversion is the question of time preference, as an aversion to borrowing to invest may indicate high discount rates. Delaney and Doyle (2012) examines children's time preferences at age 3 as represented by a range of behaviours and summarised in two factors – compulsivity, and impulsivity and inhibition. Although the authors write that their results provide "very strong evidence for a socioeconomic gradient across all measures of time preferences", I would argue that the results are less clear. Maternal education is associated with behaviours belonging to both groups, but family income is only associated with impulsivity and inhibition. I do not think that maternal education alone provides a good measure of family background, especially because of the endogeneity of parental education as a determinant of children's time preferences. All the same, the paper does indicate that young children's time preferences as expressed in certain behaviours are related to family income and maternal education, even when a range of other factors are controlled for. On the other hand, Levy (1976) found that social class was not a strong predictor of impulse control and found than in an experimental setting, middle-class boys were in fact more likely to select an immediate reward than lower-class boys. Thus whilst there is some support for the idea that time preferences may differ systematically by family background factors, especially education, this is limited and somewhat ambiguous. Relating to one's own characteristics rather than family background, Becker and Mulligan (1997) discuss the determinants of people's time preferences and present several arguments to support the proposition that "wealth causes patience". Furthermore, a paper by Warner and Pleeter (2001) examines differential discount rates by various personal characteristics using evidence from individual responses to separation packages offered during a military downsizing program. They find that more highly educated individuals have lower discount rates.

However, it is important to distinguish between debt aversion and time preference, as the two will not necessarily coincide. For example, in Oosterbeck and van den Broek (2006), described above, the authors find a correlation between their measures of debt aversion and personal discount rate of only -0.11. The work that has been done to date is far from providing a clear picture on the relationship between socio-economic background and degree of debt aversion. This chapter will add further insight in this area.

3.2.3 Family Income and University Participation

There is a large raw gap in university participation rates between rich and poor, as is documented by various government measures (see introduction). This gap has existed for a long time and, despite various government policies, does not appear to have fallen substantially. In fact, Blanden and Machin (2004) show that the rapid HE expansion that has taken place especially since the early 1990s has not been equally distributed across people from richer and poorer backgrounds, but has disproportionately benefited children from relatively well-off families, leading to further increases in educational inequalities. Furthermore, there is evidence that the importance of ability in determining participation in higher education is declining relative to the importance of family background (Galindo-Rueda and Vignoles, 2005). These authors show that low ability children from well-off families have experienced the greatest increases in educational attainment.

Most of the difference in university participation is accounted for by prior school attainment. Several studies (including Chowdury *et al*, 2010; Dearden, McGranahan and SIanesi, 2004; Cairnero and Heckman, 2003; and Bekhradnia, 2003) have shown how drastically the participation gap is reduced when prior educational performance is considered Chowdury *et al* (2010) addresses the question of *when* educational inequalities arise. Including school results at ages 11, 14, 16 and 18 in a regression with university participation as the dependent variable raises the R-squared from 10% when only individual and school characterises are included to 58%. The raw gap in participation between the top and bottom income quintiles is 40%, this falls to 9% when GCSEs and 4% when A level results are included. Bekhradnia (2003), writes that “once they have achieved the relevant qualifications, students from all social groups are equally likely to participate in higher education”, basing this on data from the Youth Cohort Surveys (2000). Thus although at face value, school results are the key determinant of university participation (i.e. because of entry requirements), this in fact captures a lot of the variation in the different participation rates between family income groups.

On the other hand, there is also a link between school results and the possibility of debt aversion affecting participation in the sense that both are reflections of a young person’s discount rate. Not liking the idea of working hard at school now for future returns indicates a high discount rate, as does not liking the idea of borrowing to invest (debt aversion). Furthermore, school results themselves will also be influenced by the young person’s expectations and aspirations regarding higher education, as someone who is not intending to go to university will have less motivation to attain good A-levels. The data used for this chapter show a very strong correlation between school results and family income and the modelling strategy employed will attempt to take account of this issue.

A substantial body of evidence (see Carneiro and Heckman (2003) for an in depth review and Dearden, McGranahan and Sianesi (2004), who replicate their results with UK data) indicates that family income influences university participation primarily through long run factors rather than through introducing short run credit constraints at the point of entry. Dearden *et al* (2004) follows the reasoning and methodology of Cairnero and Heckman (2003) to separate the effect of family income on staying at school past 16 and on completing a HE qualification into short-term effects (credit constraints) and long-term factors. The effect of credit constraints is defined as the gap in participation rates that remains when ability, parental education, family size and structure, father's social status at 16, race and region of residence at 16 are controlled for. (Since it is not possible to control fully for all long-term, formative factors, or indeed to know to what extent these have been controlled for, the authors write that the estimates are an upper bound to the possible effect of credit constraints). They find that once these factors are controlled for, not much difference remains, i.e., that credit constraints do not play a big role. They therefore recommend that funding be targeted at young people aged 16 or below, when the gaps are still emerging.

Why is debt aversion still an important consideration if credit constraints are not the issue? Debt aversion is likely to be more of an issue than short-term credit constraints in the UK because of the way student finance works – all fees are paid by the government in advance and repaid by the student through taxes after graduation. Furthermore, student loans for maintenance are readily available to all undergraduates. The burden of payment for fees and living expenses therefore falls on the student themselves rather than their family and is financed to a large degree through debt during their studies. The system effectively deals with the issue of liquidity constraints as a hindrance to participation, but introduces debt as an almost unavoidable element of undertaking a university education.

Several studies have examined the effect of the introduction of fees on participation rates. For the Australian case, Andrews (1999) and Chapman and Ryan (2005) both found that the introduction of the Higher Education Contribution Scheme (HECS) had no significant impact on the participation rates of young people from disadvantaged backgrounds. Dwenger *et al* (2012) study the impact of the introduction of fees in some

German states using difference-in-differences methodology, and find young people in those states were 2% less likely to apply in their home state, but their data prevents them exploring family background effects. In the UK, the changes that have taken place essentially reduced the cost to those from less affluent families and therefore the impact on participation was felt by the more affluent, while there does not appear to have been an impact on those from less affluent backgrounds (Urwin *et al*, 2010). This is confirmed by a HEFCE report (Corver, 2010) which shows that after taking changes in the population into account, there is no suggestion of any substantial reduction in young participation coincident with changes to HE tuition fees and student support arrangements.

There is an extensive literature on family income and university participation, exploring many channels through which family income affects the university participation decision. This chapter focuses on separating out the effect of debt aversion from the other channels through which family income affects university participation.

3.3 Theoretical Model – Defining Debt Aversion

In his work on loans and grants for university participation in Canada, Finnie (2005) defines debt aversion as "situations where individuals are unwilling to take out loans to finance their post-secondary schooling even though they know the schooling represents a good investment *and* it could be facilitated by the loans in question". He identifies three distinct kinds of debt aversion. These are:

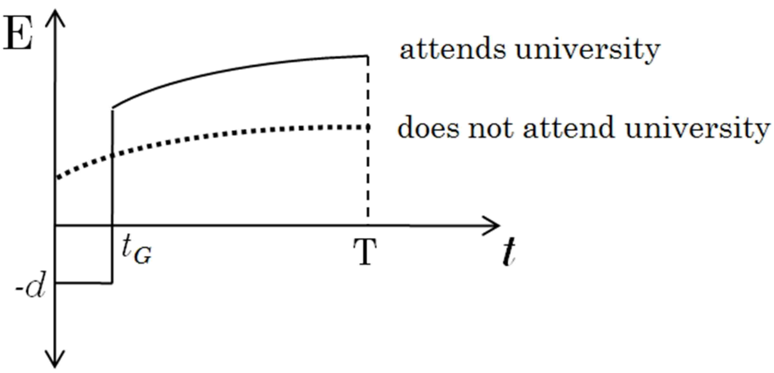
1. Value-based debt aversion (owing/borrowing money is wrong)
2. Risk-based debt aversion (e.g. concerns about ability to repay)
3. Sticker price debt aversion (expected total debt to be incurred seems "excessive")

Value based risk-aversion is related to personal, religious, class-based or other culture-related values. Risk-aversion is unlikely to pose as much of an issue in the UK, given the present system of student loans repayment out of wages post-graduation and only when wages are above a certain threshold, with outstanding debt being cancelled after a certain number of years. Sticker price debt aversion is likely to become more of an issue in coming years, due to increases in the fee cap. This kind of debt aversion is also related to information as studies have shown that students and their families (especially those from lower incomes backgrounds) tend to overestimate the debt that is likely to be incurred (Burdman, 2005).

In this section, I present a simple mathematical model that extends the traditional model of university participation choice in human capital theory (for example as presented in Borjas, 2001) to include debt aversion, based on the idea that people will not make their choice by comparing expected income streams absolutely, but rather their interpretation (perception, evaluation) of these income streams, and that they derive different utility from positive and negative assets of the same absolute value. This model draws on insights presented in Tversky and Kahneman (1992) regarding prospect theory and the way that people treat losses and gains differently.

In human capital theory, education is seen as an investment that is made in order to generate returns at a future point in time, in much the same way that investments in physical capital generate profits for companies. The decision regarding whether or not to participate in university will depend on the costs involved (including opportunity costs) and the expected future returns. It is often represented by a simple graph, as per the below:

Figure 3-1: Lifetime Earnings of a Graduate / Non-Graduate



Source: own representation, based on Borjas (2001)

This graph depicts two income streams. One is the income stream of a secondary school graduate who does not progress to university, but rather starts working straight after secondary school. He enjoys a positive income stream for the whole period displayed and sees this rise slightly year by year. The other income stream is that of a person who decides to undertake a university degree. This person's earnings are negative for the first few years (however long it takes him to complete the degree) due to fees and other direct costs. He also forgoes the earnings he would have had from working. However, after graduation, his earnings are higher than the other person and also increase faster. The decision to participate or not is made by weighing up the direct and opportunity costs incurred while studying against the present value of the additional earnings enjoyed from the point of graduation until retirement.

Describing this in equations, let the earnings at a given point in time for the person who attends university be given by E^{uni} where

$$E^{uni} = \begin{cases} -d & 0 < t < t_G \\ W(t) & t \geq t_G \end{cases} \tag{3.1}$$

and $W(t) = P\sqrt{t - t_g} - d$ (for example) (3.2)

and the earnings of the person who does not attend university be given by E^{nouni}, where

$E^{nouni} = Q\sqrt{t}$ (for example) (3.3)

-d is the amount of debt the person incurs at each year of university for fees (the direct costs of university attendance). d may be different for each individual depending on their access to credit or if there are differential fees for different courses/ institutions. Living expenses (which they would have incurred either way) are represented by the opportunity cost of what they would have earned if working – in reality, the student will need to make up these costs through grants or bursaries, taking out a student loan or a bank loan, relying on their family, working part-time, using their own personal savings, or some combination of these. t_G represents the point where the person graduates. W(t) is the graduate's wage path and P and Q represent individual ability, which affects how much the person earns.

Assuming for simplicity that there is no consumption, the net present value of the persons total lifetime earnings are defined as A (assets). The person who decides to study will have negative assets while they are at university and for a period after this until their debt is paid off, namely t_B.

To allow for different perceptions of assets in periods where the person is in the red / in the black, I define

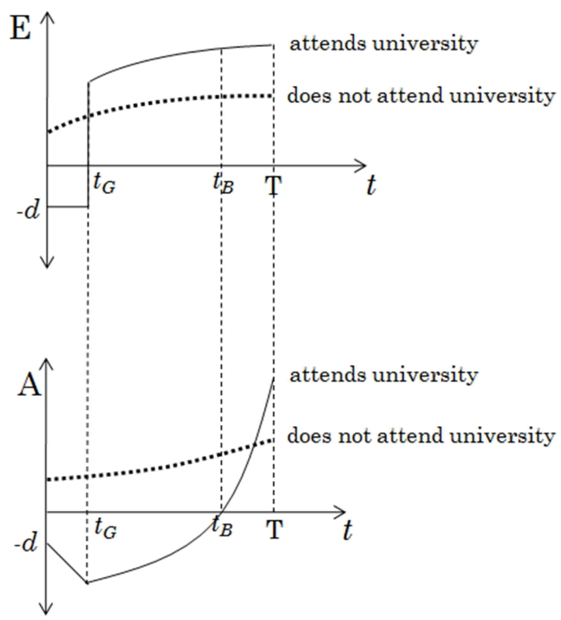
$$A_R = \int_{t_0}^{t_B} E \tag{3.4}$$

and

$$A_B = \int_{t_B}^{T} E \tag{3.5}$$

Integrating the earnings profile gives us an assets profile similar to the graph below:

Figure 3-2: Lifetime Earnings and Assets of a Graduate / Non-Graduate



Source: own representation

This can be represented by the following equations:

The net present value of the total lifetime earnings of the person who attends university is given by A^{uni} where

$$A^{uni} = \int_{t_0}^{T} E^{uni} = \int_{t_0}^{t_G} -d\delta^t dt + \int_{t_G}^{t_B} W(t)\delta^{t_B - t_G} dt + \int_{t_B}^{T} W(t)\delta^{t - t_B} dt \tag{3.6}$$

or
$$A^{uni} = \int_{t_0}^{T} E^{uni} = \int_{t_0}^{t_G} -d\delta^t dt + \int_{t_G}^{T} W(t)\delta^{t - t_G} dt \tag{3.6b}$$

and assuming, once again for simplicity, that debt is only incurred for the purposes of studying, the total lifetime assets of the person who does not attend university are given by A^{nouni} where

$$A^{nouni} = \int_{t_0}^{T} E^{nouni} = \int_{t_0}^{T} Q\sqrt{t}\delta^t dt \tag{3.7}$$

where δ represents the persons discount rate, including interest rate and time preferences.

The contribution of this model is to illustrate the effect of the person's *interpretation* of assets gained under the two income streams on the university participation decision. People will not base their decision solely on the comparison of A^{uni} and A^{nouni}, but rather on their interpretation of these amounts, i.e on $U(A^{uni})$ and $U(A^{nouni})$.

It is not necessary to fully define the utility function, however, the following assumptions are made concerning U(A):

a) U(0) = 0
b) U(A) is increasing in A

Debt aversion can be said to mean that the negative utility associated with a debt will be greater than the positive utility associated with an asset of the same absolute value as the debt. As such, it is defined as associating a greater absolute value of utility to negative amounts than to the equivalent positive amount

i.e.
$$-U(-x) > U(x) \qquad \forall x \tag{3.8}$$

or alternatively $-KU(-x) = U(x)\ where\ K > 1$ (3.9)

Allowing the person to associate different utility to assets of the same absolute value depending if they are negative or positive, I define

$$U(A) = -KU(A_R) + U(A_B) \tag{3.10}$$

where K represents the person's attitude towards debt and it is assumed that A_R enters as a positive number.

The person should be indifferent between attending / not attending university if U(A^{uni}) = U(A^{nouni}),

i.e if $KU(A_R^{uni}) + U(A_B^{uni}) = KU(A_R^{nouni}) + U(A_B^{nouni})$ (3.11)

which simplifies to $KU(A_R^{uni}) + U(A_B^{uni}) = U(A_B^{nouni})$ (3.12)

as the person does not incur any debt unless they attend university, solving for K gives, $K = \frac{U(A_B^{nouni}) - U(A_B^{uni})}{U(A_R^{uni})}$ (3.13)

This shows that the participation decision depends not only on the expected earnings differential for graduates / non-graduates, and the amount of debt incurred, but also on the way the individual perceives the positive utility of greater earnings as a graduate relative to the negative utility of being in debt. As debt increases (holding the earnings differential constant), the person must be more and more debt tolerant to remain indifferent between the two options. There will be a critical level of K such that a person will switch their decision from *uni* to *nouni* due to debt aversion, i.e where U(A^{uni}) < U(A^{nouni}) even though (A^{uni}) > A(^{nouni}).

Expanding the equations to include the full specification introduced at the start of the section, we can also see how family income influences almost every parameter. The equation below is a long form of the expected utility of participating in university:

$$
\begin{aligned}
U(A^{uni}) &= KU(A_R^{uni}) + U(A_B^{uni}) \\
&= KU(\int_{t_0}^{t_B} E^{uni}) + U(\int_{t_B}^{T} E^{uni}) \\
&= K(U(\int_{t_0}^{t_G} -d\delta^t dt) + U(\int_{t_G}^{t_B} W(t)\delta^{t-t_G} dt)) + U(\int_{t_B}^{T} W(t)\delta^{t-t_B} dt) \\
&= K(U(\int_{t_0}^{t_G} -d\delta^t dt) + U(\int_{t_G}^{t_B} P\sqrt{t_B - t_G} - d)\delta^{t-t_G} dt)) + U(\int_{t_B}^{T} (P\sqrt{t - t_B} - d)\delta^{t-t_B} dt)
\end{aligned}
\tag{3.14}
$$

Family income will especially affect how a student funds themselves while at university: someone who cannot rely on their parents for money is much more likely to work part-time during term time, which may have an adverse effect on their grades and future earnings, on the other hand, grants and bursaries are more readily available for students from poorer backgrounds. The level of student loans available also depends on family income. Studies have shown that young people from poorer backgrounds tend to leave university with more debt and have lower expected earnings on graduation (Callender *et al*, 2003). This relates to parameters d and P in the model[7]. Low family income may also affect a person's access to credit, possibly making it more expensive to borrow, and there is some evidence (see Delaney and Doyle, 2012) of a link between family background and time preferences, both of which would affect δ. It is the hypothesis of this chapter that family income affects K. It could also affect the time taken for the studies, t_G, especially through part-time work. Thus every parameter is influenced by family income. This shows how integral the effects of family income are to the university participation decision.

This simple model expresses the idea that someone's decision whether or not to invest in further education will not depend on the actual total lifetime earnings expected for each pathway, but rather their perception of these flows. If people associate utility to positive and negative sums differently, this will impact on their assessment of the two options, as negative assets are only experienced by those who chose to study. Debt

[7] More precisely – it relates to the gap between -d and their potential earnings stream if they had not studied, and to a potential employer's perception of their ability P based on their grades.

aversion may thereby act as a barrier to university participation by causing those who would otherwise have chosen the stream with higher lifetime earnings post-graduation to evaluate this less positively than the alternative stream due to the large negative utility experienced at the outset. The model also reveals how multifaceted the effect of family income on the participation decision is, as it impacts a range of factors associated with the decision.

3.4 Data

This section provides a brief introduction to the dataset used in this analysis and provides descriptive statistics of the key variables.

3.4.1 Longitudinal Study of Young People in England (LSYPE)

This study uses data from the Longitudinal Study of Young People in England (LSYPE), a large-scale longitudinal panel study of young people managed by the Department for Education. It began in 2004 when its sample of young people were aged between 13 and 14 and has followed them at yearly intervals, called ‘waves’. The fieldwork for the most recent wave (wave 6) ran from the 12th of May 2009 to the 14th of October 2009, when the sampled young people were aged 18-19 and some were in their first year of university. The data have been linked to administrative data held on the National Pupil Database (NPD). This is a pupil-level database which matches pupil and school characteristic data to pupil-level attainment, through which variables such as Key Stage test scores and GCSEs gained and grades are available.

The original sample drawn for the first wave was of over 33,000 young people in Year 9 attending maintained schools, independent schools and pupil referral units (PRUs) in England in February 2004. The final issued sample was approximately 21,000 young people. The final issued sample was smaller than the initial drawn sample mainly due to school level non-response. Of the 892 schools selected in total, 647 schools (73%) co-operated with the study. In Inner London, only 56 per cent of schools responded and in the independent sector, only 57 per cent co-operated. All sample members were those born between 1st September 1989 and 31st

August 1990. In the maintained sector, they were selected using selection probabilities based on ethnicity while at independent schools and PRUs the selection was random. Ethnic minority pupils were over-sampled in the maintained sector to ensure an adequate representation of the relevant sub-populations in England. Pupils in the 20% of schools with the most pupils in receipt of Free School Meals were also over-sampled for the same reason. The survey provides weights to deal with this issue and with attrition, so that the general population of England for these ages is reflected in the data. The regressions included in this chapter are all run using the appropriate survey weights. Looking at wave 6, the most recent wave for which data is available, 11,225 young people were issued and the survey reached 9,799 households (87%). This was made up of 3,803 (39%) online interviews, 4,705 (48%) telephone interviews and 1,291 (13%) face to face interviews. While in waves 1 to 4, both the young person and their parents were interviewed, at waves 5 and 6, only the sampled young person completed the interview.

The advantage of this data set is that it is based on a representative sample of students in year 9 and not only those studying HE qualifications or those already in HE. To explore the question of university participation choice, samples consisting of students are clearly not useful. Furthermore, surveys of pupils pursuing HE entrance qualifications (such as A-levels or Access courses) suffer from a similar selection issue and unless they are longitudinal, can only report on participation intention rather than if the pupil actually starts university. Having followed the young people over several years, the LSYPE can report on the actual participation (or not) of young people from a representative cross-section of society.

3.4.2 Key Variables Used in the Regressions

3.4.2.1 University Participation

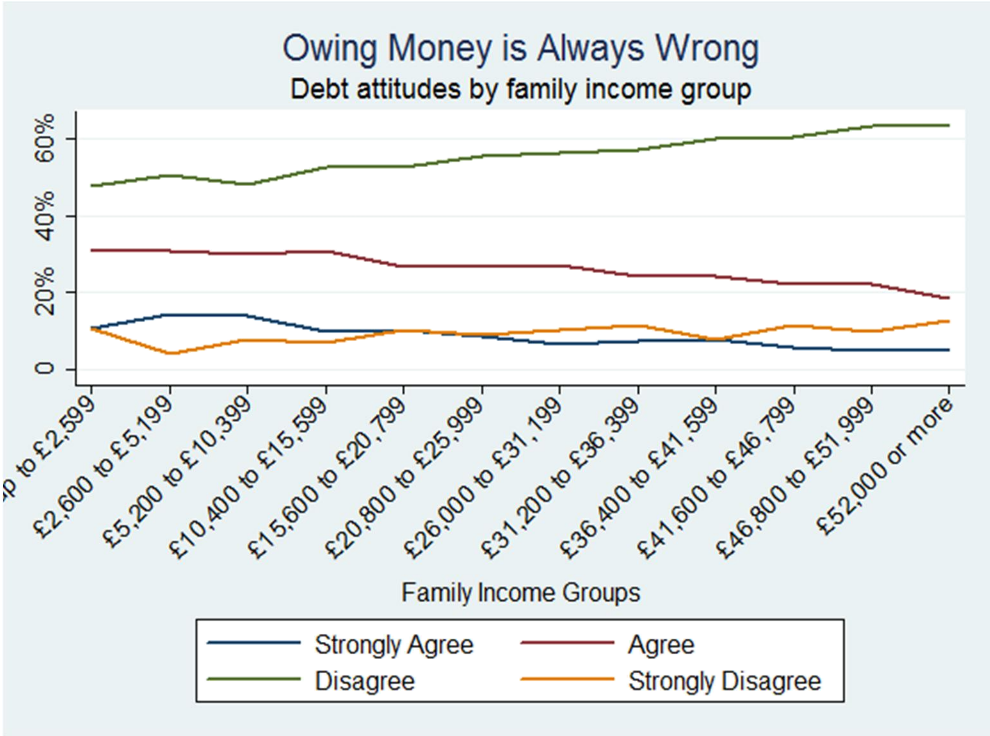
The dependent variable used in this analysis is a binary variable (which takes the value of either zero or one) describing whether someone is at university in wave 6 (age 18). Since this is the earliest year anyone could normally have started university, it represents a lower bound on the participation rates of all income groups. This may cause some bias to the estimates if people from poorer backgrounds start university slightly later (possibly through a different route). On the other hand, young people from richer households are more likely to take a gap year. Since it has been shown that delaying entrance to university, even by one year, can reduce the returns to a degree (Holmlund *et al*, 2008), it is still of interest to analyse participation rates at age 18, even though some young people may still enter university at a later date. Importantly, the effects of debt aversion should be interpreted as either hindering or delaying entry, as some of the young people not at university in wave 6 may still enter university at a later date. For reference, HEFCE uses entry at age 18 and 19 into HE institutions and FE colleges in the UK. The average participation rate for males in the data is 30% and for females is 37%, which is in line with overall participation rates in the total population (32% for men and 40% for women; Corver, 2010).

3.4.2.2 Debt Aversion

The LSYPE contains 6 questions on debt attitudes, although some of these are related to university participation as well and are not purely about debt. The clearest question is the statement “owing money is always wrong” with which students who answered could either strongly agree, agree, disagree or strongly disagree. According to the definition of three types of debt aversion as per Finnie (2008), this is clearly related to the first kind: “value-based debt aversion”. An alternative question posed in the survey is “Once you get into debt it is often very difficult to get out of it” with the same four possible responses. This is more closely linked to “risk-based debt aversion”.

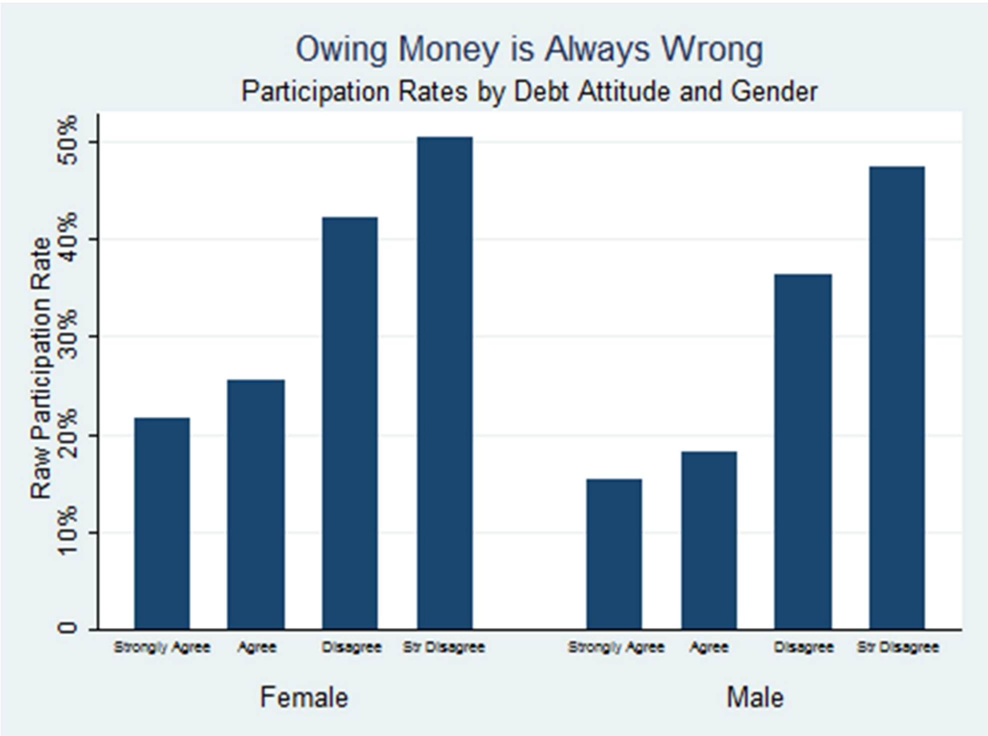
Key Relationships in the LSYPE variables:

Figure 3-3: Debt Attitudes by Family Income Group (Value-based Debt Aversion)



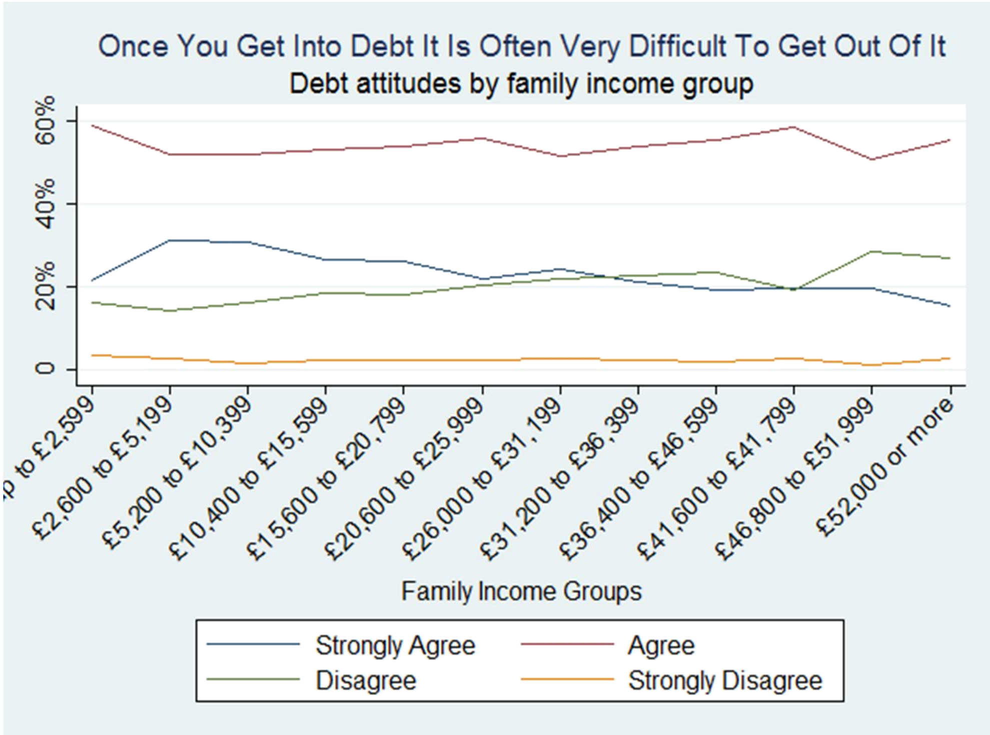
Source: LSYPE

Figure 3-4 University Participation Rates by Debt Attitude and Gender (Value-based Debt Aversion)



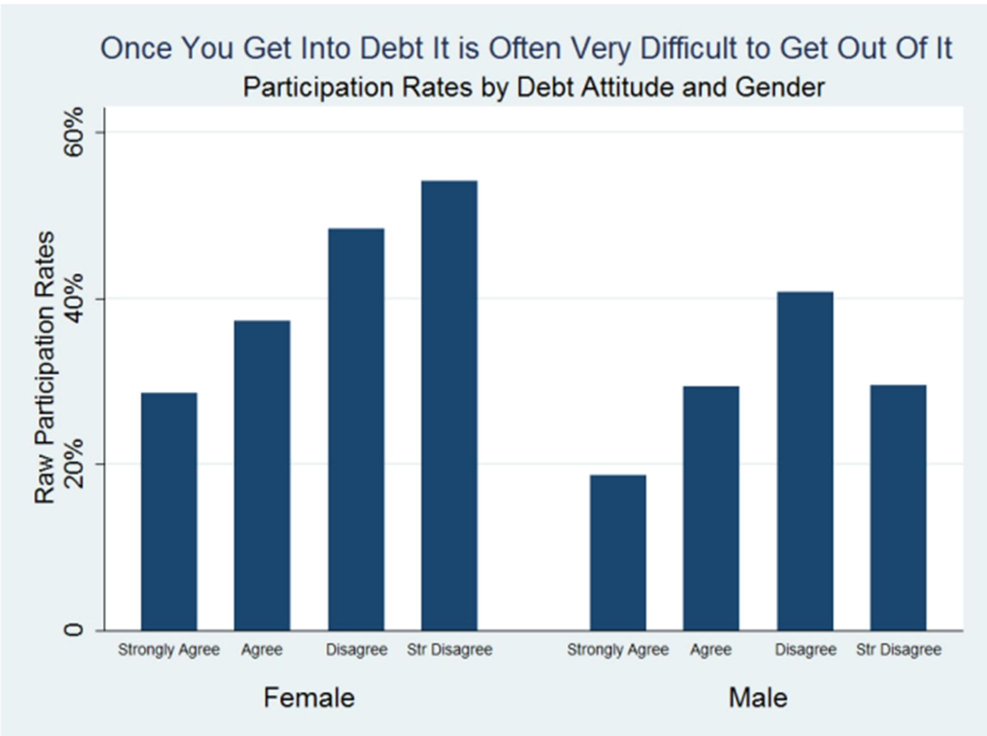
Source: LSYPE

Figure 3-5: Debt Attitudes by Family Income Group (Risk-based Debt Aversion)



Source: LSYPE

Figure 3-6 University Participation Rates by Debt Attitude and Gender (Risk-based Debt Aversion)



Source: LSYPE

The survey also contains the question, “the idea of leaving university with big debts puts people off going there”. Although this could potentially relate to sticker-price debt aversion (since it refers to “big” debts), it is a much murkier indicator of the young people’s debt attitude as it mixes debt attitude and the effect on participation, and refers to “people” generally rather than their own personal attitude. I do not use this variable in the analysis[8].

There is a clear negative relationship between family income and value-based debt aversion in this data: the proportion who disagree that owing money is always wrong – i.e. are accepting of debt, rises with income, from 45% at the lowest income band to over 60% for the highest income band. There is also a clear relationship between this variable and university participation, with young people who disagree or strongly disagree that “owing money is always wrong” more likely to be at university in wave 6 (see graphs above).

Examining the alternative measure of debt aversion, which is more closely related to fear of debt: “once you get into debt it is often very difficult to get out of it”, a large portion (around half) of young people from every income band selected “agree”, however, we can see that the proportion of young people selecting “strongly agree” falls as family income levels rise, whereas the proportion selecting “disagree” rises. Nearly a third of young people from the poorest families “strongly agree” that it is often very difficult to get out of debt once you are in it, compared to 15% from the richest families, while nearly a quarter of young people from the richest families “disagree” that it is difficult to get out of debt compared to 15% from the poorest families. The graph above shows that in general, university participation rates rise for both males and females as tolerance to debt increases. Furthermore, those that are not at university in wave 6 are more likely to strongly agree that it is hard to get out of debt (27% of those who

[8] A further reason for excluding this variable as a possible indicator of sticker price debt aversion is that in logistic regressions with the same control variables as the other models, dummies for this variable have odds ratios of more than positive 2, which would mean that agreeing that “the idea of leaving university with big debts puts people off going there” makes someone much more likely to go to university.

are not at university strongly agree with the statement compared with 17% of those who are at university).

3.4.2.3 Family Income

In this chapter, I use total gross income for both parents from wave 4 (when the young people were around 16). There is a clear positive relationship between family income and university participation for both males and females.

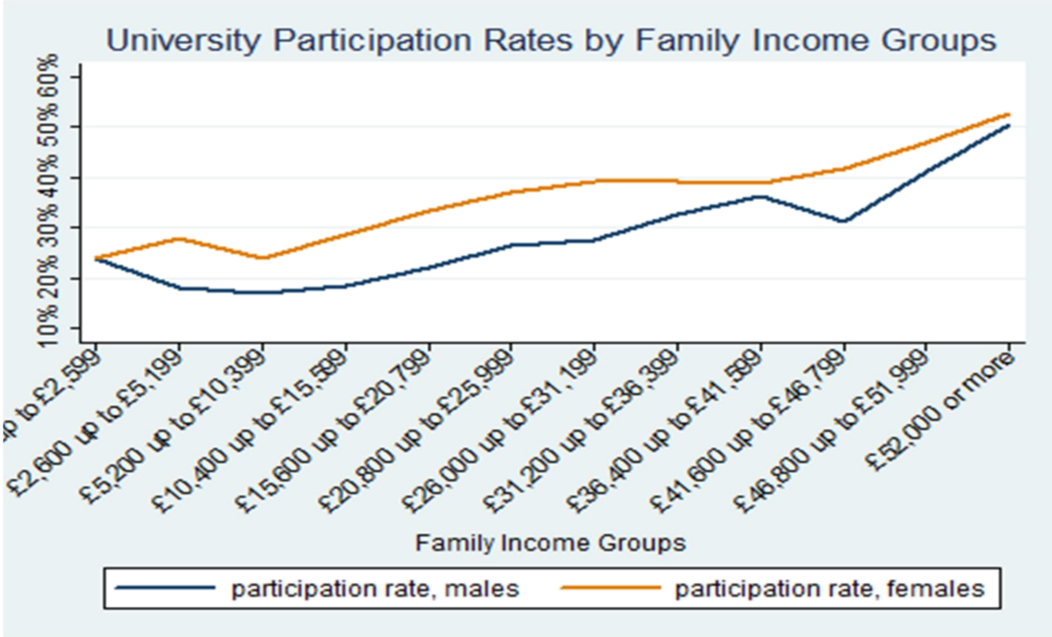
The variable is banded, and I create four groups from these bands to simplify the analysis. The maximum student grant is available to students whose family income lies below £25,000. The cut off of income group 2 is the closest possible figure to this amount. Participation rates for males and females for each group are shown in Table 3.2 below.

Table 3-2: Family Income Groups.

Family Income Group	Total gross Income (both parents)	Percentage Share	Male Participation Rate	Female Participation Rate
.	missing	20%	-	-
1	up to £10,399	12%	18%	25%
2	£10,400 to £25,999	27%	22%	33%
3	£26,000 to 41,599	19%	32%	39%
4	from £41,600 up	22%	45%	49%

There is a clear increase in participation rates when moving from the poorest to the richest families, for males from 18% to 45% and for females from 25% to 49%. The figure below shows the participation rates for all groups reported in the raw data.

Figure 3-7: University Participation Rates by Family Income Groups



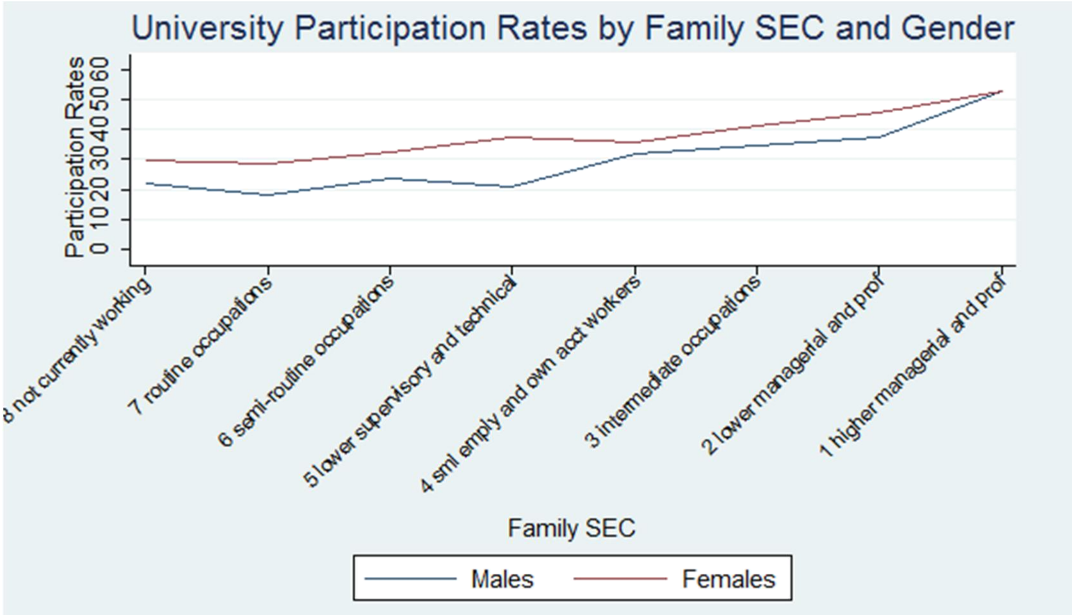
Source: LSYPE

3.4.2.4 Family Socio-Economic Class

It is also interesting to look at social class as an alternative to family income. Although the two measures are correlated, much of the literature on the university participation decision (particularly in the field of sociology) focuses on social class rather than family income as this affects factors such as expectations, aspirations and familiarity with university, all of which strongly influence the participation decision (Reay *et al*, 2005).

The graph below shows a clear link between socio economic class and university participation. Males (females) whose fathers are in higher managerial or professional occupations have university participation rates of 53% (52%) in this data, compared to fathers in routine occupations, where the young people have participation rates of 18% for males and 28% for females.

Figure 3-8: University Participation Rates by Family Socio-Economic Class



Source: LSYPE

As per family income, I create sub-groups to simplify the analysis:

Table 3-3: Family Socio-Economic Class Groups

Family SEC Group	Family SEC	Percentage Share	Male Participation Rate	Female Participation Rate
.	missing	32%	26%	31%
1	6,7,8	28%	22%	30%
2	3,4,5	17%	29%	38%
3	1,2	22%	41%	47%

3.4.2.5 Controls

All regressions include the following control variables: ethnicity dummies with white as the base, number of siblings, an ability proxy (test scores at age 11), a dummy variable showing if the young person lives in a rural or urban area, region of residence[9], a dummy variable indicating if they have a long-standing health problem or disability, and dummy variables indicating whether or not they come from a non-traditional family and if their mother or father has a degree.

[9] An alternative specification using local unemployment rates returned essentially equivalent results

One important issue relates to the inclusion of school results, since we saw above that differences in university participation rates between young people from different family backgrounds essentially disappear when school results are considered. The LSYPE is linked to the National Pupil Database (NPD) and as such, detailed test scores are available in the data. These include: key stage 2 test scores (at age 11), GCSE scores and the number of A-levels the student is taking at wave 5[10]. It is important to include a measure of ability in the regressions as otherwise there will be strong omitted variable bias in the key variables – debt aversion and family income. For this reason, key stage 2 test scores will be included as they are the earliest available measure.

On the other hand, there are reasons not to include GCSE results and A-levels. Firstly, these are endogenous as they are partly determined by the expectations and aspirations of the pupil and their family concerning their future pathway - a young person may not be as motivated to achieve good results if they have no intention of going to university. Secondly, school results will capture much of the formative effect of family income on the child such as the influence on their learning environment, school choice and so on. Other studies have shown that once school results are accounted for, not much variability remains in participation rates across family income groups (Chowdury *et al*, 2010; Bekhradnia, 2003). To allow the full influence of these effects to be captured by the family income variable, I have chosen not to include school performance results past the key stage 2 scores included as a measure of ability.

All the same, GCSE results and A-levels will not just capture family income but are also correlated with debt aversion if both are related to the persons discount rate. As a robustness check on the effects of debt aversion, a supplementary section will be included in the results section that includes models with progressively more measures of performance at school, right up to A-levels. This will help to certify that debt aversion itself is affecting participation rather than just being a reflection of some other factor related to school results.

[10] A level results are being linked and will most likely be available in the future.

3.4.3 Missing Data

The discussion and tables above have already indicated that there is a not insignificant degree of missing data in the data used for this analysis. Data can be missing for various reasons, including non-response, questions which are not applicable for certain respondents, and errors with data entry. It is important to identify the reasons for which data may be missing and in particular for the case of non-response, assess whether this is correlated with other variables or with the value of that variable itself.

Missing data can be classified as Missing Completely at Random (MCAR), Missing at Random (MAR) – if the missingness is correlated with one of the other explanatory variables, or Missing Not at Random (MNAR) – if the missingness is correlated with the value of the variable itself, for example, people with low income being less likely to answer questions about their income levels (Allison, 2001). The major potential problem caused by missing data is this can lead to biased parameter estimates, which is especially applicable if the data are MNAR. A further potential problem is if cases with missing observations being removed from the sample causes either an insufficient sample size for the analysis to be performed, a reduction in statistical power such that no statistical significance is achieved, or thirdly if the sample becomes unrepresentative due to the non-random nature of cases being dropped.

It is also important to note whether the missing data affects the dependent variables or the independent variables. In general, missing data on the dependent variable tends to have more severe consequences that missing data on the covariates (Lynch, 2003). For the data in the LSYPE, the dependent variable – university participation – is constructed in such a way that there are no missing observations for this variable. A participant is defined as being at university based on their main current activity. Out of the total sample of 9,799 young people, 3,306 people gave a clear response indicating that they are at university. All other responses, including ambiguous responses such as “waiting for a course or job to start” (317) were defined as not at university.

The main issue regarding missing responses for this dataset and my research question relates to family income and family SEC. As can be seen in Tables 3.2 and 3.3 above, 20% of the sample has missing data on Total Gross Income (both parents) and 33% has missing data on Family SEC. Looking at these jointly, of the people who have missing data for family income, half of these also have missing data on family SEC, and the other half are more concentrated in the lower SEC group (21%) compared to the higher SEC group (9.5%). This (and other characteristics such as parents' education) may indicate that missing data on family income is MNAR, in that it depends on the level of family income, with people from lower family incomes less likely to report their income.

The rate of missingness for the debt aversion variables is much lower, as for value-based debt aversion only 3.27% of observations are missing, and this is similar, at 3.56%, for the risk-based debt aversion variable. Most other variables have low rates of missingness as well, including gender (0%), ethnicity (0%), having a health problem or disability (0.96%), number of siblings (1.22%), urban dwelling and region of residence (both 2.7%), not living in a traditional family (5.46%), mother's education (6.2%) and key stage two test scores (7.82%). Apart from family income / family SEC, the control variable with the highest rate of missingness is father's education, at 29.7%. This is due to two reasons – firstly, where there is no father present in the household, and secondly, where the father is present but his education is not reported. The second reason is quite minor, with the father's education level generally being reported if he is present in the household.

In all, 11.49% of the sample of 9,699 has a missing observation for at least one variable, excluding family income, family SEC, parents' education and the debt aversion variables. Once these are also considered, the percentage of observations missing data rises to 53.22%. This indicates that missing data is quite a serious issue for this data set, particularly in regards to family income and family SEC. Methods to address this issue will be discussed in the methodology section.

3.5 Methodology

There will be two stages to the investigation. Firstly, I will examine whether or not debt aversion has an impact on university participation straight out of school. Secondly, I will seek to determine if this effect differs by family background.

3.5.1 Logistic Regression

The first stage of analysis involves regression analysis with university participation as the dependent variable of the model. This variable takes on either the value of one if the subject is attending university, or otherwise zero. The two standard choices for regressions with binary dependent variables are probit and logit models. Both of these are special cases of a more general latent variable model such as

$$y* = \boldsymbol{x\beta} + \varepsilon,\ y = 1\{y* > 0],\tag{3.15}$$

where y takes the value of 1 or 0 depending on an underlying, generally unobserved, latent variable $y*$. Based on the assumption that ε is a continuously distributed variable independent of $\boldsymbol{x}$ and where $G\,(.)$ is the cumulative distribution function of ε and takes on values in the open unit interval $0 < G(z) < 1$ for all $z\ \in \mathbb{R}$, it can be shown that

$$P(y = 1|x) = P(y* > 0|x) = P(\varepsilon - \boldsymbol{x\beta}|\boldsymbol{x}) = 1 - G(-\boldsymbol{x\beta}) = G(\boldsymbol{x\beta})\tag{3.16}$$

The logit model arises from this more general form when it is assumed that ε has a standard logistic distribution. It takes the form

$$G(z) = \Lambda(z) = \exp(z)\,/[1 + \exp(z)]\tag{3.17}$$

Thus in logistic regression, the conditional probabilities are transformed into log-odds ratios. The main assumption required for the logit model is that the true conditional probabilities are a logistic function of the independent variables. Other standard assumptions required are that no important variables are omitted from and no extraneous variables are included into the vector $\boldsymbol{x}$, the independent variables are measured without error and are not linear combinations of each other (to avoid multicollinearity), and that the observations are independent. Logistic regression assumes a linear relationship between the logit of the independent variables and dependent variables, but does not assume a linear relationship between the dependent and independent variables themselves. Furthermore, there is no assumption of normality, linearity or homogeneity of variance for the independent variables.

The interpretation of partial effects is more complicated than in a standard OLS or a limited dependent variable (LDV) model, since the partial effect of x_j depends on the values of the other explanatory variables. Where $P(y=1|x) = G(\boldsymbol{x\beta}) \equiv p(\boldsymbol{x})$, the partial effect of x_j on $p(x)$ depends on $\boldsymbol{x}$ through $g(\boldsymbol{x\beta})$, i.e. $\frac{\partial p(x)}{\partial x_j} = g(\boldsymbol{x\beta})\beta_j$, where $g(z) = \frac{dG}{dz}(z)$ for continuous variables x_j. For binary explanatory variables, the partial effect is equal to $G(\beta_1 + \beta_2 x_2 + \cdots + \beta_{K-1}x_{K-1} + \beta_K)$- $G(\beta_1 + \beta_2 x_2 + \cdots + \beta_{K-1}x_{K-1})$. This is true for both logit and probit models, however, since logit allows the possibility of comparing odds ratios for the independent variables, i.e between different family income groups, social class groups, ethnicities etc., the effects are easier to interpret than in a probit model. Facilitation of the interpretation of results is one reason I have chosen logistic regression over probit regression for the analysis in this chapter.

The econometric model in this chapter will have the form:

$$atuni = \alpha + \sum_{j=1}^{3} \beta_j famigrps + \sum_{k=1}^{3} \beta_k debtaversion + \sum_{l=1}^{n} \beta_l X + \varepsilon \tag{3.18}$$

where atuni is a binary variable of the form $y_i = \begin{Bmatrix} 1 & subject\ is\ attending\ university \\ 0 & subject\ is\ not\ attending\ university \end{Bmatrix}$ and the variables on family income groups and debt aversion are sets of dummy variables. There are three dummy variables for family income groups since all young people were divided into one of four groups and one group is excluded to avoid perfect collinearity. The debt attitude questions have four possible responses so there are three dummy variables included for debt aversion as well. The Xs are controls including ethnicity, gender and other factors. A further set of regressions will be run with social class dummies rather than family income. The *i* notation has been dropped for convenience.

The dependent variable in the regressions is a binary variable indicating whether or not the young person is at university at age 18 (wave 6). The parameters of interest are the parameters on the debt aversion dummies, with the other variables acting as controls. I argue these provide a good indication of the causal effect of debt aversion on university participation straight out of school. This is discussed later in more detail.

Whilst the parameters of interest are the parameters on the debt aversion variables, it is also interesting to examine the effect on the family income dummies when debt aversion is/is not included in the model, since we have seen that there is a strong relationship between family income and debt aversion, both in the data at hand and according to the theoretical model. For this reason, regressions including family income or father's SEC (and the other controls) are initially run without the debt aversion variables, and these are then included subsequently to show not only their own effects but also the change in the family income variables. The second stage of the analysis will be to further explore the combined effects of family income and debt aversion through decomposition analysis based on the initial logit models.

3.5.2 Dealing with Endogeneity

One issue with this model is the problem of endogeneity, as family income and debt aversion can both be seen as being endogenous. This is a common issue in this area and I discuss below some implications and possible solutions, as well as the issues in applying these.

Family income is endogenous if it is correlated with unobserved omitted variables contained in the error term (such as parents' expectations). Estimating the equation without dealing with this issue would cause the parameter estimates to be biased. The extent of bias in the family income variables will depend on the strength of correlation between this variable and the omitted variables, as well as the explanatory power of the omitted variables themselves. Various solutions to the issue of endogeneity present themselves, with the first being the possibility of using proxy variables for the unobserved (and therefore omitted) variables.

In this model, one of the key issues is unobserved ability, which is correlated with both family income and the error term. Omitted variable bias would certainly arise if no proxy for unobserved innate ability could be found. However, using a variable which is strongly correlated with the young person's ability mitigates this bias. I use their key stage 2 tests scores (an average of their standardised English, math and science scores at age 11) as a proxy for ability. This is the earliest measure available in the data, which also contains GCSE results and some information about A-levels. Using the earliest possible measure minimises the influence of school type etc. as we are primarily interested in capturing the individual's innate ability.

If there are still other factors (besides ability) contained in the error term that are correlated with family income, we need to explore further possibilities for dealing with the endogeneity of the family income variable. With panel data, it is possible to deal with this issue by using fixed-effects models or first differencing to eliminate individual time-invariant unobserved heterogeneity. However, that is not an option in this case as the data is not true panel data, with each wave containing different variables (for example my family income variables are derived from a question that only appeared in wave 4).

One popular means of dealing with endogeneity is to use an instrumental variables approach. Certain papers have applied this method in schooling choice models to deal with the endogeneity of family income, although it is not easy to find an instrument for family income that is both relevant (i.e. correlated with the variable you want to instrument) and uncorrelated with the error term (this second condition requires that the only channel through which the instrument affects the dependent variable is through its influence on the endogenous explanatory variable, Angrist and Pischke, 2008).

Blanden *et al* (2003) acknowledges the difficulties in separating out income effects from other characteristics associated with income. To abstract from this difficulty, they focus on describing the way that the effect of income is changing over time rather than attempting to quantify absolutely the effect of an additional pound of income. However, to check the robustness of their results, they apply instrumental variable methodology, using as an instrument for parental income the usage of computers in the parents industry (arguing that technology has been a factor driving inequality in incomes). The first stage is reasonably strong, which is important as using weak instruments, i.e. instruments that are not strongly correlated with the endogenous variable they are instrumenting, can lead to large asymptotic biases in the presence of even minor correlation between the instrument and the error term. All the same, this seems a strange choice of instrument given the broad array of industries and differing uses of computers within these, and highlights the difficulties in finding appropriate instruments for family income.

In general, most studies simply try to include as broad a range of variables relating to family background as possible in order to reduce the effects of omitted variable bias (e.g. Carneiro and Heckman, 2003). That is the approach I have chosen to follow as well. As well as the ability proxy, the regressions also contain parent's education, number of siblings, ethnicity, health, region of residence, whether the person comes from a non-traditional family and whether they live in an urban or rural area as control variables. The richness of the LSYPE dataset makes it possible to include a broad range of control variables, thereby strongly mitigating any potential omitted variable bias relating to the family income variables.

Debt aversion is endogenous if it is determined within the system – it is not clear if debt aversion affects participation or if participation affects debt aversion (i.e. – if starting to have a student loan changes people's attitudes towards debt, possibly making them more debt tolerant as their attitudes change to reflect their situation; Davies and Lea, 1995). Debt attitudes are recorded for the entire sample in wave 6, and in wave 5 for those young people who had applied to university or stated that they were likely to do so in the future. Comparing the debt attitudes in waves 5 and 6 for this sub-sample reveals that:

1) There was very little change between waves for those who disagreed or strongly disagreed that “owing money is always wrong” in wave 5.
2) For those who agreed with this statement in wave 5, 51% disagreed or strongly disagreed in wave 6. This raises the question of whether commencing university and starting to have a student loan had affected the debt attitudes of these young people. However, looking at the 582 people who agreed with the statement in wave 5 but disagreed with it in wave 6, only 48% of them were at university in wave 6. The split between participation / non-participation for these people is very even (around half-half), suggesting it was not university participation itself that had affected this change in attitudes.

Another issue is that of selection into university. If there are unobservables that affect the university participation decision and also debt attitudes, the debt variables will be endogenous for this reason also. In particular, one could argue that debt aversion is negatively related to intelligence, as being debt friendly (or neutral) postulates the ability to smooth income by using future income streams although they have not yet been realised – on the other hand, it could be positively related to self-discipline, if getting into debt is the inability to postpone current spending until funds are available. Intelligence and self-discipline could both be positively correlated with university participation as both are characteristics of successful students.

One paper that uses instrumental variable methods to deal with the possible endogeneity of debt aversion is Oosterbeek and van den Broek (2009) who use parents’ debt attitudes as an exogenous source of variation in students’ debt attitudes. This is a valid instrument assuming that “given parents’ income, parents with a higher degree of debt aversion take no actions to affect their children’s borrowing behaviour other than through their debt aversion … [and] …parents’ debt aversion is not affected by their children’s borrowing behaviour” (p175). Using parent’s debt attitudes as an instrument for the debt attitudes of the young people in the survey, they find that the effects of debt aversion are even greater than in the original specification. In fact, the size of the effect of debt aversion doubles after instrumenting – they conclude there may be measurement error in the student's debt aversion variable. Unfortunately, the LSYPE does not contain any indication of parents' attitudes towards debt. It is very difficult to think of another variable that is correlated strongly enough with debt aversion, uncorrelated with participation, and for which data is available, making it difficult to apply instrumental variable techniques.

Belzil and Leonardi (2007) deal with the endogeneity of their measure of risk in a study on risk-aversion[11] and university participation by developing a complex mathematical model where risk aversion is allowed to depend on wealth and background risk variables. They find that accounting for endogeneity changes the sign of their results such that higher education is seen as a risky investment and risk aversion decreases the probability of participation. Such methodology is beyond the scope of this chapter. The approach I adopt instead is detailed below.

We have seen that endogeneity can cause bias in the model's parameters and that both family income and debt aversion are potentially endogenous in this model. Regarding family income, I include in the model a proxy variable for ability as well as control variables broadly covering family background and a variety of individual characteristics. The richness of the LSYPE data makes it possible to control for a wide range of personal and family characteristics and the fact it is linked with the National Pupil Database furthermore provides test scores that act as a proxy for innate ability. Both of these precautions should serve to strongly mitigate the effects of omitted variable bias.

Regarding debt aversion, the direction of causality seems to be that debt attitudes affect the participation decision. Although it cannot be ruled out *a priori* that students adjust their attitude to debt to maintain consistency once they find themselves in debt, examining the debt attitudes in wave 5 of the subsample of which debt attitude questions were asked, with the debt attitudes in wave 6 of the same sample indicates that any shift in the debt attitudes of these young people was not caused by starting to attend

[11] Their measure of risk aversion is endogenous as it is measured quite late in life after the person has finished education

university (as those who changed their minds were split half-half between university participants and non-participants). Furthermore, the inclusion of the ability proxy should help to deal with any relationship between debt aversion, intelligence (and potentially also self-discipline) and university participation.

Although both debt aversion and family income are potentially endogenous, the control variables capture a large amount of the unobserved heterogeneity. This remains a limitation of the analysis, however, the breadth of control variables available gives confidence in asserting that the effect of debt aversion captured here is close to the causal effect.

3.5.3 Dealing with Missing Data

As discussed in Section 3.4.3 above, there is a substantial degree of missing data for the explanatory variables, especially family income. There are various ways of dealing with this issue, including listwise deletion, using indicator variables, and multiple imputation or maximum likelihood estimation. These will now be discussed in turn.

Listwise deletion means that observations for which there is missing data for at least one variable are dropped from the sample, such that only complete cases are used (Allison, 2001). For logistic regression, this has the advantage of maintaining the unbiasedness of parameter estimates and appropriateness of standard error estimates if the missing data is missing at random, however, it leads to a fall in sample size and a loss of statistical power, especially where there is a large amount of missing data.

Another method is dummy variable adjustment, or the use of indicator variables, where the variable takes the value of 1 if the data is missing for that observation and zero otherwise. An equivalent approach for categorical variables is to add an extra category to indicate missingness. This method preserves the sample size and uses all available information, but has been criticised for producing bias in coefficient estimates (see Jones, 1996). Despite this criticism, it is still appropriate for “does not apply” data, such as the case where father’s education is not reported because the father is not present in the household.

Other more complex but more robust methods include multiple imputation and maximum likelihood. These both have the properties that they are consistent, asymptotically efficient and asymptotically normal. Maximum likelihood requires a likelihood function which expresses the probability of data being missing as a function of the data and the unknown parameters which would, if true, maximise the probability of observing what has been observed. The likelihood function is maximised to uncover these parameter estimates. Multiple imputation builds on standard regression imputation (which leads to bias especially in the standard errors) by adding a random component and repeating the process multiple times to improve efficiency. For the research question in this chapter, the main issue is the missing data on family income. A future development for this research would be to use a maximum likelihood or multiple imputation methodology for the family income variable using the data that is available on family SEC, parents' education and labour force attachment, and family structure, for example.

Due to the large proportion of observations that have missing data for at least one variable, I have used the dummy variable adjustment method rather than listwise deletion in this chapter. As such, I create a missing variable for each continuous or binary explanatory variable, such that this additional variable takes the value of 1 if the data is missing for that observation and 0 otherwise; and similarly for the categorical variables, I create an extra category to indicate missingness. Although this approach is effective in preserving the original sample, it can lead to some degree of bias. An important future development would thus be to impute the values of the family income variable where they are missing. This would then mean that using listwise deletion to deal with the other missing data would not impact as strongly on the sample size. Such an approach would improve the reliability of the reported results and would be a useful future development for this research.

3.5.4 Interaction Effects in Non-linear Models and the Use of Sub-Samples

In order to explore the relationship between the effects of debt aversion and family income as part of the second stage of the investigation, I will examine interaction effects between these variables. Interaction effects can be used when it is expected that the effect of one variable depends on the size or existence of another factor. In this case, I want to test if the effect of debt aversion differs depending on the young person's family income group. Ai and Norton (2003) show that while there is a simple interpretation of interaction effects in linear models, in non-linear models, the effect is more complicated. This is because the full interaction effect is not reflected in the marginal effect of the interaction term itself only, but rather by the full cross-partial derivative of the expected value of the dependent variable. Interaction effects will therefore also depend on the values of the covariates. I take account of this in my model and report interaction effects across the range of predicted values of the dependent variable.

Secondly, I divide the sample into groups depending on family income and run regressions separately for these groups in order to compare the size and significance of the effect of debt aversion across regressions. Because the sample size is limited, I divide the sample into "rich" and "poor" by gender rather than reporting results for each of the four family income groups. "Poor" means the young person belongs to family income group 1 or 2 (£0 to £25,999), while "rich" means they belong to family income group 3 or 4 (£26,000 and above). The cut off is the closest possible point to the amount (£25,000) below which young people are entitled to the maximum possible maintenance grant[12]. I also include more or less school performance variables in different specifications and restrict the sample according to school results and participation intention to further explore the relationship between family background and debt aversion on the participation decision.

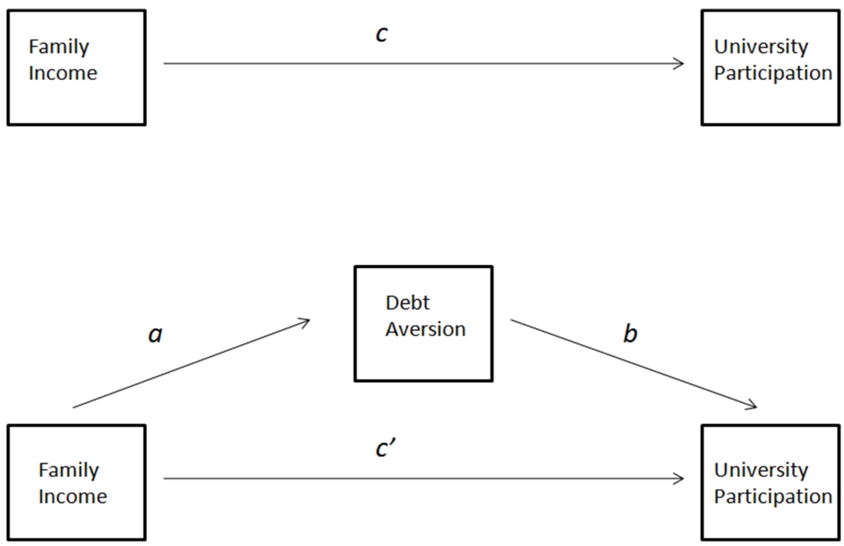
3.5.5 Direct and Indirect Effects: A Decomposition Analysis

The theoretical model presented in section 3 shows how family income influences the participation decision through its impact on factors such as time preferences, access to credit or family resources, and debt

[12] This refers to the system that was in place at the time that the survey was carried out

aversion. Having seen in the LSYPE data that there is a strong correlation between family income and debt attitudes, this section accounts for that relationship explicitly and seeks to measure the impact on the university participation decision of family income working through debt aversion. Estimating this effect for different pairs of family income groups allows us to see if low family income influences participation through its effect on debt attitudes more strongly than high family income does. Using this framework makes it possible to incorporate the relationship between debt aversion and family income directly rather than modelling interaction effects between the two variables.

Figure 3-9: Direct and Indirect Impact of Family Income of University Participation



Source: own representation based on Preacher and Hayes (2008)

This framework can be depicted as follows: The total effect of family income on university participation (*c* above) is assumed to consist of a direct effect (*c’* in the diagram above) and an indirect effect working through debt aversion (*ab* above).

In the initial stage, several logit models were estimated, all of which used “atuni” as the dependent variable, which is equal to 1 if the young person was at university when interviewed in wave 6 and zero otherwise. The first model was run with family income but without any debt aversion variable, as follows:

$$atuni = \alpha + \sum_{j=1}^{3} \beta_j famigrps + \sum_{l=1}^{n} \beta_l X + \varepsilon \tag{3.15}$$

The second included both family income and debt aversion as explanatory variables and has the following functional form:

$$atuni = \alpha + \sum_{j=1}^{3} \beta_j famigrps + \sum_{k=1}^{3} \beta_k \, debtaversion + \sum_{l=1}^{n} \beta_l X + \varepsilon \tag{3.16}$$

where the variables on family income groups and debt aversion are sets of dummy variables and the Xs are controls.

In linear regression, it would be possible to break down the effect of family income into a direct component and the indirect component coming through debt aversion by simply examining the change in the family income coefficients between models such as the ones described above, where one model includes debt aversion as an explanatory variable and the other excludes it. However, this is not possible in a logit context, due to a structural bias which can be explained as follows. A logistic regression is a comparison of proportions that have first been transformed into log-odds ratios. Probabilities at each possible value of the mediating variable (debt aversion in this case) are transformed into log-odds ratios. When this transformation is performed for probabilities close to 0 or 1, they become less tightly clustered together than they were as probabilities (i.e. values at the extremity are more extreme in the log odds metric than in the probability metric). When the mediating variable (debt aversion) is left out of the regression, the model in effect takes an average of the proportions before transforming this average into a log odds ratio. Computing the average proportion before transforming the proportions into log odds means that the extreme values are less influential than they would have been if the means were computed in the log odds metric, so the average is pulled towards the less extreme categories. The consequence of this is that the effect in terms of log odds will be less when the mediating variable is left out of the model, even if there is no indirect effect (Buis, 2008).

Erikson *et al* (2005) develop a solution to this problem which uses counterfactuals. In their study of student choices to progress to A-levels based on performance at key stage 3, they assume that the choice characteristics of students of one class can be combined with the performance distribution of students of another class to produce a counterfactual or potential outcome. They implement this using numerical integration to produce a hypothetical intervention in which the choice characteristics change but the performance distribution is unchanged (and vice versa). This makes it possible to investigate the relative contributions of choice and performance.

Based on Erikson *et al* (2005), Buis (2008) presents a generalisation that allows the variable through which the indirect effect occurs to follow any distribution (not just a normal distribution as per Erikson *et al*). This is useful for this chapter as the debt aversion variable from the LSYPE is a categorical variable that only loosely follows a normal distribution. Buis (2008) also suggests bootstrapping as a method for obtaining standard errors and shows how to control for other variables. Using an explanatory variable producing a direct effect that is a categorical variable, it is possible to produce a decomposition for all pairwise combinations of categories. The explanatory variable is family income group – performing a decomposition using this variable makes it possible to see the relative contribution of debt aversion for different pairs of family income groups. Factors described above suggest the possibility that debt aversion is a greater hindrance for poorer families. This would be confirmed by a falling indirect effect for groups of progressively higher family income compared to a base group with the lowest income.

For clarity, the following points describe the components required for the comparison of income groups 1 and 4:

- The total effect is given by log odds of success for family income group 4 minus the log odds of success for family income group 1.
- The indirect effect is given by the log odds of success of family income group 1 with the debt aversion profile of family income group 4 minus the log odds of success of family income group 1 (using their own debt aversion profile)
- The direct effect is given by the log odds of success for family income group 4 minus the log odds of success of family income group 1, given the debt aversion profile of family income group 4.

These calculations should also be carried out for the complimentary counterfactual (i.e. using family income groups 1 and 4 the other way around). As these two methods produce similar but not identical results, an average of the two can be taken as the final result.

The equations below provide more detail:

$$\underbrace{\ln(O_{x=4,z|x=4}) - \ln(O_{x=1,z|x=1})}_{total} = \underbrace{\ln(O_{x=1,z|x=4}) - \ln(O_{x=1,z|x=1})}_{indirect} + \underbrace{\ln(O_{x=4,z|x=4}) - \ln(O_{x=1,z|x=4})}_{direct} \quad (3.17)$$

Using the rule that ln(*a*) – ln(*b*) = ln(*a*/*b*),

$$\underbrace{\ln\frac{(O_{x=4,z|x=4})}{(O_{x=1,z|x=1})}}_{total} = \underbrace{\ln\frac{(O_{x=1,z|x=4})}{(O_{x=1,z|x=1})}}_{indirect} + \underbrace{\ln\frac{(O_{x=4,z|x=4})}{(O_{x=1,z|x=4})}}_{direct} \quad (3.18)$$

By exponentiating both sides of this equation, the decomposition can also be presented in terms of odds ratios. Since exp(*a* + *b*) = exp(*a*) x exp(*b*), the total effect is given by the product of the two effects:

$$\underbrace{\frac{O_{x=4,z|x=4}}{O_{x=1,z|x=1}}}_{total} = \underbrace{\frac{O_{x=1,z|x=4}}{O_{x=1,z|x=1}}}_{indirect} + \underbrace{\frac{O_{x=4,z|x=4}}{O_{x=1,z|x=4}}}_{direct} \quad (3.19)$$

Using this technique will make it possible to examine and compare the direct effect of family income on university participation with the indirect effect working through debt aversion, whilst avoiding any bias arising from the functional form of the model.

3.6 Results

3.6.1 Results of Logistic Regressions

3.6.1.1 Overall Results

Initially, several regressions were run with the dependent variable being a binary variable indicating if the young person was at university in wave 6. Separate models were run for the two family background measures (gross family income and family social class), the two debt-aversion types (value-based debt aversion: “Owing money is always wrong” and risk based debt aversion: “Once you get into debt it is often very difficult to get out of it”, as well as a model without any measure of debt aversion) and for males and females: 12 models in total.

In all models, controls were included for ability as measured by test scores at age 11, parental education, ethnicity, living in an urban area, having a long-term health problem or disability, region of residence, whether the family is a non-traditional family (for example, if the parents are divorced) and the number of siblings. The variables included as controls generally have expected signs and significance levels. The full results for the six models using family income can be found in appendix A. Ability is proxied by test scores at age 11 (key stage 2). These are divided into quintiles and there is a strongly significant relationship, with the parameter values rising for each category. Ability is, as expected, strongly positively correlated with university participation. Furthermore, ethnicity is also very important, with Indians and Bangladeshis respectively having odds of being at university more than 4 times and 3 times greater than the odds of the base group (whites). Having a health problem is statistically insignificant, possibly because the sample size of those with this problem is quite small (7.5%). The number of siblings has a negative and precisely measured effect, with the odds ratios falling further from unity as the number of siblings increases. If the home is a non-traditional family, the young person is also less likely to be at university in wave 6. Having a father or a mother with a degree has a precisely measured positive impact, and the effect of the father’s degree is stronger than that of the mother’s (for females as well as males, in fact, for females the effect of the mother’s degree is not statistically significant). Young people from rural areas are also more likely to attend university in wave 6 than those from urban areas.

Table 3-4: Logistic Regression Results for Gross Family Income and Debt Attitudes – by Gender

atuni		Males			Females	
	(1)	(2)	(3)	(4)	(5)	(6)
Family Income Groups						
1: up to £10,399 #						
2: £10,400 to £25,999	1.188	1.151	1.165	1.409**	1.372**	1.376**
	(0.211)	(0.202)	(0.208)	(0.223)	(0.217)	(0.217)
3: £26,000 to £41,599	1.591**	1.506**	1.540**	1.605***	1.591***	1.566***
	(0.287)	(0.268)	(0.28)	(0.275)	(0.273)	(0.267)
4: £41,600 and above	1.949***	1.850***	1.861***	1.771***	1.725***	1.718***
	(0.353)	(0.33)	(0.34)	(0.303)	(0.297)	(0.293)
Owing Money Is Always Wrong						
Strongly Agree		0.353***			0.375***	
		(0.075)			(0.079)	
Agree		0.409***			0.371***	
		(0.063)			(0.055)	
Disagree		0.857			0.764**	
		(0.115)			(0.099)	
Strongly Disagree #						
Once You Get Into Debt It Is Often Very Difficult To Get Out Of It						
Strongly Agree			0.937			0.347***
			(0.265)			(0.113)
Agree			1.511			0.469**
			(0.405)			(0.149)
Disagree			1.969**			0.708
			(0.538)			(0.23)
Strongly Disagree #						
Controls	YES	YES	YES	YES	YES	YES
Observations	4920	4920	4920	4869	4869	4869
R-squared	0.234	0.249	0.242	0.201	0.215	0.209

Exponentiated coefficients; Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.010, # base category

(NB: Full results including the control variables can be found in appendix A)

Table 3.4 above demonstrates the effects of family income and debt aversion on university participation for males and females. These results show a clear relationship between family income and participation with the odds ratio of young people from the richest family income group at 1.95 for males (1.77 for females) compared to the base of the poorest family income group. This relationship is statistically significant at the 1% significance level. Introducing the first debt aversion variable ("owing money is always wrong") reduces the odds ratios on the family income variables slightly, demonstrating a decreased effect of family income by bringing them closer to one. This is what was expected, as we understand debt aversion to be part of the effect of family income - when it is included explicitly, it captures some of the effect that had previously been included in the coefficients on the family income variables.

The odds ratios for the debt aversion dummies themselves demonstrate a negative relationship between debt aversion and university participation. The highest degree of debt aversion (those who "strongly agree" that owing money is always wrong) has an odds ratio of 0.353 (0.375 for females), indicating that the odds of participation of the most debt averse are 65% (62%) lower than those of the least debt averse (who "strongly disagree" that owing money is always wrong), holding all other variables constant.

Looking at risk-based debt aversion– responses to the statement "once you get into debt it is often difficult to get out of it" –shows an almost identical effect on the family income dummies for males. Once again, the odds ratios move closer to one, indicating the family income variables may have been capturing some of the effect of risk-based debt aversion. In this regression, however, the debt aversion dummies themselves are not statistically significant (except that the difference between "strongly disagree" and "disagree" is precisely measured). Given that this variable represents risk-based debt aversion, it is as expected that its effect on university participation is less marked, given the current UK system of student loan repayment. However, for females, the variable still has a statistically significant effect. The dummy for the most debt averse people has an odds ratio of 0.347 which is statistically significant at the 1% level. This shows their odds of participation are 65% lower than the odds of the least debt averse females.

The fact that the odds ratios on the "always wrong" variables are well below unity and statistically significant for both genders and the "hard out" variables are statistically significant for females indicates that debt attitudes impact on university participation, even after other factors are controlled for. Given the literature on the relative unimportance of short-term credit constraints (Carneiro and Heckman, 2003; Dearden *et al*, 2004), this is an important result. It confirms the findings of Callender and Jackson (2005), that debt attitudes are an important factor affecting the university participation decision.

The next set of regressions uses social class rather than family income. The social class variables are statistically significant for both males and females and show a positive relationship between belonging to one of the higher classes and university participation. Young males with fathers from the highest social class group (higher and lower managerial and professional occupations) have odds of participation 52% higher than males from the lowest classes, while the odds for females are 51% higher. The middle group has odds that are 30% higher for males and 32% higher for females.

On the whole, the results are very similar to the regressions using family income. Considering the regression results for males, the odds ratios on the family class dummies come slightly closer to one when either type of debt aversion is added to the model (although for females there is little change). The odds ratios on the value-based debt aversion variables are statistically significant at the 1% level, revealing the important impact of this kind of debt aversion. The most debt averse have odds of participating that are 65% lower for males (62% for females) than the odds for the least debt averse, while the second most debt averse group has 59% (63%) lower odds than the least debt averse group. Looking at risk-based debt aversion, females who strongly agree have an odds ratio of 0.335 which is statistically significant at the 1% level, while the odds ratio for those who agree is significant at the 5% level. Females seem to be more affected by risk-based debt aversion in this context than males.

Table 3-5: Logistic Regression Results for Family Social Class and Debt Attitudes – by Gender

atuni		**Males**			**Females**	
	(1)	(2)	(3)	(4)	(5)	(6)
Family NS-SECs						
Lowest SECs #						
Middle SECs	1.300**	1.258**	1.279**	1.318***	1.315**	1.318***
	(0.145)	(0.141)	(0.143)	(0.139)	(0.14)	(0.14)
Highest SECs	1.522***	1.495***	1.489***	1.506***	1.487***	1.477***
	(0.166)	(0.165)	(0.164)	(0.151)	(0.15)	(0.149)
Owing Money Is Always Wrong						
Strongly Agree		0.346***			0.378***	
		(0.073)			(0.079)	
Agree		0.407***			0.369***	
		(0.062)			(0.055)	
Disagree		0.853			0.762**	
		(0.114)			(0.098)	
Strongly Disagree #						
Once You Get Into Debt It Is Often Very Difficult To Get Out Of It						
Strongly Agree			0.911			0.335***
			(0.259)			(0.111)
Agree			1.473			0.453**
			(0.397)			(0.147)
Disagree			1.934**			0.679
			(0.532)			(0.225)
Strongly Disagree #						
Controls	YES	YES	YES	YES	YES	YES
Observations	4920	4920	4920	4869	4869	4869
R-squared	0.233	0.248	0.241	0.203	0.216	0.21

Exponentiated coefficients; Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.010, # base category

These results show that debt aversion has a negative effect on university participation for both males and females. Someone who believes that "owing money is always wrong" is less likely to be at university straight out of school, and this effect is statistically significant, even after controlling for a broad range of other determinants of participation. Furthermore, among females, the belief that "once you get into debt it is often difficult to get out of it" also has a negative effect on university participation straight out of school.

3.6.1.2 Inclusion of School Performance

As discussed above, school results are highly correlated with family income and of course are strong determinants of participation. Key Stage 2 test scores were included in the earlier regressions as a proxy for ability, as they are the earliest test scores available in the data - the regressions below explore the effect on the debt aversion and family income variables when progressively more school results are included in the regressions, and when the sample is restricted to suitably qualified individuals (defined here as those undertaking two or more A-levels at wave 5).

As expected, the family income variables lose their significance. When key stage 2 and GCSE scores and the number of A-levels taken are included or when the sample is restricted to males taking 2 or more A-levels in wave 5, the family income variables show no statistical significance. This is a similar result to what Chowdury *et al* (2010) saw using linked NPD, NISVQ and HESA data.

On the other hand, debt aversion still shows a statistically significant effect. Even in the restricted sample, those that "agree" that owing money is always wrong are less likely to be at university than those who "strongly disagree", with this effect being statistically significant at the 1% level when key stage 2 and GCSE results are included and at the 5% level when the number of A-levels taken is included as well. In terms of the size of the effect of debt aversion on participation, including school results past age 11 brings the odds ratios closer to 1, reducing the size of the effect. This indicates there is a relationship between school results and debt aversion, which may have several sources - firstly, both may well be correlated with ability, school results for obvious reasons, and debt aversion because tolerance towards debt (and especially towards borrowing for investment) requires the ability to think ahead, apply discounting etc. Secondly, both may also be correlated with discount rates, as discussed above.

Table 3-6: Logistic Regression Results with School Performance and Other Controls – Males

Sample:	**All Males**				**At least 2 A levels**	
Included School Results:	None	Key stage 2	plus GCSEs	plus A levels	key stage 2	plus GCSEs
Family Income Groups						
1: up to £10,399 #						
2: £10,400 to £25,999	1.428**	1.151	1.127	1.016	0.837	0.801
	(0.232)	(0.202)	(0.233)	(0.206)	(0.202)	(0.206)
3: £26,000 to £41,599	2.004***	1.506**	1.395	1.281	1.051	1.009
	(0.331)	(0.268)	(0.288)	(0.259)	(0.259)	(0.263)
4: £41,600 and above	2.748***	1.850***	1.448*	1.241	1.041	0.898
	(0.459)	(0.332)	(0.298)	(0.252)	(0.253)	(0.23)
Owing Money Is Always Wrong						
Strongly Disagree #						
Strongly Agree	0.246***	0.353***	0.607**	0.736	0.66	0.919
	(0.05)	(0.075)	(0.14)	(0.177)	(0.197)	(0.304)
Agree	0.296***	0.409***	0.581***	0.640**	0.574***	0.630**
	(0.043)	(0.063)	(0.098)	(0.112)	(0.112)	(0.127)
Disagree	0.812	0.857	1.056	1.096	1.021	1.105
	(0.103)	(0.115)	(0.155)	(0.167)	(0.168)	(0.188)
Controls	YES	YES	YES	YES	YES	YES
Observations	4920	4920	4920	4920	2040	2029
R-squared	0.157	0.249	0.367	0.404	0.089	0.14

Exponentiated coefficients; Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010, # base category

Table 3-7: Logistic Regression Results with School Performance and Other Controls – Females

Sample:	**All Females**				**At least 2 A levels**	
Included School Results:	None	Key stage 2	plus GCSEs	plus A levels	key stage 2	plus GCSEs
Family Income Groups						
1: up to £10,399 #						
2: £10,400 to £25,999	1.528***	1.372**	1.105	1.198	1.107	0.976
	(0.231)	(0.217)	(0.194)	(0.212)	(0.258)	(0.241)
3: £26,000 to £41,599	2.017***	1.591***	1.229	1.323	1.305	1.117
	(0.327)	(0.273)	(0.23)	(0.251)	(0.322)	(0.29)
4: £41,600 and above	2.484***	1.725***	1.208	1.226	1.263	1.045
	(0.408)	(0.297)	(0.227)	(0.232)	(0.308)	(0.269)
Owing Money Is Always Wrong						
Strongly Agree	0.225***	0.375***	0.513***	0.618**	0.559*	0.608
	(0.045)	(0.079)	(0.121)	(0.149)	(0.17)	(0.191)
Agree	0.261***	0.371***	0.527***	0.600***	0.557***	0.639**
	(0.038)	(0.055)	(0.084)	(0.101)	(0.111)	(0.13)
Disagree	0.661***	0.764**	0.905	0.955	0.833	0.904
	(0.084)	(0.099)	(0.124)	(0.139)	(0.138)	(0.151)
Strongly Disagree #						
Controls	YES	YES	YES	YES	YES	YES
Observations	4869	4869	4869	4869	2355	2351
R-squared	0.137	0.215	0.328	0.372	0.07	0.114

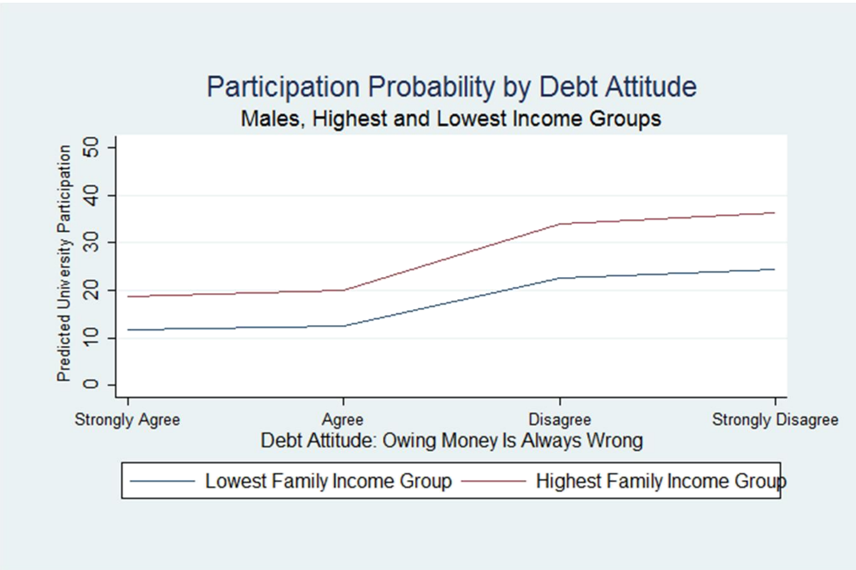
Exponentiated coefficients; Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.010

School results reflect a person's ability, their level of motivation and determination (which is also linked to intentions for future study), their discount rate, the benefits derived from their family background, and many other factors. As we are not interested in the rather more obvious relationship between school results and participation *per se*, but rather in the relationship between family income and participation and debt aversion and participation (and later – debt aversion and participation by family income group), the preferred specification of this model includes school results only in as far as they are required to control for innate ability. This allows for the effects of family income and debt aversion to be reflected more fully in the parameter estimates for those variables. All the same, it is important to note that the “agree” dummy on debt aversion is statistically significant in all relevant specifications (i.e. even when all available school results are included in the regression).

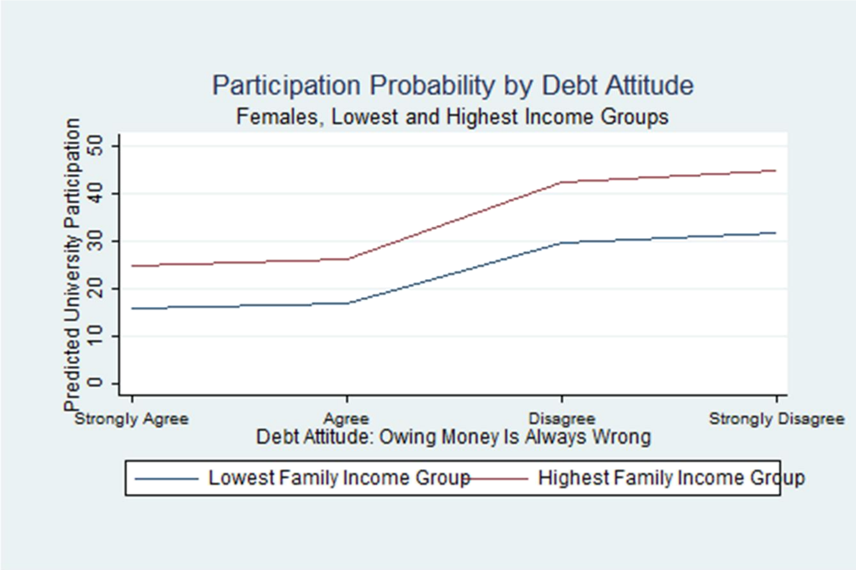
3.6.1.3 Predicted Probabilities

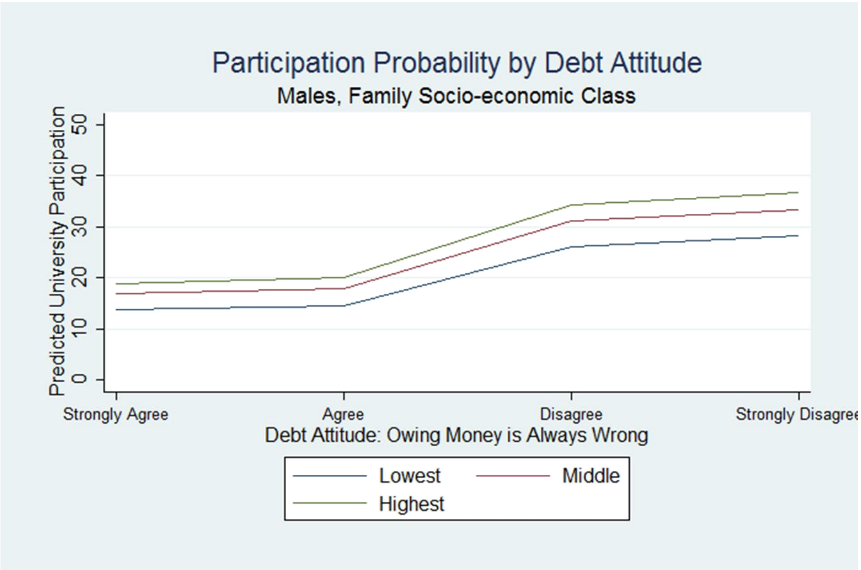
Using the preferred specification of the logistic regressions, which includes key stage 2 results and the other controls (but not GCSE or A level variables), to calculate the probability of being at university in wave six while holding the control variables constant[13] gives us predicted probabilities by gender, family background group and debt attitude.

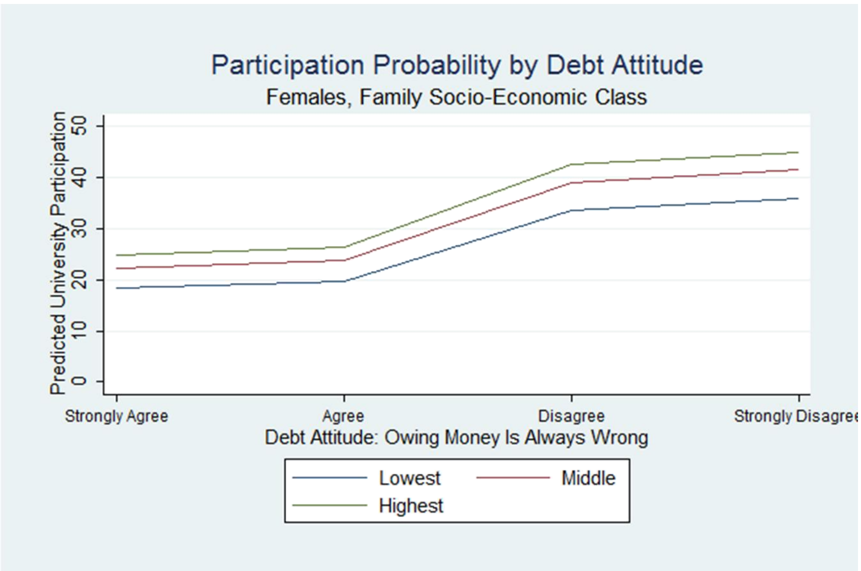
Figure 3-10: Participation Probabilities by Value-Based Debt Attitude, Gender and Family Background



[13] I calculate probabilities for someone who is white, of median ability, where neither parent has a degree, they have no siblings and do not come from a broken home, who lives in an urban area (in fact, London) and has no long-standing health problem or disability. Calculating probabilities for the average individual – all variables at means – gives very similar results.


Participation Probability by Debt Attitude
Females, Lowest and Highest Income Groups
Predicted University Participation
0
10
20
30
40
50
Strongly Agree
Agree
Disagree
Strongly Disagree
Debt Attitude: Owing Money Is Always Wrong
Lowest Family Income Group
Highest Family Income Group


Participation Probability by Debt Attitude
Males, Family Socio-economic Class
Predicted University Participation
0
10
20
30
40
50
Strongly Agree
Agree
Disagree
Strongly Disagree
Debt Attitude: Owing Money is Always Wrong
Lowest
Middle
Highest


Participation Probability by Debt Attitude
Females, Family Socio-Economic Class
Predicted University Participation
0
10
20
30
40
50
Strongly Agree
Agree
Disagree
Strongly Disagree
Debt Attitude: Owing Money Is Always Wrong
Lowest
Middle
Highest

Predicted probabilities are summarized in the graphs above. I focus on value-based debt aversion as this had the clearest results from the logistic regressions. These graphs show that there is a large difference in participation probability across all income groups and socio-economic backgrounds for those who (strongly) agree and (strongly) disagree that "Owing money is always wrong", even after controlling for a broad range of other factors. Both males and females who agree with this statement are less likely to be at university straight out of school. There is no large difference for those who agree / strongly agree or those who disagree / strongly disagree, but between those who agree and those who disagree, the difference in participation probability is very clear and economically significant. The next section will explore whether this effect is greater for young people from disadvantaged backgrounds.

3.6.2 Family Income and Debt Aversion

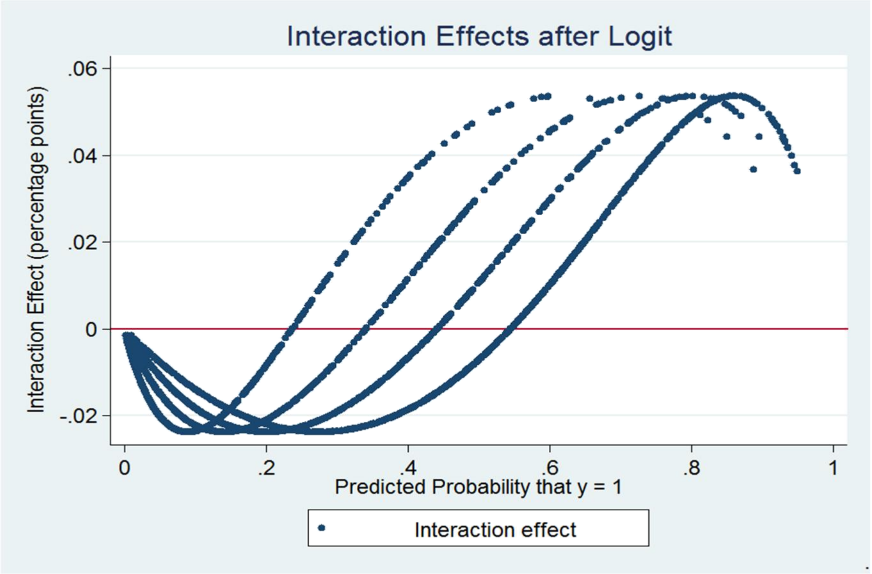
This section addresses the question of whether or not the impact of debt aversion on university participation is more severe for young people from poorer families. Since the last section showed the clearest results for value-based debt aversion and no great differences when using family income or family social class, this section will focus on value-based debt aversion and family income.

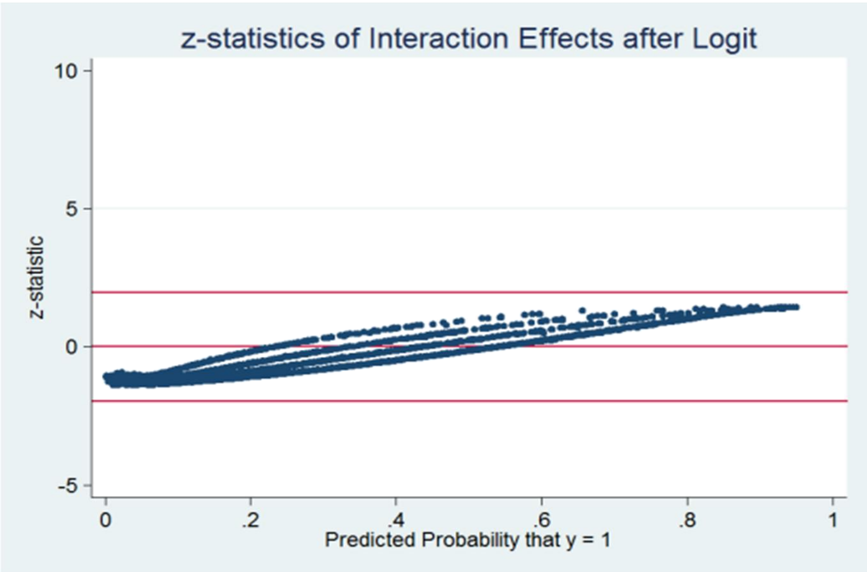
3.6.2.1 Interactions

To address the question of whether the effects of debt aversion are more severe for low-income families, I first used interaction effects between a single debt aversion dummy (agree/disagree that owing money is always wrong) and a single rich/poor dummy (family income groups 1 and 2 vs family income groups 3 and 4). Using two dummy variables in this way rather than the full set of replies to the debt aversion statement and all family income groups simplifies the analysis but does not introduce any major changes otherwise.

Due to the functional form of the model (as it is a logit model rather than a linear probability model), it is important to calculate interaction effects by using the full cross-partial derivative rather than just the marginal

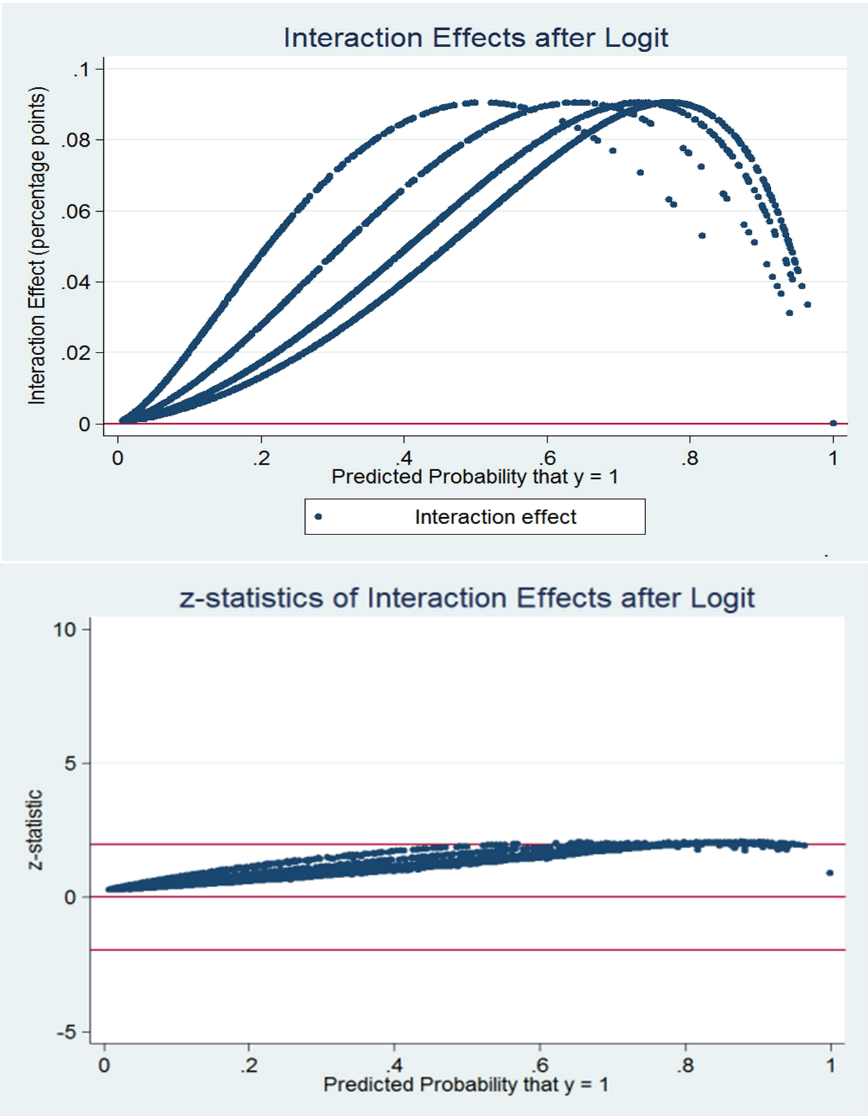
Figure 3-11: Interaction effects and statistical significance: Males





effect of the interaction term itself. Using this methodology, I did not find evidence of statistically significant interaction effects either in terms of the average interaction effect or for individual estimates across the range of predicted participation probabilities. For males, this held true in models of value-based and risk-based debt aversion, including varying measures of school performance, and when the full sample was used as well as samples restricted to qualified individuals (two A-levels or more or alternatively individuals pursuing a qualification at wave 5 in order to apply for university later). The graphs above report the interaction effects for each observation from a model run on the full sample and with only key stage 2 test scores included. Interaction effects are small in size for all four groups[14] and statistically insignificant at the 5% level, although this is the model that is most likely to see statistically significant interaction effects. The first graph shows point estimates which demonstrate the small size of the interaction effect (between -0.03 and 0.06 percentage points) while the second graph shows that all z-statistics fall within the insignificance range at the 5% significance level (-1.96 to 1.96). This indicates that the effects of debt aversion are not more or less severe for young males from poor families compared to richer families.

Figure 3-12: Interaction effects and statistical significance: Females



[14] Rich-debt averse, poor-debt averse, rich-not debt averse, and poor-not debt averse. Results for these groups can be seen in the four distinct lines on the various graphs.

For females, all point estimates are positive and slightly larger than for males, up to 0.1 percentage points, though this is still very small. In terms of statistical significance, some observations at the upper end are borderline significant, although the average interaction effect (0.04 percentage points) is insignificant at the 5% level with a z statistic of 1.08. Changing the specification to include school results past age 11 or to restrict the sample as was done with males further decreases the statistical significance of the estimated interaction effects. This indicates that, as is the case with males, the university participation of females from poorer families is no more strongly affected by debt attitude than are their counterparts from richer families. Debt aversion affects young people to a similar degree across the board.

3.6.2.2 Sub-samples

To test further for differing effects of debt aversion across family income groups, I ran separate regressions for the rich /poor family income groups to see if they show different odds ratios and varying degrees of statistical significance on the debt aversion dummy. Table 3.8 below reports the odds ratios on the value-based debt aversion dummy variable for twenty separate regressions, split by gender and family income group and also by the school results included as controls. The first set of regressions, including all males (or females) and controlling only for key stage 2 test scores (and the other controls from above, but not GCSE scores or the number of A-levels taken), shows that debt aversion has a statistically significant negative effect for both family income groups and that the effect is slightly stronger for poor versus rich. For males, the poor group shows an odds ratio of 0.392 on this variable compared to 0.421 for the rich group, while for females, the odds ratios are 0.373 and 0.529 respectively. Figure 3.13 graphs these estimates within their confidence intervals. For males, these graphs make it clear that there is no economically significant difference in the effect between the two groups. For females, the confidence interval for the rich group is entirely above that of the poor group, which gives a suggestion that may be a stronger effect of debt aversion among females from low income groups compared to high income groups.

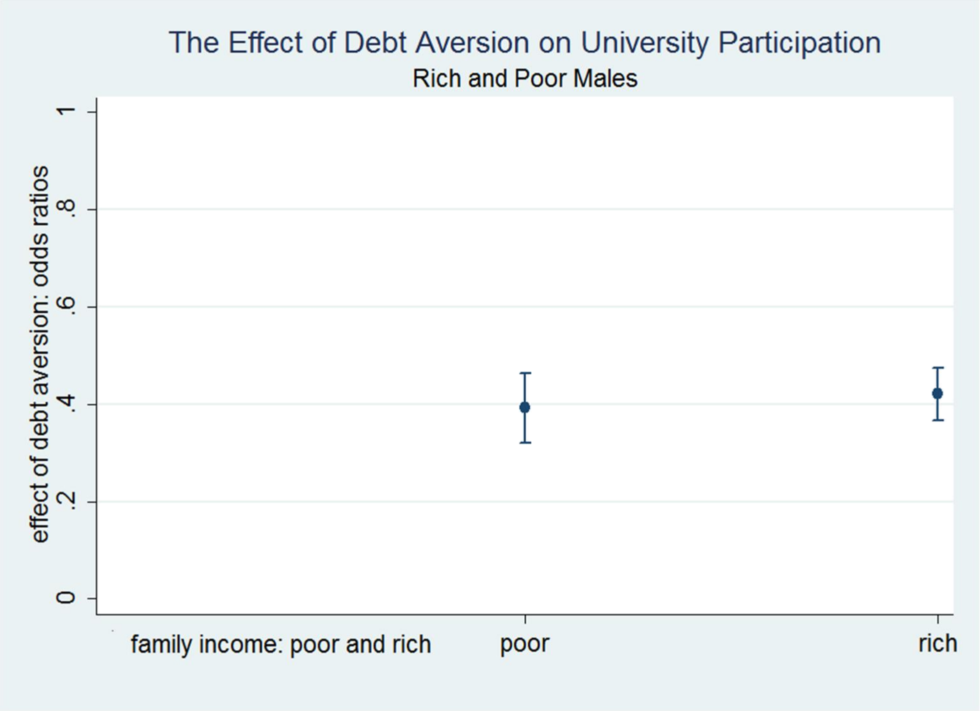
Table 3-8: Odds Ratios on Value Based Debt Aversion Dummy (Agree/Disagree) for various sub-sample regressions

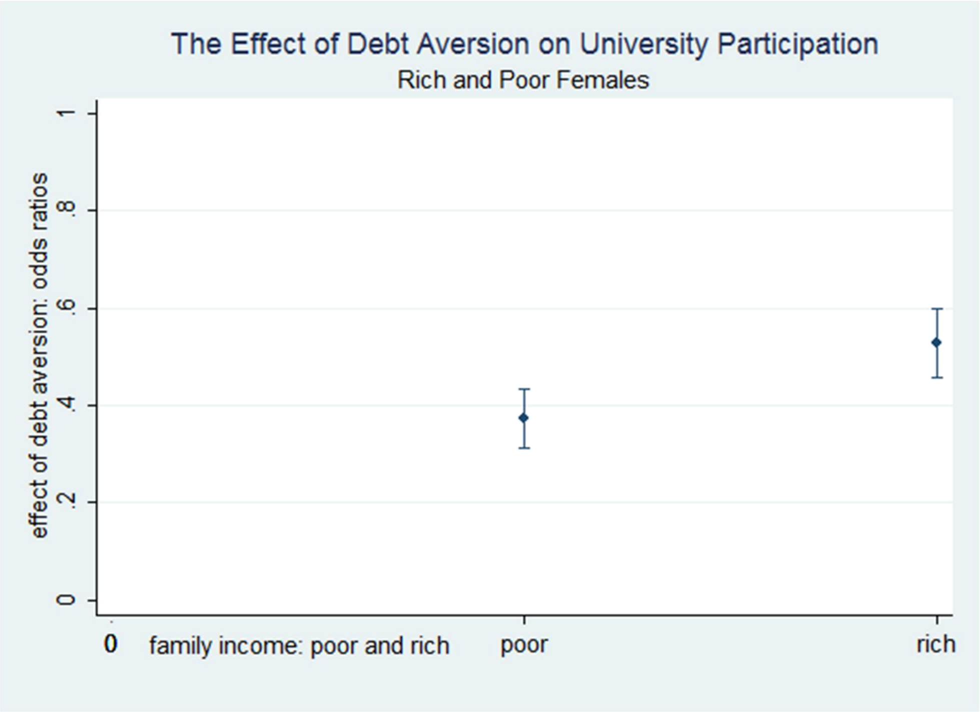
SAMPLE	**Included school results**	**Rich Males**	**Poor Males**	**Rich Females**	**Poor Females**
All Males / Females	key stage 2	0.421*** (0.054) *2180*	0.392*** (0.071) *1748*	0.529*** (0.07) *1989*	0.373*** (0.062) *1755*
All Males / Females	key stage 2 and GCSEs	0.519*** (0.072) *2080*	0.446*** (0.089) *1748*	0.639*** (0.092) *1948*	0.437*** (0.078) *1755*
All Males / Females	key stage 2 and GCSE scores and number of A levels taken	0.549*** (0.079) *2080*	0.478*** (0.103) *1748*	0.730** (0.108) *1948*	0.457*** (0.087) *1754*
All males / females taking 2 or more A levels at wave 5	key stage 2 and GCSEs	0.625** (0.115) *1115*	0.376*** (0.107) *546*	0.773 (0.144) *1173*	0.467*** (0.134) *681*
All males / females taking qualifications at wave 5 with the intention of applying to university later	key stage 2 and GCSEs	0.813 (0.142) *1232*	0.528*** (0.124) *802*	0.779 (0.14) *1271*	0.505*** (0.119) *903*

Exponentiated coefficients; Standard errors in parentheses; Sample size in italics

* p<0.10, ** p<0.05, *** p<0.010

Figure 3-13: Comparing point estimates and confidence intervals between rich / poor family income groups





When GCSEs and A-levels are included, the sizes off the effect are more similar across family income groups. This is most likely due to the fact that the included school results take account of the effect of family income. It is especially interesting to note how the sample sizes differ between groups when the sample is restricted to those taking 2 or more A-levels at wave 5. The sample sizes are smaller for the poorer groups as only 31% of males and 40% of females in the poor category were undertaking at least two A-levels compared to 51% of males and 59% of females in the rich category. Among the sample of males taking two or more A-levels at wave 5, the effect of debt aversion is statistically different from zero at a reasonable significance level for both family income groups, for the poorest group at 1% and for the richest group at 5%. In the last set of regressions, run on those taking a qualification at wave 5 with the intention of applying for university later, debt aversion only has a statistically significant effect among the poorest families.

3.6.2.3 Results of Decomposition Analysis

Having examined the effects of family income and debt aversion separately in the above regressions and explored possible interaction effects, debt aversion will now be treated as an indirect effect of family income and the total effect of family income on university participation will be decomposed into the indirect effect (through debt aversion) and the direct effect (the effect of family income through all other channels). Using the decomposition technique as described in the methodology section makes it possible to compare the direct and indirect effects between all possible pairs of family income (or social class) groups.

These tables show the odds ratios for the effects (total, direct and indirect) of family income on university participation. They are calculated for each pairwise combination of family income groups. For males in the richest and poorest groups, the total effect of family income has an odds ratio of 2.05, which means the odds of the young people from the richest group participating in university are 2.05 times greater than the odds of the poorest group, holding everything else constant. Poorer young people would have 1.17 times greater odds of participating with the richest group's

Table 3-9: Summary of Logistic Regression Decomposition Results: Odds Ratios and Percentage Share for the effect of family income on university participation, Value-based debt aversion

MALES		**1**	**2**	**3**	**4**
1	total		1.23	1.69 ***	2.05 ***
	indirect		1.05 ***	1.11 ***	1.17 ***
	direct		1.17	1.53 **	1.76 ***
	% indirect		**22%**	**19%**	**22%** ***
2	total			1.38 ***	1.67 ***
	indirect			1.06 ***	1.11 ***
	direct			1.30 **	1.50 ***
	% indirect			**18%**	**21%** ***
3	total				1.21 *
	indirect				1.05 ***
	direct				1.15
	% indirect				**27%**

* p < 0.10, ** p < 0.05, and *** p < 0.01
Family income groups: 1 - lowest, 4 - highest

FEMALES		**1**	**2**	**3**	**4**
1	total		1.43 ***	1.66 ***	1.86 ***
	indirect		1.04 **	1.06 ***	1.09 ***
	direct		1.37 **	1.58 ***	1.70 ***
	% indirect		**11%** *	**11%** **	**14%** **
2	total			1.16	1.30 **
	indirect			1.01	1.05 ***
	direct			1.15	1.24 **
	% indirect			**10%**	**18%**
3	total				1.12
	indirect				1.03 ***
	direct				1.08
	% indirect				**30%**

* p < 0.10, ** p < 0.05, and *** p < 0.01
Family income groups: 1 - lowest, 4 - highest

Pair-wise combinations of family income groups, odds ratios for the total effect (family income), the direct effect (family income) and the indirect effect (debt aversion), % indirect shows the contribution of the indirect effect to the total effect.

Table 3-10: Summary of Logistic Regression Decomposition Results: Odds Ratios and Percentage Share for the effect of family income on university participation, Risk-based debt aversion

MALES							
	1	**2**		**3**		**4**	
1	total	1.2		1.62	***	1.87	***
	indirect	1.01		1.03	***	1.05	***
	direct	1.17		1.57	***	1.78	***
	% indirect	**7%**		**7%**		**8%**	*
2	total			1.37	***	1.57	***
	indirect			1.02	***	1.04	***
	direct			1.34	***	1.52	***
	% indirect			**7%**	*	**8%**	***
3	total					1.15	
	indirect					1.02	*
	direct					1.13	
	% indirect					**11%**	

* p < 0.10, ** p < 0.05, and *** p < 0.01
Family income groups: 1 - lowest, 4 - highest

FEMALES							
	1	**2**		**3**		**4**	
1	total	1.4	***	1.58	***	1.71	***
	indirect	1.04	***	1.05	***	1.08	***
	direct	1.32	**	1.51	***	1.59	***
	% indirect	**12%**		**10%**	*	**14%**	**
2	total			1.16		1.25	**
	indirect			1.01		1.04	***
	direct			1.15		1.21	*
	% indirect			**7%**		**16%**	
3	total					1.08	
	indirect					1.03	***
	direct					1.06	
	% indirect					**33%**	

* p < 0.10, ** p < 0.05, and *** p < 0.01
Family income groups: 1 - lowest, 4 - highest

Pair-wise combinations of family income groups, odds ratios for the total effect (family income), the direct effect (family income) and the indirect effect (debt aversion), % indirect shows the contribution of the indirect effect to the total effect.

debt aversion profile than with their own debt aversion profile (indirect effect), while the high family income group would have 1.76 times greater odds of attending than the poorer young people if the debt aversion profile is held constant (direct effect). The indirect effect measures the effect of changing the debt aversion profile (holding family income group constant), while the direct effect measures the effect of changing family income group (holding the debt aversion profile constant). For this pair, 22% of the effect of family income is due to debt aversion. The indirect effect (debt aversion working through family income) is statistically significant at the 1% level comparing any group with the richest group (standard errors are calculated by bootstrapping). The percentage contribution of debt aversion is statistically significant comparing the poorest and second poorest groups with the richest group, but not for the other pairs. Debt aversion makes up a relatively large proportion of the total effect, around one fifth of the total effect for most pairs.

However, there is no clear pattern of debt aversion having stronger effects for poorer families. The contribution of debt aversion to the total effect is 22% comparing the two poorest family income groups (although this is not statistically significant) and also 22% comparing the poorest and richest groups. For females, the contribution of debt aversion appears smaller than for males and is only significant (at the 5% level) comparing the poorest group with either of the two richest groups. Comparing the poorest and richest groups, the total effect has an odds ratio of 1.86 and 14% of the effect is due to debt aversion. The percentage contribution of debt aversion is highest for both males and females when comparing the two richest groups, however, in both cases this is highly imprecisely measured, with very large standard errors.

Looking at risk-based debt aversion, direct, indirect and total effects are highly statistically significant for both males and females when comparing the poorest group with either of the two richest groups. The percentage contribution of this kind of debt aversion is smaller than value-based debt aversion for males (8% compared to 22% for the richest-and-poorest pair) but for females both kinds of debt aversion show the same contribution for this pair (14%). Once again, the greatest percentage contribution of debt aversion is seen between the two richest income groups for both males and females, but this is not statistically significant.

Table 3-11: Summary of Logistic Regression Decomposition Results: Odds Ratios and Percentage Share for the effect of family SES on university participation, Value-based Debt Aversion

MALES		**lowest**	**middle**	**highest**
lowest	total		1.31 ***	1.64 ***
	indirect		1.06 ***	1.12 ***
	direct		1.24 **	1.47 ***
	% indirect		**22% ***	**23% *****
middle	total			1.25 **
	indirect			1.05 ***
	direct			1.19 *
	% indirect			**23%**
* p < 0.10, ** p < 0.05, and *** p < 0.01				

FEMALES		**lowest**	**middle**	**highest**
lowest	total		1.36 ***	1.51 ***
	indirect		1.03 ***	1.07 ***
	direct		1.32 ***	1.42 ***
	% indirect		**10% ***	**16% *****
middle	total			1.11
	indirect			1.04 ***
	direct			1.07
	% indirect			**35%**
* p < 0.10, ** p < 0.05, and *** p < 0.01				

Pair-wise combinations of family NS-SEC groups, odds ratios for the total effect of family class group, the direct effect (family class group) and the indirect effect (debt aversion), % indirect shows the contribution of the indirect effect to the total effect.

Next, the effect of social class group will be examined rather than family income. The results are very similar to the results for family income. For value-based debt aversion, the contribution to the total effect is greater among males than among females. The pair of the highest and lowest groups shows a precisely measured effect (at the 1% significance level) – 23% for males and 16% for females. The greatest contribution occurs between the highest and middle groups, but once again this is not precisely measured.

Table 3-12: Summary of Logistic Regression Decomposition Results: Odds Ratios and Percentage Share for the effect of family SEC on university participation, Risk-based Debt Aversion

MALES						
		lowest	**middle**		**highest**	
lowest	total		1.28	**	1.55	***
	indirect		1.01		1.03	***
	direct		1.27	**	1.50	***
	% indirect		**4%**		**8%**	**
middle	total				1.21	*
	indirect				1.02	**
	direct				1.18	
	% indirect				**12%**	
* p < 0.10, ** p < 0.05, and *** p < 0.01						

FEMALES						
		lowest	**middle**		**highest**	
lowest	total		1.33	***	1.48	***
	indirect		1.02	***	1.05	***
	direct		1.30	***	1.41	***
	% indirect		**7%**	**	**12%**	***
middle	total				1.12	
	indirect				1.03	***
	direct				1.09	
	% indirect				**24%**	
* p < 0.10, ** p < 0.05, and *** p < 0.01						

Pair-wise combinations of family NS-SEC groups, odds ratios for the total effect of family class group, the direct effect (family class group) and the indirect effect (debt aversion), % indirect shows the contribution of the indirect effect to the total effect.

For risk based debt aversion (above), the contribution of debt aversion to the total effect is smaller for males than for females, e.g. between the lowest and highest class groups, it is 8% for males and 12% for females. For females, the odds ratio on the indirect effect is statistically significant for every pair, but quite small – between 1.02 and 1.05.

In summary, debt aversion makes a significant contribution to the effects of family income and social class on university participation for both males and females. Value based debt aversion seems to be more important for males, while for females, risk-based debt aversion is more important. There is no clear pattern of debt aversion being more of an issue for poorer families or families from lower socio-economic classes - it appears to effect young people similarly across the board.

3.7 Conclusion

In the current policy context of recent increases in undergraduate university fees up to £9,000 per year and the increased debt levels this means for new students (but using survey data from before the increase occurred), this chapter has explored the issue of debt aversion and university participation. In particular, it explored the question of whether the effect of debt aversion on university participation is greater for young people from poorer families or lower SECs.

Firstly, a theoretical model was developed by extending the standard model of university participation in the human capital theory to include debt aversion. Debt aversion was defined as associating greater negative utility to holding negative assets than the positive utility associated with positive assets of the same absolute value. The model incorporates debt aversion based on the idea that people’s university participation decision will not be based on total expected lifetime earnings but rather their overall utility arising from these streams, only one of which (university participation) includes a period of negative earnings. Their evaluation of negative assets relative to positive assets (i.e. their degree of debt aversion) will therefore impact on the university participation decision. This model also demonstrated the importance of family income to the decision, as almost every parameter is related to family income on some level.

Secondly, econometric analysis was carried out using the LSYPE. This data set has several advantages, in that it is based on a representative sample of young people (including weights that align it more fully with the total population), rather than a sample made up of students or young people pursuing HE entrance qualifications, and furthermore follows these young people over time allowing us to observe actual university participation (or not) as opposed to participation intention. The richness of the data also makes it possible to control for a wide range of personal and family characteristics. In particular, the fact that the dataset is linked to the National Pupil Database proves test statistics that can be used as proxies for innate ability. Although both debt aversion and family income are potentially endogenous, the control variables capture a large amount of the unobserved heterogeneity. This remains a limitation of the analysis, however, the breadth of control variables available gives confidence in asserting that the effect of debt aversion captured here is close to the causal effect. The data used in this chapter comes from surveys that were carried out before the increase in undergraduate fees that occurred in October 2012. It could therefore be argued that the effects found here are likely to be even greater now that the debt levels of undergraduates have increased.

One key aim of this chapter was to address the question of whether the effects of debt aversion are more severe for poorer families. This was firstly explored by using interaction effects; secondly, by running regressions of sub-samples of the data and comparing the size and significance of the effect of debt aversion across models. Finally, I treated debt aversion as an indirect effect of family income on university participation and looked at the contribution of the indirect effect relative to the total effect, for all pairwise combinations of family income groups. There was no clear evidence from these results that debt aversion is having a greater impact on the university participation decisions of young people from disadvantaged backgrounds.

The regressions run and supplementary analysis carried out were able to demonstrate several key findings:

- Debt aversion is negatively correlated with university participation and this relationship is statistically significant, even controlling for other factors.
- The size of the effect is quite large, reducing the participation probability by as much as 20 percentage points in some cases.
- Value based debt aversion seems to have more of an impact than risk-based debt aversion, although for females, risk-based debt aversion is also important.

- There is no clear pattern of debt aversion affecting poorer families more severely; although there is some indication the effects are greater for poor females.

The impact of debt aversion on the participation decisions of young people from all family income / socio-economic class groups is an important societal and political issue. The recent increase in fees will see a large increase in indebtedness on graduation for undergraduates, which may well have implications for young people's decisions regarding university participation. The findings of this chapter together with early estimates of the effect of the fee increase on participation will be explored further in the concluding chapter.

4 The Effect of Family Income, Schooling and Other Factors on Children's Cognitive Development

4.1 Introduction

The previous chapter established that although there are differences in debt attitudes depending on family background, debt aversion has an effect on university participation for young people from all backgrounds. As such, it is apparent that debt attitudes are not a major driver of the gap in university participation rates between children from advantaged and disadvantaged family backgrounds. The data I have used indicates that these gaps appear well before age 17. For example, the proportion of students taking A-levels was very different comparing the highest and lowest family income groups. This chapter therefore looks to the early, formative years of a child's life and seeks to identify the important influencing factors that determine the gaps at that stage of life. In particular, it examines gaps in cognitive development between ages 5 and 7. A clear understanding of the factors which benefit children's cognitive development in the first few years of school is imperative as a foundation for the formation of clear and effective government policies to address educational inequality.

In this chapter, I examine three key areas which are potentially important drivers of cognitive development: family background, especially focusing on family income; schooling, including school quality; and a third group which I call "other factors" including parental behaviours, neighbourhood factors and the like. Reducing inequalities in educational outcomes is a government objective in and of itself and is also of further importance due to the role of education in social mobility, either as a facilitator or a hindrance. Extending the work that has previously been done in this area, (e.g. Violato *et al*, 2011, Dearden *et al*, 2011b), this chapter uses new, nationally-representative data and innovative panel data techniques (described below) to identify the key factors behind children's rates of cognitive development between ages 5 and 7.

Looking firstly at family income, there is a large literature which examines the issue of whether it is the money itself which provides an advantage, or if family income rather acts as a proxy for other important factors, such as the provision of a stimulating home environment (Mayer, 1997; Gregg *et al*, 2007). Using the Millennium Cohort Study makes it possible to control for a broad array of factors, which helps in isolating an independent, direct effect of income. Nonetheless, the endogeneity of family income is a serious methodological issue in this context. Family income is strongly correlated with a range of other influences on the child and even with very rich datasets it is not possible to 'mop up' all individual heterogeneity. The use of panel data techniques can help in this regard, although a lack of variation in family income between waves presents a further difficulty. I develop a novel augmented random effects approach which helps address these two issues.

The second set of factors to be examined relates to schooling. I have already discussed at length the role of education in general as a possible facilitator or hindrance to social mobility. This chapter focuses more specifically on school-related factors expressing the quantity and quality of schooling each child experienced between age 5 and 7. Through exploiting variation in months of school attendance, teacher tenure, class size and whether the school charges fees and is a coeducational school, it is possible to test the significance of these factors in promoting the child's cognitive development over this period. Using the panel models mentioned above extends this analysis beyond descriptives. While it is not possible to claim the identification of truly causal effects, these models aim to estimate the direct effect of schooling in a more methodologically robust way. I focus on individual fixed effects as, unfortunately, teachers are only identified in one wave and there are too many missing values on the school identifiers in waves 3 and 4 to make school fixed effects feasible. This is the first study I am aware of which uses the latest two waves of MCS data to explore the effect of schooling. Since assessing the effectiveness of schooling in reducing inequalities in cognitive and later outcomes is of such significance, this chapter makes an important contribution in this regard.

Finally, the richness of the dataset provides a good opportunity to ask which other factors may be important promoters of children's cognitive development in the first few years of school. I include a broad range of variables in the OLS and panel data models such as variables relating to family structure, parental labour force engagement, health, various parental behaviours, neighbourhood factors and early influences such as birthweight and breastfeeding. As such, I am able to examine an extensive collection of factors that could be influential for children's cognitive development. Most importantly, I aim to identify factors which can be targeted as policy vehicles to impact positively on children's cognitive development.

A major contribution of this chapter is to present a methodological approach to these questions which deals, on the one hand, with the likely endogeneity of the key variables and on the other hand with the limited amount of variation within individuals. Although the MCS (and other similar longitudinal datasets) provides an excellent data source with multiple waves, a large sample size and a very broad array of variables, these two key data issues do still remain.

On the one hand, some individual heterogeneity that is correlated with the variable of interest will always remain unobserved and unaccounted for by the other covariates. This applies primarily to family income, making it difficult to identify a direct causal effect of this variable, but also applies to the other covariates since the included variables are all strongly correlated amongst themselves. At the same time, there is a lack of within-variation in key variables, especially since just two time-points are being considered and many of the explanatory variables are binary. These two issues make it very difficult to achieve robust results. While fixed effects models present a possible means of eliminating unobserved individual heterogeneity, they require more variation than is contained in the data. And while random effects models make use of between subject variation, they are subject to much stricter exogeneity assumptions which are very unlikely to hold in this case.

In this chapter, I present a possible solution to these problems via an augmented random effects model which can be tested for consistency against a fixed effects model via the Hausman test. The random effects model is brought closer to the fixed effects model by allowing the between and within effects of certain variables to be estimated separately where appropriate. Augmenting the standard random effects model in this way makes it possible to combine the between and within variation in the data to help generate more precise estimates, whilst maintaining confidence in the consistency of the results.

The next section reviews the relevant literature, covering papers which consider the influence on children's development of family income, schooling and other factors. I then describe the data used in the analysis in section 3. The same dataset is used as in the following chapter, however, in this section I introduce data issues that are relevant to this chapter and provide descriptive statistics overall and by family income quartile for all variables used in the analysis. Section 4 provides a more detailed description of my methodology, followed by the results obtained in section 5, together with a discussion of these results. Section 6 draws the various strands together and concludes.

4.2 Literature Review

Since this chapter examines three groups of variables, this literature review will have three sections. The first key influence to be examined is family income. A comprehensive review of different approaches to determining the direct, causal effect of income was included in the literature review in chapter 2, as such, in this section, I focus on four major papers concerning the effect of family income on children's early years cognitive development and the way this effect changes as an increasing number of mediating factors are added to the model. Secondly, the literature on schooling will be introduced, especially in relation to school resources and quality and their impact on cognitive development. Finally, I review papers which focus on the impact of other specific factors, such as family size or neighbourhood effects. This will help to put the findings from this chapter into the context of current research.

4.2.1 The Impact of Family Income on Children's Early Years Cognitive Development

Violato *et al* (2011) uses data from the first three waves of the MCS and reports the significance of a family income variable regressed on various child cognitive and behavioural outcomes and the way this impact decreases in size and statistical significance as various mediating factors are included in the model. They combine the approaches of economics and developmental psychology in breaking up the mediating pathways into groups called “parental stress”, “parental investment”, and “other family related pathways”.

Overall, they find that the direct effect of family income over and above the other factors is absent or at most weak. Their results vary for different cognitive assessments when adding the additional factors one group at a time and contemporaneously. For BAS (British Ability Scales) naming vocabulary at 3 years, the income variable becomes very small and statistically insignificant when additional factors are added to the original specification containing only income and the dependent variable. For BAS naming vocabulary at 5 years, the income variable retains its significance when some factors are added but becomes insignificant when all explanatory variables are included. For Bracken School Readiness at age 3 and BAS Picture Similarity at age 5, the income variable is still positive and statistically significant (at 1% and 5% levels respectively) even when all other mediating factors have been included, however, it is much smaller in magnitude than in the most parsimonious model[15].

Furthermore, the authors also report the results for each individual explanatory variable. This indicates which factors are more or less important to the child’s outcomes at each age. In particular, they find that breastfeeding, mother’s mental health, parenting practices and the home environment have important implications for the child’s cognitive and behavioural development. The final section of their article includes a fixed effects model, although the authors present this model with an important caveat, namely the fact that children develop differentially over time which makes this kind of model less robust than it would be for adults (this idea is discussed further in the methodology section below).

[15] These are the results for two parent families and permanent income. Results for lagged income show smaller magnitudes but are similar in terms of statistical significance. For lone mother families, the income variable is statistically significant for BAS naming vocabulary at 5 years but insignificant for BAS Picture Similarity at 5 years when other factors are included in the specification beyond the raw correlation between family income and these outcomes.

Since the data used in this chapter includes an extra wave, I have been able to extend their findings by including additional explanatory variables, especially in relation to schooling. A further difference is that the baseline test scores are not included in any of their models. This means that they can only be interpreted as static models, whereas my models include a baseline score and therefore give an indication of the effects of the covariates on the children's cognitive development over time. Furthermore, the inclusion of a baseline ability measure helps to control for unobserved individual heterogeneity contained in the test scores in an earlier period.

Gregg *et al* (2007) uses data from the ALSPAC cohort, another UK longitudinal dataset, to explore the relationships between a range of child outcomes (including cognitive ability, behaviour and fat mass) and income; family characteristics such as household composition and parental occupation; and proximal factors directly affecting child outcomes such as the home learning environment. They first show that children from disadvantaged households perform more poorly on every outcome measure at ages 7 to 9 than children from well-off families. In order to examine *why* low-income children are behind their peers, they examine which aspects of low-income children's environments account for their developmental deficits and focus on the processes that mediate the relationship between family income and child outcomes.

They employ a decomposition approach to examine on the one hand, the impact of income in comparison to other aspects of family disadvantage, and on the other hand, how the various measures of disadvantage, including income, are associated with the behaviours of parents and the immediate environment in which children live. They find that the most important proximal factors influencing children's cognitive outcomes are their parents' psychological functioning and the home learning environment, as well as health related factors including breastfeeding. One key finding is that different outcomes (cognitive, socio-emotional and health related) appear to be driven by quite different aspects of the socio-economic disadvantage that underlie parental poverty. Furthermore, proximal factors explain only around a third of the relationship between family income and cognitive outcomes, whereas they explain almost all of the income gradients in socio-emotional outcomes and health outcomes. They also find that parental education has a large and significant role, but that it is not transmitted by the proximal factors included in the model. Interestingly, single parenthood in itself does not seem to be a source of the income gradient or to directly influence the child's cognitive outcomes.

Whilst it is not their aim to establish a causal effect of income in itself, they nonetheless build a case for a distinct causal impact of income *per se* on cognitive outcomes by controlling for quite a vast array of family background characteristics, parental behaviours and other possible mediating factors. They show that a lack of income is one of a host of disadvantages faced by poorer children and that it has an economically significant effect on outcomes, independent of other factors.

Dearden *et al* (2011b) adopts the same theoretical framework as Gregg *et al* (2007). They use the first three waves of the MCS to examine the factors that influence the cognitive development gap at ages three and five, as well as the widening of this gap over time. They identify an important role for the early childhood caring environment, including such aspects of the home learning environment as the frequency of reading to the children. However, they also show that other aspects not related to this play a key role (e.g. mothers age), and that a large amount of the variation remains unobserved. In this chapter, I build on their findings by including data from an additional wave of the survey when the children are aged 7. Furthermore, I use panel data methods to try to address the issue of unobserved individual heterogeneity.

McCulloch and Joshi (2002) explore the effect of deprivation on children's cognitive functioning. They approach this question by running a regression on a measure of cognitive functioning (the Peabody Picture Vocabulary Test, PPVT) with family income as the only regressor and then adding progressively more explanatory variables to identify the direct effect of income and to discover which other factors are driving the relationship. In terms of the theoretical understanding of possible channels through which family income could exert an influence, they describe first of all a direct effect (e.g. through a lack of stimulating resources), secondly, that there could be mechanisms working through the locality and the services available there, thirdly, that behavioural factors such as the effect of poverty on the parents mental state and therefore parenting practices may play a role, and fourthly, that family income and child outcomes could both be the joint outcomes of other factors such as parental human capital.

Using data from the NCDS, they estimate variance components models with different combinations of explanatory variables. There is strong evidence of a raw gap in the cognitive outcome by family income group. Adding the family structure variables in the second specification slightly reduces the effects of income. There is a negative effect of family size and young motherhood, but in general the family structure and parental labour force engagement variables do not add a great amount of explanatory power. Introducing information on the mother's qualifications renders the income coefficients insignificant and appears to act as an alternative signal of the resources available to the child.

Adding indicators of material deprivation *instead of* the maternal qualifications variables also removes the statistical significance from the family income group dummies. In particular, living in social housing and the family not owning a car have the largest negative impacts. Including parental behaviour instead of the material deprivation variables also restricts the significance of the family income variables and shows interesting results in its own right, with a stimulating home environment and the level of maternal emotional support both showing important effects. In a model where all of these variables are included, all the income terms are insignificant. This shows that the large raw impact of family income on the cognitive outcome in question apparently reflects other mediating influences. In particular, long-term measures of deprivation (expressed in car usage and housing tenure) seem to be more important than current income, the mothers' education is a key influence and a stimulating home environment and parental 'competence' are both important contributors to higher test scores among lower family income children.

In summary, these four papers all start by establishing the large raw correlation between a child's family income and their cognitive ability outcomes. As further explanatory variables are added to the model, the size and statistical significance of the income coefficients fall. While McCulloch and Joshi (2003) observe that adding the additional factors completely removes the independent impact of family income, Gregg *et al* (2007) observe a remaining, direct impact of family income. Violato *et al* (2011) observe that the family income coefficient remains statistically significant for certain tests and certain family types, though overall, the direct effect of income is either absent or quite weak. Dearden *et al* (2011) focuses on socio-economic position and uses family income as one element of this, hence they do not discuss the direct role of income *per se*.

Aside from a child's family, further influences on their academic achievement can derive from their school and the neighbourhood they grow up in. The next section will focus on schooling and school quality, whilst neighbourhood factors will be considered together with a broad range of other possible influences in the third section.

4.2.2 School Resources, Quality and Quantity of Schooling and Cognitive Development

There is a longstanding debate regarding the importance of school factors on children's educational outcomes. Whilst early work (for example "Equality of Educational Opportunity", more commonly known as the Coleman Report, 1966) indicated that the influence of family background and cohort factors far outweighed the effect of schools, later papers have found that schools are in fact extremely important (Hanushek, 1986, 2003, 2005).

Apart from the issue of self-selection into schools, or moreover, parental selection of schools, which conflates family and school effects, another issue is the difficulty in measuring school and teacher quality. In terms of teaching quality, studies which have focused on measures such as years of experience and qualifications have found that these effects are in general insignificant (e.g. Todd and Wolpin, 2007). However, empirical work that examines teacher characteristics more broadly, using teacher fixed effects for example, finds that differences between teachers have an important effect on pupil's outcomes (e.g. Rivkin *et al*, 2005). Card and Krueger (1998), reviewing literature on the effect of schooling on earnings later in life and educational attainment, concluded that it was "unfortunate and frustrating" that not more was known about the outcomes of schooling, even 30 years after the Coleman report was produced. There still remains a great deal of ambiguity as to the strength and mechanisms of the effect of schools and teachers on pupils' outcomes.

A recent study (Holmlund *et al*, 2010) makes use of excellent UK data to control for school fixed effects as well as detailed individual characteristics. They examine the effect of rising school expenditure on children's test scores at age 11 and find that school expenditure has a consistently positive and significant effect and that this effect is higher for students who are economically disadvantaged. On the other hand, Todd and Wolpin (2007), which examines a broad range of specifications and employs various controls, does not find any significant relationship between the schooling input measures and test scores, but rather finds that the key contributors to ethnic test score gaps are mother's "ability" (as measured by AFQT scores[16]) and home inputs. The evidence on this issue certainly remains mixed.

Baird (2012) introduces a further element by investigating achievement gaps (between high and low SES background pupils) for 19 high-income countries and finds that in some countries achievement gaps can be largely explained by differences in the characteristics of schools attended, whilst in many other countries, the gap appears more closely related to differences in the characteristics of the students. This finding seems to indicate that broader institutional factors also have an important role to play.

Hanushek (1986) discusses the distinction between the overall influence of a child's school and teachers and the influence of specific components of this such as average school expenditure and years of teacher experience. Using teacher fixed effects, he finds that teachers and

[16] Armed Forces Qualification Test scores – often used as an indication of cognitive ability

schools differ dramatically in their effectiveness; however, this is not well reflected in traditionally measured components. He argues that existing measures, including school expenditure, class size, salary levels, teacher experience and whether the teacher has a master's degree, are flawed measures of true school quality.

This is an argument he has developed further over a long time period, for example in Rivkin, Hanushek and Kain (2005) where the authors use a large and detailed Texan dataset to identify the effect of teacher quality explicitly. Their estimator is based on patterns of within-school variation in achievement gains and ignores differences in teacher quality between schools, which cannot easily be disentangled from student differences and the influence of other school factors. Rich data with repeated performance observations for individual students and multiple cohorts makes it possible to use fixed effects models, thereby providing a means of controlling explicitly for student heterogeneity and the non-random matching of students, teachers, and schools. Their paper uses excellent data to provide robust evidence for the abovementioned finding, namely that schools and teachers do matter for students' achievement, but that their effectiveness is not well measured through standard variables such as school expenditure and teacher experience. One outcome of this research is that it has led to calls for different incentive structures within schools which will be more effective at identifying and rewarding effective teachers, such as rewards based on head teacher reports, which would provide a more comprehensive perspective (Hanushek, 2003).

A further approach taken in the recent literature is to employ instrumental variables to identify causal impacts of certain school characteristics. Papers using this approach aim to overcome endogeneity problems by isolating a credible source of exogenous variation in school inputs, and are often quite innovative in their reasoning. For example, Haegeland *et al* (2012) examines the influence of school resources in Norway using variation that is induced by proximity to waterfalls. The waterfalls lead to higher local tax revenues from hydropower plants and this leads to higher school expenditures in those areas. Simple OLS regressions show insignificant effects of school expenditure on outcomes at age 16. This may be due to compensation of disadvantaged schools by local authorities, which is likely to bias the effect of school resources downwards. Using an IV approach helps to overcome this issue. The authors run two-stage IV regressions on the whole sample and also on a restricted sample of “comparable” municipalities and furthermore perform several robustness checks to explore possible biases arising from selective mobility into these areas or the influence of other local amenities. They find an economically and statistically significant positive effect of school expenditures using the IV approach.

Possibly the best known paper using this approach is Angrist and Lavy (1999) examining class size effects. Class size is one element of school quality for which it is particularly difficult to determine a causal effect, given that children with particular needs may often be placed in smaller classes, and on the other hand that there is a strong association class size and the pupils’ family background. In this paper, the authors use data from Israeli schools where the application of a particular rule (Maimonides rule, which states that 40 is the maximum possible number of students in a class) prompts a discontinuity in school class sizes. They note a clear pattern of up-and-down test scores that correlates strongly with the class size pattern induced by the application of this rule. Their research indicates clear, positive effects of smaller class sizes, though in comparison to work on the Tennessee STAR experiment (a randomised trial designed explicitly to measure class size effects), the effects were somewhat smaller. Other papers (e.g. Rivkin *et al*, 2005) have argued that reducing class sizes is a particularly expensive way of improving children’s educational experience and that the effects are small relative to other possible measures such as improving teacher quality.

Another element of school quality is whether the school is coeducational or single-sex. Whilst research has shown that pupils (both girls and boys) in single-sex schools perform better (e.g. Lee and Bryk, 1986), this could merely reflect student selection into school types

(Jackson, 2012)[17]. Park *et al* (2013) try to identify a causal effect of school type using data on schools in Seoul, South Korea, where a compulsory random allocation into schools ensures that attendance of a coeducational or single-sex school is unrelated to a pupil's family background and other characteristics. This research admittedly focuses on secondary school, with the two main outcome measures being the nationally standardised college entrance examination and attendance of four-year rather than two-year colleges; however, it is still informative regarding the effect of coeducational and single-sex schools more generally. The authors find a significant positive effect of single-school attendance on college entrance scores and college attendance for both boys and girls.

Finally, it is also possible to use natural experiment techniques to explore the effect of the quantity of schooling on children's outcomes. Marcotte (2007) uses snowfall in Maryland in the US as an instrument for days of school attended in a school year. The Maryland School Performance Assessment Program tests are held in the same week each year, but days lost to increment weather vary substantially by school district and by year. This provides a source of ransom and non-trivial variation in instructional time which can be exploited to determine a causal relationship between schooling and achievement. Marcotte's finding was that there was a substantial effect of instructional days on test scores, and that this was stronger for mathematics compared to other subjects and for lower grades compared to higher grades. Secondly, Carlsson *et al* (2012) uses random variation in test dates for a Swedish military preparation exam. They find that school days have a positive effect on crystallized intelligence tests (synonym and technical comprehension tests) while non-school days have no effect, but that school days have no effect on fluid intelligence tests (spatial and logic tests). These two papers provide evidence on the importance of instruction days as an input into the educational production process.

[17] Jackson (2012) also uses rule-based assignment to schools to identify a causal effect of single-sex schools, but the identification is less strong than in Park et al (2013), hence my focus on the second paper.

The key issue of the endogeneity of school inputs has continued to prove very difficult to resolve. The fact that families have so much influence on school choice and also exert a strong influence on children's academic outcomes means separating out the direct effect of schools has continued to prove difficult since the original Coleman report was produced in 1966. The review above briefly introduced two approaches that have been used to deal with this, namely fixed effects models and natural experiment (instrumental variable) techniques. My own results in this chapter are strengthened by the use of individual panel data models, although data limitations restrict what is possible in terms of teacher and school fixed effects. This will be discussed further in the data and methodology sections. My research contributes to this large body of literature by using a rich, current dataset to explore the effect of school and teacher characteristics in the UK alongside a vast array of other factors including family income, neighbourhood characteristics, parental education, labour force engagement and behaviours, family structure, the child's own characteristics and birth-related factors.

4.2.3 Papers Measuring the Impact of Specific Child, Family and Neighbourhood Related Factors

Although many papers have shown family socio-economic status to have a large effect on children's early years cognitive outcomes, SES in total is still limited in explanatory power. Melhuish (2008) quotes a meta-analysis of studies by White (1982) which estimated that SES can explain about 5% of the difference in academic achievement, and explains that the limited explanatory power of family income provides their motivation for looking further abroad for other important factors. Their paper focuses on parenting behaviours and the home environment, as well as pre-school, as factors which may be able to help explain the achievement gap. I now proceed to introduce a range of papers which have looked specifically at the possible contributing factors to the gap in children's early years test scores. Due to the vast literature on children's development, this section necessarily discusses various papers more or less briefly, and is unable to provide a comprehensive compilation. My aim is to provide an indication of the findings in the current literature as to the impact of each factor on children's cognitive development. This not only helps identify relevant variables but also shapes *a priori* expectations as to their signs and significance levels.

Looking firstly at the effects of maternal labour force engagement, the results in the literature are very mixed, as some papers show negative effects, some show insignificant effects, and some show positive effects. For example, Baum (2003) finds negative effects of maternal employment, especially early maternal employment i.e. in the first year of the child's life. However, he also finds that the negative effect is offset to some extent by the increase in family income. James-Burdumy (2005) uses blended child/family fixed effects and instrumental variable fixed effects methods and finds that there is some evidence of a negative effect of the mother working in the child's first year of life, no effect in the second year, and a positive effect in the third year. Ruhm (2008) looks at how the effect of mother's employment affects outcomes at ages 10 and 11 for different subgroups of the population, and finds substantial negative effects for youths from advantaged households compared to neutral or positive effects for disadvantaged youths. Furthermore, Waldfodel *et al* (2002), using data from the National Longitudinal Survey of Youth, finds some persistent adverse effects (lasting to age 8) of maternal employment in the first year of the child's life and some positive effects of second- and third-year maternal employment on cognitive outcomes for non-Hispanic white children, but not for African American or Hispanic children. In summary, it appears there could be a negative effect early on which is less notable in the later years as the child grows up, and furthermore that children from well-off families where the mother possibly has high ability and more social capital suffer more from her absence, whereas children from less well-off families actually benefit more from the extra income her employment brings in. While most studies focus on maternal labour market engagement, some also consider the role of the father, e.g. Brown *et al* (2007) who find the father working long hours has a negative impact on the child's time spent in language learning activities, especially in poor families. Gregg and Washbrook (2003) find that fathers are more involved in childrearing in households where mothers return to work early and that this involvement of the father has a positive impact on the child's later outcomes.

Turning to family structure, it is clear that in the US, the UK and other developed countries, ever fewer children are growing up in households with two married, biological parents. The effects of changing family structure have been documented in various papers, for example, Gennetian (2005) uses US data and methodology that allows her to control for individual specific unobserved heterogeneity and finds that the role of family structure is modest compared to the well-documented influence of family income. In general, there is a strong relationship between family income and family structure and this affects the estimates of the impact of family structure related variables on child's outcomes. Aughinbaugh *et al* (2005) for example, found that children from families with both biological parents scored significantly better on the BPI and the PIAT-math and PIAT-reading assessments than did children from non-intact families but that much of the difference disappeared when they controlled for background variables. In the same vein, Joshi *et al* (1999) found income to be among the factors which reduced the size and significance of family structure as a predictor of behavioural and cognitive outcomes.

One aspect of family structure that does appear to have a clear impact is the number of siblings. Hanushek (1992) examines the trade-off between child quantity and child quality, where child quality is defined in regards to cognitive achievement. Families are seen as making fertility related decisions to maximise their utility subject to the production function for child quality, a budget constraint and a time constraint. The empirical results show a systematic negative effect on achievement of increasing family size. This is due to the fact that the parents' finite time allocation must be spread more thinly where there is a greater number of children. More recent studies of factors effecting children's cognitive development also frequently show a negative impact of increased family size.

In terms of the characteristics of the child themselves, studies on gender are more profuse in relation to later achievement, at secondary school and following. The child's month of birth does appear to have a significant impact, as for example in Melhuish *et al* (2008) who found that ‘summer born’ tended to perform more poorly on National assessments at age 11, when compared to older, autumn born, children and were more likely to be identified as having a special educational need (SEN). This phenomenon is also known as the “August birth penalty” (Crawford *et al*, 2007) and occurs because the September cut-off for starting school in a given year makes August born children the youngest in their cohort. September born children must wait an extra year before they start and will be the oldest in their year.

Ethnicity is a strong predictor of children’s outcomes. There is an extensive literature on the black-white test score gap, especially from the US, for example, Fryer and Levitt (2005) uses a recent US longitudinal database, the Early Childhood Longitudinal Study, and reconfirms previous findings about the growth of the test score gap during the school years. They explore several hypotheses as to the cause of the gap but find that none are supported by the empirical evidence. Hanushek and Rivkin (2005) however, demonstrate some strong links to school quality. The different ethnic mix in the US and the UK makes comparison of the performance of other ethnic groups more difficult, for example, “Asian” in the US generally means Chinese, who tend to outperform Whites in educational attainment, whereas in the UK, “Asian” refers more often to people of Bangladeshi, Indian and Pakistani origin.

Another important group of factors relate to the parents investment in physical goods or particular activities which are beneficial for their child’s development. This could include books and toys in the home, and better quality pre-school or tutoring. It is also related to what parents are able to buy more generally, for example, if the family owns a car or a home computer, since this can also impact on the child’s development. A possible theoretical framework for parents investing in their child is based on the Becker-Tomes model where parents invest in their children’s education because they care about their children’s future well-being, investing up until the point that marginal benefit equals marginal cost (Becker and Tomes, 1986). If there were no credit constraints, parental income should not influence child outcomes, however, as this seems unlikely, (since not all families will be able to self-finance the investment or borrow against future earnings), poorer families may well not be able to invest optimal amounts. Datcher-Loury (1989) included measures of the child's ownership of books and toys and also considered paints, records, musical instruments, a children's dictionary or encyclopaedia, and puzzles and found some evidence of a positive impact (although parental behaviours appear to be more important).

Several factors surrounding the birth of the child have been found to have a persistent impact, which is precisely measurable several years later. Breastfeeding, for example, is a current topic and several papers have even employed an instrumental variables technique to try to identify the causal impact of this factor. These include Doyle and Denny (2010) who use emergency caesarean section as their instrument and test the impact of breastfeeding on cognitive skills at young ages; and Fitzsimons and Vera-Hernández (2012) who use being born on the weekend as their instrument (arguing that hospitals cut-down on non-essential services such as breastfeeding support on weekends and this significantly reduces the likelihood that a mother will start to breastfeed), and find that breastfeeding has large positive effects on cognitive development, especially for children of less educated mothers. There is also a growing literature on the long run impacts of higher birthweight, for example, Behrman and Rosenzweig (2004) use data on monozygotic twins to demonstrate the impact on schooling level (and adult height).

Another important area of research is the effect of parenting behaviours. Melhuish *et al* (2008) explores this in some detail. Their decision to focus on parenting practices (as well as the influence of pre-school) is based on research that shows that parenting practices such as reading to children, using complex language, responsiveness, and warmth in interactions are all associated with better developmental outcomes (Bradley, 2002), are more frequently practiced by higher SES parents (Hess *et al*, 1982), and that between 20–50% of the variance in child outcomes can be accounted for by differences in parenting (Conger *et al*, 1992). In their own work, they use parents' responses on the survey questions relating to the frequency of performing certain activities with the child to construct a Home Learning Environment (HLE) index. They find that the HLE coefficient is statistically significant for both numeracy and literacy achievement at age 5 and there is some evidence of the effects persisting until age 7. The results clearly support the importance of the HLE, as the influence of the HLE was over and above that of standard proxy measures of parental education and SES. Sylva *et al* (2008) also find a positive effect of the home learning environment and write “what is surprising is the continuing strong influence of the early years HLE” and “What parents do is therefore vitally important and can counteract other disadvantaging influences”. Several studies have found that differences in the home environment, as measured by the HOME scale (which includes items on household resources, such as reading materials and toys, and 4 parental practices, such as discipline methods), account for a substantial portion of the effect of income on the cognitive development of preschool children and on the achievement scores of elementary school children (e.g. Duncan, *et al*, 1994).

The influences on a child’s development can be seen as starting with the child’s own characteristics, their family and home environment, as well as influences from a broader sphere such as their neighbourhood and the society as a whole. Studies which have examined the influence of the neighbourhood include Sonbonmatsu *et al* (2006), on the effects of the US “moving to opportunity” lottery, who found the change of neighbourhood did not produce any significant effects on the reading or maths test scores of the children of families assigned housing vouchers by the lottery; Ginther *et al* (2000), who find that the effects of neighbourhood on children’s cognitive test scores are heavily dependent on how well unobservables are controlled for; Gagne and Ferrer (2006), using data for Canada, who find that poor neighbourhood quality has negative effects especially for girls (and that home ownership has a positive effect); and Mohanty and Raut (2009), using the PSID Child Development Supplement and the corresponding PSID main data sets, who find positive significant effects of home environment, neighbourhood quality, and residential stability on the reading and math performance of children between the ages of three and twelve (but no significant effect of home ownership).

These are just a few of the many papers that have been written on each of these topics, and there are also many other possible influences to be explored. The aim here has been to give an indication of the key factors identified in the literature and if current work on these tends to show a consensus on whether there is a positive effect, a negative effect, or no effect. Some papers on the same issues differ in their findings, this could be due to the fact that they explore data from a different context, use different methodology and control for a different array of covariates. Nonetheless, there is a relatively clear consensus on many of the factors discussed above. My own results in the results section will be discussed in the light of these findings and build on them further to contribute the understanding of the factors that have an important influence on children's early years cognitive development. The next section describes the data set used to explore the effects of these various factors.

4.3 Data

4.3.1 The Millennium Cohort Study (MCS)

This chapter uses the first four waves of the Millennium Cohort Study, a recent large-scale longitudinal dataset. The first wave was run between June 2001 and September 2002 in England and Wales and between September 2001 and January 2003 in Scotland and Northern Ireland, interviewing families of nearly 19,000 children aged around 9 months. Fieldwork for the fourth wave of the study was concluded in December 2008, with over 13,800 families with over 14,000 cohort children taking part. Children were selected using Child Benefit records and were born in all months of the year and across the UK. The sample was designed to reflect the total population, although certain sub-samples, such as children from disadvantaged backgrounds or ethnic minorities, were intentionally over-sampled. Weights are included for each wave and country to align the sample with the overall population and to deal with attrition. I make use of these weights wherever possible, namely for the OLS regressions and in all descriptive statistics in this chapter. The sampling method and other aspects of this data set are described in more detail in chapter 5.

The survey covers a huge range of factors, having been designed through consultation with specialists from a large number of fields, including psychology, sociology, economics, and epidemiology. Data on the children's siblings and parents is also collected, and the survey covers such wide ranging topics as parents' employment and education; income and poverty; parenting; child behaviour and cognitive development; child and parental health; childcare; schooling; housing, residential mobility and neighbourhood; and ethnicity. The inclusion of cognitive ability tests in the most recent three waves makes it possible to study children's cognitive development and the various factors which influence this.

Although the dataset contains multiple tests of cognitive ability, I focus on the children's pattern construction test scores, as this test was carried out at ages 5 and 7 and thus provides an opportunity to examine the influence of early schooling on cognitive development. The pattern construction assessment is taken from the British Ability Scales and assesses children's non-verbal reasoning and spatial visualisation (Chaplin Gray *et al*, 2010). It is designed to be used with children from age 3 years until 17 years 11 months with the number of items administered varying depending on the age of the child and their performance during the assessment. Importantly, the pattern construction test provides the opportunity to examine the children's development in a consistent manner as the same skill was tested at each age. Other papers (e.g. Feinstein, 2003, Sullivan *et al*, 2013) have used an ability index created using principle component analysis to combine the results of a wider range of assessments, however, I have chosen rather to take advantage of the opportunity to focus on the outcome of a single test, as this removes a possible source of bias which can arise when the results measure children's ability in different skills over time.

Furthermore, some papers make use of the vocabulary-related tests that are available at waves two, three and four, namely naming vocabulary at waves two and three and word reading at wave 4 (see Jerrim and Vignoles, 2011). Although I initially viewed this as a chance to estimate panel data models more robustly using three waves of data on a similar skill, my final analysis does not include these results as the word reading scores in fact follow quite a different distribution. For example, the raw scores fall between 55 and 145 compared to the range of 20 to 80 on the naming vocabulary scores, and the variance is also larger.

A further question is whether to use the raw scores or a standardised version of these. Magunsin *et al* (2012) discuss the limitations of either approach, describing how on the one hand, using standardised scores can remove the variation we are interested in explaining, since absolute differences tend to increase over time but standardisation removes this by equating standard deviations across time points, whilst raw scores are determined by the specificity of test construction and can thus be difficult to interpret. The raw pattern construction scores are scaled between 20 and 80 and show an increasing mean and variance between the two waves, thus the issues they discuss are relevant for the data used in this research as well. I therefore take the same approach they do and report results for both measures.

Family income is based on OECD equivalised income, which means that the family size is taken into account. I use the logarithm of this figure. A large majority of families in the lowest income quartile consist of single-mother households where the mother is not working. This has some relevance for the interpretation of the income variable as a measure of family background. On the one hand, the practical difficulties involved in bringing in an income alone with a small child are no doubt a large part of the explanation for the income levels of these families. On the other hand, the fact that the mother is a lone-mother and has not self-selected into the labour market may reflect her own personal characteristics. The demographics of this sub-sample are especially relevant for the variables on the behaviours of the father (or mother's partner). The absence of the father plays a large role in terms of them not spending time with the child, not reading to them and so forth, as well as automatically implying the absence of one income stream. Thus whilst family income is a reflection of the material resources available to the family, on the one hand, it is also an indication of a far broader set of family characteristics.

4.3.2 Descriptive Statistics

Table 4.1 shows descriptive statistics for the variables included in this analysis. The mean and standard deviation are shown for the whole sample and for the lowest and highest income quartiles. The income groups are based on the family income when the child is aged 5 and test scores are reported at ages 5 and 7. The other covariates are drawn from the first survey (when the child is aged 9 months) for the birth related factors and from the third survey (when the child is aged 5) for all other variables[18]. While this table provides a summary of the key data, it also shows that children from high income families have higher means for every variable that represents a positive influence. These children have better educated parents who are more likely to be married and in employment; the natural father is much more likely to be present in the household; they are less likely to move home and almost certainly live in a home that is owned or mortgaged; they watch less TV, have more regular bedtimes, are read to and taken to the library more frequently; they are heavier when they are born, have longer gestation periods and are less likely to have a health condition at age 5; their mother is much more likely to breastfeed and to attend antenatal classes; and their family is much more likely to own a car, take holidays abroad and live in a good neighbourhood. The analysis in the subsequent section will seek to ascertain which of these positive influences are most important for the children's cognitive development, and if there are negative influences on the children who perform more poorly which could potentially by addressed by government policy.

Whilst most of the data was gathered through interviews with the cohort family, there were also teacher questionnaires which were carried out at waves 3 and 4. At wave three, the teacher survey was administered in Northern Ireland, Scotland and Wales while in England data on children's foundation Stage Profiles was used instead. There are no questions about the teacher (e.g. their experience or qualifications) and no teacher identifier. This precludes the use of teacher fixed effects as the teacher identifier is

[18] Except car ownership which is not available in the age 5 survey and is reported for when the child is aged 7.

Table 4-1: Descriptive Statistics by Family Income Group

	Whole Sample		Low Income Families		High Income Families	
	Mean	*SD*	Mean	*SD*	Mean	*SD*
COGNITIVE ABILITY TESTS						
pattern construction age 5	50.81	*0.17*	48.02	*0.25*	52.95	*0.25*
pattern construction age 7	53.81	*0.18*	50.12	*0.28*	56.48	*0.24*
standardised pattern construction age 5	0.03	*0.02*	-0.25	*0.03*	0.24	*0.03*
standardised pattern construction age 7	0.05	*0.02*	-0.29	*0.03*	0.29	*0.02*
FAMILY INCOME						
Log (family income) age 5	5.70	*0.01*	4.79	*0.01*	6.45	*0.01*
SCHOOL RELATED FACTORS						
Months of school	31.23	*0.03*	31.43	*0.06*	31.07	*0.06*
School fees	0.03	*0.00*	0.01	*0.00*	0.09	*0.01*
Coeducational school	0.97	*0.00*	0.98	*0.00*	0.97	*0.00*
Teacher tenure	14.18	*0.06*	14.07	*0.09*	14.31	*0.11*
Class size	24.94	*0.04*	24.95	*0.06*	24.87	*0.09*
CHILD CHARACTERISTICS						
Male	0.51	*0.00*	0.50	*0.01*	0.51	*0.01*
White	0.90	*0.01*	0.82	*0.02*	0.94	*0.01*
Black	0.02	*0.00*	0.04	*0.01*	0.01	*0.00*
Asian	0.05	*0.01*	0.09	*0.02*	0.02	*0.00*
Other Ethnicity	0.03	*0.00*	0.05	*0.01*	0.03	*0.00*
HEALTH						
Child has a longstanding illness	0.20	*0.00*	0.22	*0.01*	0.17	*0.01*
Mother's gnereal health						
Excellent	0.21	*0.00*	0.14	*0.01*	0.30	*0.01*
Good / very good	0.65	*0.00*	0.62	*0.01*	0.64	*0.01*
Poor	0.13	*0.00*	0.24	*0.01*	0.07	*0.00*
Mother has a longstanding illness	0.24	*0.00*	0.28	*0.01*	0.20	*0.01*
Mother has depression	0.32	*0.01*	0.41	*0.01*	0.22	*0.01*
Partner's gnereal health						
Excellent	0.17	*0.00*	0.06	*0.00*	0.26	*0.01*
Good / very good	0.46	*0.01*	0.23	*0.01*	0.58	*0.01*
Poor	0.07	*0.09*	0.09	*0.01*	0.05	*0.00*
Missing	0.30	*0.01*	0.63	*0.01*	0.11	*0.01*
Partner has a longstanding illness	0.16	*0.00*	0.13	*0.01*	0.18	*0.01*
Partner longstanding illness missing	0.30	*0.01*	0.63	*0.01*	0.11	*0.01*
FAMILY STRUCTURE						
Mother's age at birth of child	28.63	*0.11*	25.60	*0.13*	31.55	*0.12*
Mother is Married	0.61	*0.01*	0.27	*0.01*	0.85	*0.01*
Mother has a resident partner	0.19	*0.00*	0.20	*0.01*	0.13	*0.01*
Mother is a Lone Parent	0.20	*0.01*	0.53	*0.01*	0.03	*0.01*
Number of siblings	1.37	*0.01*	1.66	*0.03*	1.12	*0.02*
Partner is child's natural father	0.76	*0.01*	0.41	*0.01*	0.95	*0.00*
MATERNAL EMPLOYMENT						
Working full time	0.20	*0.00*	0.04	*0.00*	0.33	*0.01*
Working part-time	0.39	*0.01*	0.17	*0.01*	0.47	*0.01*
Not working	0.41	*0.00*	0.79	*0.01*	0.21	*0.01*
HOME ATMOSPHERE						
0 - 12 Scale; 12 = calm and organised	7.67	*0.03*	7.08	*0.05*	8.32	*0.04*

	Whole Sample		Low Income Families		High Income Families	
	Mean	*SD*	Mean	*SD*	Mean	*SD*
PARENTS EDUCATION						
Mothers Education						
No qualifications	0.11	*0.00*	0.27	*0.01*	0.01	*0.00*
NVQ level 1	0.07	*0.00*	0.13	*0.01*	0.02	*0.00*
NVQ level 2	0.28	*0.01*	0.32	*0.01*	0.16	*0.01*
NVQ level 3	0.15	*0.00*	0.12	*0.01*	0.12	*0.01*
NVQ level 4	0.28	*0.01*	0.09	*0.01*	0.51	*0.01*
NVQ level 5	0.07	*0.00*	0.02	*0.00*	0.16	*0.01*
Overseas Qualifications	0.02	*0.00*	0.05	*0.00*	0.01	*0.00*
Partner's education						
No qualifications	0.08	*0.00*	0.13	*0.01*	0.02	*0.02*
NVQ level 1	0.04	*0.00*	0.04	*0.04*	0.02	*0.00*
NVQ level 2	0.20	*0.00*	0.11	*0.01*	0.15	*0.01*
NVQ level 3	0.11	*0.00*	0.05	*0.00*	0.12	*0.01*
NVQ level 4	0.21	*0.01*	0.04	*0.00*	0.41	*0.01*
NVQ level 5	0.08	*0.00*	0.02	*0.00*	0.20	*0.01*
Overseas Qualifications	0.03	*0.00*	0.03	*0.03*	0.01	*0.00*
Missing	0.25	*0.01*	0.59	*0.01*	0.06	*0.00*
PARENTAL BEHAVIOURS						
Hours of TV child watches per day, age 5						
No TV	0.02	*0.00*	0.02	*0.00*	0.03	*0.00*
Less than 1 hour of TV per day	0.19	*0.01*	0.15	*0.01*	0.26	*0.01*
1 to 3hrs of TV per day	0.64	*0.01*	0.61	*0.01*	0.62	*0.01*
More than 3 hrs of TV per day	0.14	*0.00*	0.22	*0.01*	0.09	*0.01*
Child has Regular Bedtimes						
Never	0.05	*0.00*	0.08	*0.01*	0.02	*0.00*
Sometimes	0.05	*0.00*	0.09	*0.01*	0.03	*0.00*
Usually	0.27	*0.01*	0.24	*0.01*	0.30	*0.01*
Always	0.62	*0.01*	0.59	*0.01*	0.65	*0.01*
Mother reads to child						
Never	0.01	*0.00*	0.03	*0.00*	0.00	*0.00*
Occasionally	0.19	*0.00*	0.24	*0.01*	0.12	*0.01*
Weekly	0.28	*0.00*	0.27	*0.01*	0.28	*0.01*
Daily	0.52	*0.01*	0.46	*0.01*	0.60	*0.01*
Partner reads to child						
Never	0.03	*0.00*	0.04	*0.00*	0.01	*0.00*
Occasionally	0.33	*0.01*	0.20	*0.01*	0.35	*0.01*
Weekly	0.23	*0.01*	0.09	*0.01*	0.36	*0.01*
Daily	0.11	*0.00*	0.05	*0.00*	0.17	*0.01*
Missing	0.30	*0.01*	0.63	*0.01*	0.11	*0.01*
Frequency of library visits						
Never	0.37	*0.01*	0.48	*0.01*	0.27	*0.01*
Once a month to once a year	0.54	*0.01*	0.42	*0.01*	0.65	*0.01*
Daily to at least once a week	0.09	*0.00*	0.10	*0.01*	0.09	*0.01*
Partner's time spent with child						
Not enough	0.63	*0.01*	0.29	*0.01*	0.84	*0.01*
Just enough	0.06	*0.00*	0.08	*0.00*	0.05	*0.00*
Plenty	0.00	*0.00*	0.01	*0.00*	0.00	*0.00*
Missing	0.30	*0.01*	0.63	*0.01*	0.11	*0.01*

	Whole Sample		Low Income Families		High Income Families	
	Mean	*SD*	Mean	*SD*	Mean	*SD*
Partner plays with child						
Less than several times a week	0.35	*0.01*	0.20	*0.01*	0.44	*0.01*
Several times a week	0.23	*0.00*	0.11	*0.01*	0.32	*0.01*
Daily	0.12	*0.00*	0.07	*0.00*	0.13	*0.01*
Missing	0.30	*0.01*	0.63	*0.01*	0.11	*0.01*
How parent disciplines when naughty						
Smack	0.54	*0.01*	0.51	*0.01*	0.51	*0.01*
Tell off	0.11	*0.00*	0.15	*0.01*	0.07	*0.00*
MONEY RELATED FACTORS						
Car ownership (age 7)	0.88	*0.00*	0.62	*0.01*	0.99	*0.00*
Holidays Abroad	0.65	*0.01*	0.32	*0.01*	0.90	*0.01*
Type of housing tenure						
Own / mortage	0.66	*0.01*	0.21	*0.01*	0.95	*0.00*
Council rented	0.14	*0.01*	0.37	*0.01*	0.01	*0.00*
Rent / other	0.19	*0.01*	0.42	*0.01*	0.04	*0.00*
NEIGHBOURHOOD FACTORS						
Urban	0.58	*0.02*	0.64	*0.02*	0.54	*0.03*
IMD Score Groups						
Low	0.18	*0.01*	0.35	*0.02*	0.06	*0.01*
Middle	0.22	*0.01*	0.17	*0.01*	0.22	*0.01*
High	0.18	*0.01*	0.05	*0.01*	0.34	*0.02*
Missing	0.42	*0.01*	0.43	*0.02*	0.38	*0.02*
EARLY FACTORS						
Child's Birthweight (kgs)	3.39	*0.01*	3.29	*0.01*	3.45	*0.01*
Days of gestation	277.45	*0.13*	276.84	*0.28*	277.82	*0.26*
Mother breastfed	0.67	*0.01*	0.51	*0.01*	0.84	*0.01*
Child was in a special care unit	0.09	*0.00*	0.08	*0.01*	0.09	*0.01*
Parents took antenatal classes	0.36	*0.01*	0.21	*0.01*	0.49	*0.01*
SHOCKS						
Family moved home	0.16	*0.00*	0.20	*0.01*	0.13	*0.01*

only observed at wave 4. At wave four a teacher survey was administered in all four countries of the UK and had an overall response rate of 70% compared to 82% for the family surveys. This survey included questions on teacher tenure and class size, which I include in the regressions. Although school ID is included at both wave 3 and wave 4, it was only available for 2,035 pupils and was only the same in both waves for 1,699 pupils, compared to around 12,000 observations on the pattern construction test scores. This amount of missing data means it is not possible to test the significance of overall school effects in a robust way. This is unfortunate, given the issues raised in the literature review regarding the limited explanatory power of school quality proxies such as teacher tenure and class size. It can only be hoped that future longitudinal surveys will continue to integrate data from teacher surveys and will be able to generate a higher response rate. Another approach would be to use administrative data, such as the National Pupil Database in England which contains pupil level data on test scores and some personal characteristics such as free school meal status, as well as school identifiers. Holmlund *et al* (2010) use this data to test the effect of school-level expenditure. They include school-level fixed effects in their preferred specification but do not report on these at all, focusing on the positive effect of expenditure on student outcomes.

Table 4.2 gives a summary of the cognitive outcome measures and family income as regards the variability of these factors over the different surveys. Since the methodology to be used here involves panel data, it important to know how these variables vary within individuals and across the different cohort members in the sample. For all of these measures, it can be seen from the table that the variation between cohort members is much greater than the variation over time for any individual. I will return to this point later in regards to the choice between fixed effects and random effects models.

Table 4-2: Family Income and Test Scores, Descriptive Statistics

	Mean	Min	Max	Standard Deviation			Sample Size	Observations per Child
				Overall	Between	Within		
Log of Equivalised Family Income (Ages 5 and 7)	5.71	2.46	7.16	0.65	0.62	0.24	14,985	1.82
Pattern Construction Scores (Ages 5 and 7)	51.83	20	80	10.59	9.62	4.88	13,362	1.84
Standardised Pattern Construction (Ages 5 and 7)	0.00	-3.04	2.94	1.00	0.92	0.45	13,362	1.84

In summary, the MCS provides an excellent opportunity to explore the effects of family income, schooling and a broad range of other factors on children's cognitive development between ages 5 and 7. I focus on the children's pattern construction scores between these two ages as this gives a good indication of their development over the first few years of school. A broad range of explanatory variables is considered. The data is very current, with the field work for the fourth wave being carried out in 2008. As far as I am aware, this is the first study to provide estimates of the effects of schooling variables on cognitive development using such current UK data. The sample size is also very good, with over 13,000 observations at wave four. Furthermore, this study can provide insight into the UK population as a whole, thanks to sophisticated sampling techniques and the provision of weights which align the sample to the population as a whole.

4.4 Methodology

The approach I take in this chapter involves the estimation of three types of models. In each of these, I focus on the results concerning family income, schooling and other factors. I firstly estimate simple OLS models with various combinations of these factors. I then use the longitudinal structure of the data to estimate fixed-effects models. This focuses on individual rather than school fixed effects due to the vast amounts of missing data on school and teacher identifiers. Finally, given the issues that arise with the fixed effects models, for example a lack of within variation in some key variables, I explore an augmented random effects framework and test the validity of this using the Hausman test. The next three sections will discuss each of these three steps in turn.

4.4.1 Single-period models

I firstly estimate OLS models using a broad array of covariates to explore the importance of family income, schooling and other factors for children's development. OLS is the most common form of regression analysis and is widely used, partly because it requires very few assumptions to be derived. The assumptions underlying the efficient and unbiased estimation using OLS are as follows: the equation to be estimated is linear in parameters, estimation is based on a random sample on n observations (where the number of observations is greater than the number of parameters to be estimated, n>k), there is no reverse causality from the dependent variable to the independent variables, the error term has a mean of zero conditional on the independent variables, there is no perfect collinearity, and error terms are *iid* (homoscedasticity). These assumptions are relatively unrestrictive and intuitive.

I start with parsimonious specifications including only a baseline score and the variables of interest, i.e. family income or the schooling variables, in turn. I then estimate fuller models including both of these sets of variables and finally a model where all the other factors are added. These function as control variables on the one hand, but are also of interest in their own right. Whilst the focus is on family income and school related factors, other variables considered include variables that are related to child characteristics (such as ethnicity), early factors (such as birth-weight and if the parents attended antenatal classes), health (e.g. the child themselves or either parent having a long term health condition), parental characteristics (such as labour force engagement, education, age and marital status), parental behaviours (such as frequency of reading to the children and taking them to the library), neighbourhood factors (i.e. urban / rural location and Indices of Multiple Deprivation (IMD) scores), money *per se* (such as car use and type of housing tenure) and shocks (such as moving home). Each variable can be seen as representing an imperfect measure of some underlying characteristic. While some factors are more concrete (e.g. birthweight), others are less tangible. For example, the frequency of the parents' reading to the child is a direct measure of a specific activity that may be beneficial for children's cognition, on the one hand, and also an indicator of a much broader set of factors relating to the parent's characteristics, behaviours and attitudes, on the other hand. Even birthweight, although it is more easily quantified, is still open to various hypotheses as to the reason why it may have a sustained influence on children's development and the other factors it may be proxying. It is therefore important to interpret the effects of these factors carefully.

One potential issue with these results is the bias caused by omitted variables. Although the MCS contains information on a great variety of factors that are thought to effect children's cognitive development, it is nonetheless unavoidable that certain factors and influences are not accounted for. One function of the baseline ability score is to act as a proxy for individual heterogeneity that cannot be measured by the factors covered in the survey. The availability of comparable test scores over two periods is an important reason to use this data as it facilitates a “value-added” approach where the covariates explain the change over two periods.

Another approach to dealing with endogeneity and unobserved individual heterogeneity is to use instrumental variables to isolate a causal effect of the factors of interest. Although there are papers which use instrumental variables to try to uncover the causal effect of the factors considered here, I do not take this approach in this paper, as I do not consider that the MCS contains a suitable and convincing instrument for the variables of interest here. In terms of income, for example, I am not aware of exogenous, policy related changes in income which may have affected some families in the sample and not others over this period. Instruments used in the United States, such as differing benefit policies between states (Dahl and Lochner, 2012), are not relevant in this context. In regards to schooling, the institutional context (as per Park *et al*, 2013) and the environmental context (as per Marcotte, 2007) do not seem to provide suitable instruments in the UK, therefore precluding this approach. Although the work that has been done on breastfeeding using the MCS with caesarean sections and weekend-births as instruments (Doyle and Denny, 2010, and Fitzsimons and Vera-Hernández, 2012) is interesting, that is not the focus of this study. I therefore concentrate on a third possible approach to dealing with unobserved individual heterogeneity, namely the use of panel data models, where the children act as their own control. This approach is described in the following section.

4.4.2 Panel Data Methods

The next stage of this analysis is to exploit the panel nature of the data in order to address the issue of unobserved individual heterogeneity. In this section, I will describe the models used, namely fixed and random effects models, together with relevant specification tests, and also introduce a variant of the random effects model.

The basic unobserved effects model can be written as

$$y_{ij} = \beta_1 + \beta_2 \boldsymbol{x}_{ij} + u_i + \varepsilon_{ij} \tag{4.1}$$

where the x variables can vary over both individual and occasion, individual only or occasion only and where u_i is an unobserved, time constant effect, also known as an individual effect or individual heterogeneity, which only varies across individual, but not across occasion, and ε_{ij} are the idiosyncratic errors which change across individuals and observations. The error terms are split into two parts because it is expected that individuals will be more similar to themselves over time than to other individuals in the sample. Separating out u_i (the individual effect) from ε_{ij} (the residual disturbance) allows us to make more efficient use of our knowledge of the structure of the data than if all unobservables were included together in a single error term (Cameron and Trivedi, 2009).

The two major models used in linear panel data analysis are fixed effects and random effects models. The key distinction relates to the correlation of the individual effect to the covariates included in the model. In random effects models, the individual effect is assumed to be uncorrelated with the explanatory variables, such that

$$\mathrm{Cov}(\boldsymbol{x}_{it}, u_i) = 0, \quad j = 1, 2 \ldots . J \tag{4.2}$$

If this assumption is violated, the estimated parameters will be biased by the omitted unobserved individual heterogeneity, just as in cross-section models.

However, in a fixed effects framework, the individual effects are allowed to be correlated with the explanatory variables, i.e.

$$\mathrm{Cov}(\boldsymbol{x}_{it}, u_i) \neq 0, \quad j = 1, 2 \ldots . J \tag{4.3}$$

However, both of these models still require that the random disturbance term ε_{ij} is uncorrelated with the covariates from any period, i.e. x_{ik}. Fixed effects models only deal with the time constant individual heterogeneity[19].

[19] It has been suggested for this reason that they may be less appropriate for data on children (Violato *et al*, 2011). Given the prevalence of the issues relating to endogeneity in studies on the effect of family income, I consider it is worthwhile to employ fixed effects models despite this difficulty. Although there may be concerns about the ability of such models to fully overcome these issues, this should be seen as a qualification on the results, rather than a reason for avoiding the use

We will now discuss each of these models in more detail.

4.4.2.1 Fixed effects

In (4.1) above, the error term is split into an idiosyncratic disturbance term and an individual effect which is constant over time. These individual effects (the u_i) can be estimated, for example in a least squares dummy variable model (LSDV). In this case, a dummy variable is created for each individual in the sample and the coefficient on this dummy provides the estimated individual effect, also known as the fixed effect. However, if there are many individuals, the loss of degrees of freedom associated with this procedure is large, and the estimated individual effects will become inconsistent as the sample size grows (although they will still be unbiased). Furthermore, capturing these effects explicitly may not even be of interest. A more efficient approach is to use a within transformation to estimate the fixed effects model. This provides a way of removing the individual effects. When there are only two time periods, time differencing is equivalent to the within transformation. The within transformation works as follows:

First, equation (4.1) should be averaged over *j* = 1, 2, …. J to get the cross section equation

$$\bar{y}_i = \bar{\boldsymbol{x}}_{\boldsymbol{i}}\boldsymbol{\beta} + u_i + \bar{\varepsilon}_i \qquad (4.4)$$

where $\bar{y}_i = J^{-1}\sum_{j=1}^{J} y_{ij}$, $\bar{\boldsymbol{x}}_i = J^{-1}\sum_{j=1}^{J} \boldsymbol{x}_{ij}$, $\bar{\varepsilon}_i = J^{-1}\sum_{j=1}^{J} \varepsilon_{ij}$.

If this is subtracted from (1) for each j, we obtain the fixed effects transformed equation which equals

$$y_{ij} - \bar{y}_i = (\boldsymbol{x} - \bar{\boldsymbol{x}}_{\boldsymbol{i}})\boldsymbol{\beta} + \varepsilon_{ij} + \bar{\varepsilon}_i \qquad (4.5)$$

The most important thing to note here is that the time constant individual effect u_i has been eliminated as it does not vary over occasions.

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of these models. Violato *et al* (2011) include such qualifications in the discussion of their results and they also apply to the analysis in this chapter. Nonetheless, as children are no doubt more similar to themselves (though they are still developing) than to other individuals, the framework is still useful in dealing with unobserved heterogeneity.

Any time-invariant explanatory variables will also be eliminated by this transformation. A key assumption for fixed-effects models is thus that unobserved factors which may be correlated with explanatory variables and the dependent variable must be time-constant. The fixed effects estimator is also known as the within-estimator, since it only uses variation within each subject, rather than across individuals. Fixed effects models are generally estimated using feasible generalised least squares (FGLS). Since fixed effects models can be used to eliminate time-constant individual heterogeneity, the results can be interpreted as providing a causal effect of the factors included. It is important to note, however, that only individual heterogeneity that is constant over time is eliminated using the within transformation.

4.4.2.2 Random Effects

In random effects models, the error terms u_i and ε_{ij} are expressed as a composite error term v_{ij} in the regression equation

$$y_{ij} = \beta_1 + \beta_2 \boldsymbol{x}_{ij} + v_{ij} \tag{4.6}$$

and the estimation of the model involves exploiting the serial correlation in the composite error term $v_{ij} = u_i + \varepsilon_{ij}$ in an FGLS framework. Strict exogeneity between the explanatory variables and the composite error is required to ensure that the estimates are consistent. This can be expressed as follows:

$$E(v_{ij}|x_i) = 0 \tag{4.7}$$

The error components are distributed as follows:

$$u_i \backsim N(0, \psi)$$

$$\varepsilon_{ij} \backsim N(0, \theta)$$

where ψ can be interpreted as the between-subject variance and θ as the within-subject variance. Within variation was described above for the fixed effects model. Between variation can be attained by averaging the response 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. The random effects model can be expressed as a weighted average of the within estimator and the between estimator, as is expressed below in terms of a single parameter to be estimated:

$$\widehat{\beta_2^R} = (1 - \widehat{\omega})\widehat{\beta_2^B} + \widehat{\omega}\widehat{\beta_2^W} \tag{4.8}$$

where $\widehat{\omega}$ determines the weights given to the between and within variation respectively and is given by

$$\widehat{\omega} = \frac{\widehat{SE}(\widehat{\beta_2^B})^2}{\widehat{SE}(\widehat{\beta_2^B})^2 + \widehat{SE}(\widehat{\beta_2^W})^2} \tag{4.9}$$

The estimator $\widehat{\beta_2^R}$ for the random-effects model approaches the within-estimator $\widehat{\beta_2^W}$ when $\widehat{\omega}$ approaches 1 (i.e. when the within standard error is much smaller than the between standard error), and the between estimator $\widehat{\beta_2^B}$ when $\widehat{\omega}$ approaches 0. Although $\widehat{\beta_2^R}$, $\widehat{\beta_2^B}$ and $\widehat{\beta_2^W}$ are all estimators of the same parameter β_2, the random effects estimator $\widehat{\beta_2^R}$ is more efficient (meaning it varies less in repeated samples) than the other estimators if the model is true because it exploits both within and between subject variation. Random effects is usually estimated by feasible generalised least squares (FGLS), but can also be estimated via maximum likelihood (MLE).

4.4.2.3 The Hausman Test

The Hausman test can be used to compare two tests where one is known to be consistent and the other is known to be more efficient if it is true. It is very useful for testing the consistency of random effects models. The test works by comparing the coefficients of a fixed effects and a random effects model. A statistically significant difference between the coefficients of the two models is taken as evidence against the assumption that the individual effects are uncorrelated to the error terms, in which case the random effects model is inconsistent. Not all parameters can be included in the test; in particular, time-invariant parameters and time dummies cannot be tested. This can be expressed as follows:

$$y_{ij} = \boldsymbol{x_{ij}\beta} + u_i + \varepsilon_{ij} = \boldsymbol{z_i\gamma} + \boldsymbol{w_{ij}\delta} + u_i + \varepsilon_{ij} \tag{4.10}$$

Where $\boldsymbol{z_i}$ includes the intercept and any other time-invariant variables. The Hausman test tests the parameters $\boldsymbol{\delta}$. Since the inclusion of time-invariant variables in the random effects model can influence the other parameters, it is still important to carefully consider the controls to be included, as a random effects analysis with rich controls in $\boldsymbol{z_i}$ can yield very different estimates of $\boldsymbol{\delta}$ than if these are not included, which may bring the model much closer to the fixed effects estimate. This will be important later when different variants of the random effects models are tested.

The Hausman test statistic is given by:

$$H = \left(\widehat{\delta_{FE}} - \widehat{\delta_{RE}}\right)'[V\left(\widehat{\delta_{FE}}\right) - V\left(\widehat{\delta_{RE}}\right)]^{-1}\left(\widehat{\delta_{FE}} - \widehat{\delta_{RE}}\right) \tag{4.11}$$

and has a χ^2 distribution under the null hypothesis.

For the Hausman test results to hold, the strict exogeneity assumption made for both the fixed effects and random effects models must hold, since correlation between x_{ik} and ε_{ij} for any periods *k* and *j* will cause both models to be inconsistent. A variant of the Hausman test for use in samples with limited within-variation has been suggested (Hahn, Ham and Moon, 2010), although an application of this (seemingly untested) methodology is beyond the scope of this investigation. I will use the standard Hausman test to test the consistency of the random effects models in these models. Rejection of the random effects model implies there is a problem of endogeneity. Below follows a description of various options that can be taken to try to deal with this problem.

4.4.2.4 Further Extensions: Augmented Random Effects Model

How can one proceed if the random effects models are rejected as inconsistent? If the Hausman test rejects the consistency of the random effects model, this implies there is a problem of endogeneity, i.e. that the individual effects are correlated with the covariates included in the model. One option is simply to abide with the results of the fixed effects model. However, if the data covers only a few occasions and there is a lack of within-variation, being able to use a random effects model would help solve this problem and improve efficiency by making use of the between variation as well as the within variation. It is therefore beneficial to consider what options there are for improving the performance of the random effects estimator.

One well-known method is to use the Hausman –Taylor estimator to find consistent results of the time-invariant variables. To do this, one must partition covariates into exogenous variables and endogenous variables. The exogenous time varying factors are used as instruments for the endogenous time invariant factors. However, for identification, the number of exogenous time varying factors must be greater than the number of endogenous time invariant factors. That means that this approach is not feasible in this context as I do not have a large number of exogenous time-varying covariates. As discussed above in the context of single period models, I neither have any suitable external instruments; which precludes the use of that approach as well.

Another approach, often referred to as the Mundlak technique (e.g. see Proenca *et al* (2012), Hanchane and Mostafa (2012); based on Mundlak (1978)) is to include the group means of the explanatory variables. In this study, for each explanatory variable, this would be the mean for each child, averaged over the survey waves available. This approach ensures consistent estimation of all within effects because the deviations from the cluster means are uncorrelated with the cluster means themselves, with any time varying covariates and with the individual effects u_i. However, the means themselves may still be correlated with u_i, producing inconsistent estimates of the between effects and the random intercept variance ψ (Cameron and Trivedi, 2009). Proenca *et al* (2012) writes that although this proposal can often be found in the literature, it has several disadvantages such as making the overall effect of a factor more difficult to compute and making the estimation numerically less stable for short panels.

Including the group means can also simply be away of relaxing the assumption that between and within effects are the same for a particular explanatory variable. A correlation between the explanatory variables and the individual effect (i.e. the problem of endogeneity) can lead to an 'ecological fallacy', where between-cluster relationships (ecological relationships) can differ substantially from within-cluster relationships. Including the group means makes it possible to separate out the within effect from the between effect. The within effect is consistent by definition, while the presence of the between effect can improve the consistency of the whole model.

As such, the following model can be defined:

$$y_{ij} = \beta_1 + \beta_2^1(x_{2ij} - \bar{x}_{2\cdot j}) + \beta_2^2\bar{x}_{2\cdot j} + \cdots + \beta_p x_{pij} + \zeta_j + \epsilon_{ij} \quad (4.12)$$

which collapses to the original random-effects model in (4.6) if $\beta_2^1 = \beta_2^2 = \beta_2$.

An advantage of setting the within and between effects of a covariate equal is that the common effect may be more precisely estimated than separate effects because it pools the within and between information. I will set the within and between effects equal where this appears to be appropriate but allow different within and between effects when such equality restrictions are inappropriate. This can be done by comparing fixed effects and random effects models without any group means originally, and introducing group means for the variables which have significantly different results. In terms of the functional form of the model including means, it is possible either to include the variables for which the mean value is included as they are, or as the deviation from the mean. The only difference is in the interpretation of the coefficients, as the within variation and the between variation for the latter, or as the within variation and as the difference in within and between variation in the former case.

This is a useful approach as it makes it possible to employ a random effects model (i.e. to make use of between subject variation as well as within subject variation) where we can obtain either the overall effect of a variable or its between and within effect separately, and test it against a fixed effects model to ensure consistency of the results. In this way, it is also possible to include time-invariant factors, since the framework of the random effects model makes this possible. Including a richer set of controls also improves the estimates of the coefficients on the other factors. It is important to note that using the Hausman test to test this model does not ensure the consistency of the coefficients on the time invariant factors or the group means, but only the factors which are also included in the fixed effects models, including the coefficients which represent a combination of between and within effects, and the coefficients on the deviations from the group means. This novel approach deals with the two major issues presented by the data, namely endogeneity of key variables and a lack of within-variation. Applying this approach generates some interesting findings, which are discussed below.

4.5 Results

4.5.1 Results from Simple Regression Models

The results of the OLS models are reported in Table 4.3 below. Looking firstly at the effect of family income, it is clear that it has a positive and statistically significant effect in all six specifications where it is included. For both the raw scores and the standardised scores, the magnitude of the coefficient halves when the extended list of covariates is included, but it is still statistically significant and positive. Given that such a large range of other covariates was considered, including the IMD score of the neighbourhood and money related factors such as type of housing tenure, this is not a trivial finding. It confirms the finding of Gregg *et al* (2007) who found a significant direct effect of family income on children's development using the ALSPAC dataset despite controlling for a large range of additional control variables. All the same, as mentioned above, it is important not to lay too much weight on the results of simple OLS models in this context due to the endogeneity of family income. I will therefore come back to this when discussing the results of the panel data models.

Table 4-3: The effect of family income and school-related variables on test scores at age 7, various specifications

	(1) Pattern construction age 7	(2) Pattern construction age 7	(3) Pattern construction age 7	(4) Pattern construction age 7	(5) Std. Pattern construction age 7	(6) Std. Pattern construction age 7	(7) Std. Pattern construction age 7	(8) Std. Pattern construction age 7
Baseline Test Score age 5	0.607***	0.583***	0.582***	0.563***				
	(0.013)	(0.013)	(0.013)	(0.013)				
Standardised Baseline age 5					0.554***	0.532***	0.531***	0.514***
					(0.012)	(0.012)	(0.012)	(0.012)
Log(family income) age 5		2.226***	2.154***	0.934***		0.203***	0.196***	0.085***
		(0.166)	(0.168)	(0.230)		(0.015)	(0.015)	(0.021)
Months of school by age 7	-0.092**		-0.078**	0.002	-0.008**		-0.007**	0.000
	(0.038)		(0.037)	(0.037)	(0.003)		(0.003)	(0.003)
School fees age 5	2.340***		0.889*	0.944*	0.213***		0.081*	0.086*
	(0.533)		(0.536)	(0.551)	(0.049)		(0.049)	(0.050)
Coeducational school age 5	0.925		0.893	0.786	0.084		0.081	0.072
	(0.771)		(0.736)	(0.760)	(0.070)		(0.067)	(0.069)
Teacher tenure age 7	0.034**		0.030**	0.019	0.003**		0.003**	0.002
	(0.015)		(0.015)	(0.015)	(0.001)		(0.001)	(0.001)
Class size age 7	-0.019		-0.033	-0.021	-0.002		-0.003	-0.002
	(0.033)		(0.032)	(0.032)	(0.003)		(0.003)	(0.003)
OTHER COVARIATES				YES				YES
N	11,222	11,138	11,138	11,138	11,222	11,138	11,138	11,138
r2	0.302	0.316	0.318	0.346	0.302	0.316	0.318	0.346

Standard errors in parentheses
* p<0.100, ** p<0.050, *** p<0.010

Table 4-4: Results of other covariates, specifications (4) and (8) of Table 5.3

Positive Significant	**Negative Significant**	**Insignificant**
Month of birth: September; Child watches at least one but less than three hours of TV per day; Birthweight; Mother breastfeed; Parents attended antenatal classes	Months of birth: May, July, August; Ethnicity: Black, Asian; Mother has no educational qualifications; Father has no or low educational qualifications; Mother reads daily / never to the child; Mother smacks child when naughty; Child has a longstanding illness; Family moved house since last wave	Child's gender; Mothers age at birth of child; mother's marital status; Number of siblings; Presence of the natural father; Mother working part-time or full-time; Regular bedtimes; Partner reads to the child; Frequency of library visits; Partner has plenty of time with the child; Frequency of partner playing with the child; Mother tells off child when naughty; Home atmosphere; Mother's general health; Mother has a longstanding illness; Mother has depression; Partner's general health; Partner has a longstanding illness; Car usage; Type of housing tenure; Holidays abroad; Family lives in an urban area; IMD decile of neighbourhood; Length of gestation; Child was in a special care unit after birth

Secondly, in regards to the schooling variables, we can see that the months of school variable has a significant negative effect in the more parsimonious specifications, which becomes insignificant when further variables are included in the model. The coefficient is very small, with one extra month of schooling leading to a reduction of less than 0.1 test score points or less than 0.1% of a standard deviation. Although the coefficient is statistically significant, it is so small as to preclude any real interpretation. Furthermore, once more extensive control variables are added to the model, it becomes insignificant. Thus the quantity of schooling the children had received up to this point appears to have no real influence on their test score. Testing this with interactions terms with family income did not add any further nuance to this finding. It may be that this measure of the quantity of schooling is too rough (especially as it is not possible to control fully for school holidays and other days missed). Alternatively, since this test examines the children's non-verbal reasoning and spatial visualisation, it may support the finding of Carlsson *et al* (2012) who found that days of schooling had no effect on fluid intelligence tests (specifically spatial and logic tests).

The second schooling variable is school fees, which shows a positive coefficient. Less than four percent of children surveyed were at a school which charged fees at age 5 and over 80% of these where still at fee paying schools at age 7. Children at fee paying schools had a mean score over 3.5 points higher than children at non-fee paying schools. Attendance at fee paying schools is strongly correlated with family income, as less than ten percent of the children at these schools came from the lowest family income quartile, while over 60% came from the highest family income quartile. By age 7, less than five percent of children at a fee paying school came from the lowest family income quartile. Furthermore, the size of the coefficient is much smaller in specification (3) than in (1) due to the correlation of family income with attendance at a fee paying school. In regards to the issue of the role of education in social mobility, either as a facilitator or a hindrance, this finding points to the perpetuation of advantage through education via access to better quality schooling.

The third coefficient is whether or not the school is coeducational, which in all specifications is statistically insignificant. Only a very small number of children (less than 3%) were at single-sex schools at age 5, with slightly more children from the highest income quartile attending such schools. The major study in the literature to have identified a causal beneficial effect of single-sex schooling (Park *et al*, 2010, using compulsory random allocation to schools in Seoul, South Korea) measured the effect of outcome variables at the end of secondary school. It is quite likely that any benefits of single-sex schooling would emerge later than the ages considered here, when the children are still very young.

Finally, two traditional school quality proxies are considered – namely teacher tenure and class size. Teacher tenure shows a positive but small effect and is insignificant in the full model, while class size has the expected negative sign but is insignificant in all specifications. There is a great deal of literature (e.g. see Hanushek, 1986) that argues that the insignificance of these types of variables does not indicate that school quality is unimportant in children’s development, but rather than these variables do not provide a good indication of true school quality. He argues that teaching ability, for example, is not well reflected by years of teaching experience, as some great teachers have relatively little experience, while others may have taught for a long time but may still be ineffective in assisting the progress of their students.

A further point is that these two variables were only available at wave 4, which means they are contemporaneous with the outcome measure. There is some danger of reverse causality in that students who have performed poorly in the past may be allocated to smaller classes or classes with more experienced teachers. In fact, the data displays no correlation between past performance and teacher tenure but there is some correlation between the age 5 pattern construction score and class size at age 7. In a model that contains only past performance and class size, the coefficient on class size is negative and statistically significant. This gives credence to the result as being a genuine finding and not just the product of reverse causality. All the same, the size of the coefficient remains extremely small. Unfortunately, it was not possible to explore teacher or school quality more broadly using teacher or fixed effects due to the fact that teachers were only identified in one wave and schools had a great deal of missing data such that less than two thousand children could be identified as having attended the same school at two waves.

In general, none of the schooling variables demonstrate a sizable and significant effect except school fees. Assuming that schools which charge fees are of a higher quality, this shows how education can start to perpetuate social advantage and possibly limit social mobility even from the first few years of school.

Moving on now to the other variables included in specifications (4) and (8), table 4.4 above shows that many of these are statistically insignificant. The variables that do have a positive effect include month of birth, TV and early factors. The month of birth variables demonstrate the well-known "August birth penalty" (Crawford *et al*, 2007), with a significant negative sign on the May, July and August dummies and a significant positive coefficient on September. The TV variables give the same result as in Violato *et al* (2011) in regards to age 3 naming vocabulary scores, namely, that a small amount has a positive impact. Violato *et al* (2011) interpret levels of daily TV watching as potentially reflecting either parental engagement with their children or alternatively a more limited physical environment or a result of unsafe neighbourhoods, which would restrict children's outdoors activity. Following either of these interpretations, it is unclear why there would be a positive effect on naming vocabulary scores. The same applies to the effect on pattern construction at age 7. This issue requires further research.

There is also a positive effect of birthweight, breastfeeding and parental attendance of antenatal classes. The positive correlation between both birthweight and breastfeeding and later outcomes has already been documented. However, it is interesting to see here that they both have a significant effect on outcomes as late as age 7 and in a model that controls for such a broad range of other factors. In terms of attendance at antenatal classes, Dearden *et al* (2006) find it is positively correlated with birthweight and breastfeeding and also depends heavily on ethnicity; however, this is the first piece of research to my knowledge which finds a significant effect on cognitive development as the child grows up. If there is a direct effect of antenatal classes so many years later, promoting the attendance of such classes among groups that are less likely to attend them (e.g. among blacks) could be an effective and cost-efficient strategy. Unfortunately, however, this variable is likely to be very strongly correlated with other unobservable characteristics of the families who attend such classes (such as their attitude towards parenting more generally), which means that the positive coefficient may in fact reflect no more than selection into this activity.

The ethnicity and education variables display the expected signs, with low or no education negative and significant for both the mother and the father, and black and Asian ethnicity also negative compared to the base category of white. There is also a negative sign on the frequency the mother reads to the child - somewhat counter-intuitively for both daily and monthly reading (with weekly as the base category), although these are both very small in size[20]. The mother smacking the child when they are naughty also has a negative sign, as does the child having a longstanding illness (as would be expected) and the family moving home since the last wave. All three of these variables are also correlated with family income with more children from the lowest family income quartile experiencing smacking, having long-standing illnesses and moving home more frequently.

For the OLS results in general, although there are some interesting results, it cannot be argued that they represent causal effects since it is not possible to control fully for the unobserved individual heterogeneity. However, the models do control for a very extensive list of factors and this gives confidence in placing some weight on these findings. The results of the panel data models which make use of the longitudinal structure of the data to generate more robust estimates will now be examined.

4.5.2 Panel Data Methods

This section looks more closely at the various factors that are important for children's cognitive development and exploit the panel data structure of the data to deal with the problem of endogeneity which is so prevalent in studies of this kind. Although the OLS models included a wide array of covariates, it is still possible that unobserved individual

[20]This may simply be a consequence of the fact that more families read to their children daily at age 5 rather than age 7, but the overall performance in the pattern construction test was higher at age 7.

heterogeneity still remains in the error term. If the covariates are correlated with this, there is reason to be cautious about giving too much weight to those findings. Panel data methods make it possible to address this issue, as discussed more fully in the methodology section above.

This section will proceed as follows –firstly, the results of a fixed effects model using two waves of raw and standardised pattern construction test scores (at ages 5 and 7) as the outcome measures will be considered. I then proceed to discuss the results of a test of the assumptions required for the random effects models to be consistent, the well-known Hausman test. The results of this test lead to the inclusion of cluster means in the random-intercept model and I proceed to discuss the findings this gives us. This leads to a Hausman test which accepts the augmented model as consistent. Through this, it is possible to discuss a broader range of variables in a panel framework that is nonetheless consistent, given the necessary exogeneity assumptions.

4.5.2.1 Fixed Effects Models

Table 4.5 reports results from the fixed effects models with the raw scores and the standardised scores as the outcome measures in the two specifications. Family income is not significant. This is most likely due to the lack of within-subject variation in family incomes between ages 5 and 7. Of the school variables, none are significant except months of school in the raw scores. The second test has a higher mean score and since months of school increases by construction over time, this result is most likely an artefact and not a real indication of the importance of the quantity of schooling at these early ages. Of the other variables, most are insignificant, and of the variables that do show statistical significance, some are counter intuitive. The main problem appears to be a lack of within-variation. This is partly due to the fact that it is a very short panel, including only two waves of data, and also to the fact that there are very few continuous variables included – most are binary variables.

The variety of cognitive tests available in the MCS data does appear to present an opportunity to run fixed effects models over three waves of data, especially as there are vocabulary related tests available at waves 2, 3 and 4. However, on closer inspection, the word reading test at wave 4 is in fact quite different from the naming vocabulary tests at waves 2 and 3. Apart

Table 4-5 Results of Fixed Effects Models - Income and Schooling Variables

	Fixed effects	
	(1)	(2)
	Raw PC Scores	Std. PC Scores
Logged Family Income	-0.225	-0.017
	(0.237)	(0.022)
Months of School	0.110***	-0.001
	(0.006)	(0.001)
School charges fees	0.671	0.037
	(1.011)	(0.096)
Coeducational school	-0.109	0.021
	(2.295)	(0.217)
Other variables	YES	YES
Constant	49.353***	-0.065
	(3.187)	(0.302)
N	21,490	21,490
r2	0.080	0.011

Standard errors in parentheses
* p<0.100, ** p<0.050, *** p<0.010

from testing receptive rather than expressive vocabulary, it is also quite differently distributed with raw scores between 55 and 145 compared to the range of 20 to 80 in the naming vocabulary tests. The correlation coefficient between the standardised naming vocabulary scores is 0.56, while the correlation coefficient between the standardised naming vocabulary score at wave 3 and the standardised word reading score at wave 4 is just 0.35. As such, I decided not to run panel data models over three waves, but rather to focus on the pattern construction scores from waves 3 and 4 which measure exactly the same skill in both waves. This demonstrates the need for consistent measures of children’s cognitive ability longer periods over time. Although this is not easy to achieve because of the way children develop, it should nonetheless be a priority in the design of future surveys.

The other reason there is a lack of within-variation is that most variables are binary. In order to create more continuous variables I tried creating variables which report on the frequency with which parents undertake certain activities per month. For example, converting categorical variables with six categories for how often the parents read to the children to a continuous variable on how many times per month this occurs. However, this requires assumptions that are not reliable given the level of detail that is actually available in the data and furthermore didn't significantly alter the results, so I did not use these variables in the final specification. IMD decile could also have entered as a continuous variable except that there were a great deal of missing observations it would have been difficult to incorporate, especially given the complex survey design.

Since it was not possible to increase the amount of variation through increasing the number of waves or using more continuous variables, I explored possibilities of exploiting the between-subject variation in the data whilst maintaining the consistency of the results. Almost all variables displayed substantially more between-subject variation than within-subject variation. My approach to incorporating this is discussed in more detail in the methodology section with the results discussed below.

4.5.2.2 Using the Hausman Test to Compare FE and RE Models

As discussed in the methodology section, fixed effects models only use within subject variation while random effects models use a weighted combination of between and within-subject variation. One of the major issues with the results of the fixed effects models above is a lack of within-variation. For this reason, it would be beneficial to be able to make use of the between-subject variation in the data by using a random effects model. However, as described above, the random effects framework relies on the exogeneity of the covariates which for this data is an assumption which is unlikely to hold. The Hausman test provides a good way to test the consistency of the random effects model. If the chi-squared value from a Hausman test comparing a fixed effects model to a random effects model is too high, we reject the consistency of the random effects model. The p-value is generally easier to interpret than the chi-squared statistic, with the general rule being that a p-value greater than 0.05 means that the model should be accepted.

Table 6.6 below reports the chi-squared statistics and p-values for three Hausman tests. Model A refers to fixed effects and random effects models which contain only time invariant variables. The random effects model is strongly rejected as inconsistent in this case. Model B uses the same covariates but also adds time varying variables. These are automatically dropped from the fixed effects model and as such are not considered explicitly by the Hausman test (which can only test the comparability of variables that appear in both models), however, the presence of these variables in the random effects model controls for some of the individual heterogeneity and leads to more precise estimates of the other coefficients. Although the second random effects model is also rejected as being inconsistent, the chi-squared value has fallen somewhat from 233.65 to 197.13 for the models which use raw pattern construction scores and from 220.10 to 184.74 for the models using standardised pattern construction scores.

Table 4-6: Hausman Test statistics, fixed effects and random effects models

		Raw PC Scores		Standardised PC Scores	
Model	Variables included	Chi2 Value	P statistic	Chi2 Value	P statistic
A	Time-varying variables only	233.65	0.0000	220.10	0.0000
B	A + time invariant variables	197.13	0.0000	184.74	0.0000
C	B + means of relevant variables	99.36	0.0518	97.03	0.0712

Model C represents the augmented models described in the methodology section, where some variables enter as means and deviations from means in order to allow the between and within effects to differ. The variables that entered in this way were family income, school fees, coeducational schooling, parents' education, child has a longstanding illness, regular bedtimes, urban dwelling and neighbourhood IMD score group. Once these variables were allowed to show different coefficients for between-cluster and within-cluster effects, the model came much closer to the fixed effects model and could be accepted as consistent, with a chi-squared value of 99.36 (p-value 0.0518) for the raw pattern construction scores models and 97.03 (p-value 0.0712) for the standardised pattern construction scores models. Given that the augmented random effects model can be accepted as being consistent, the results of this model will be discussed in detail below.

4.5.2.3 Augmented Random Effects Specification - Results

We now explore the results of the random effects model including group means (which I am called the “augmented random effects” model, or ARE). This model was accepted as consistent by the Hausman test described above and the results are reported in full in Table 4.7. The first and third columns report the results of the ARE models, while the fixed effects results are provided in columns 2 and 4 for comparison.

Table 4-7 Augmented Random Effects and Fixed Effects Results

		ARE (1) Raw PC Scores	FE (2) Raw PC Scores	ARE (3) Std. PC Scores	FE (4) Std. PC Scores
FAMILY INCOME					
Log (family income)	Mean:	0.597***	.	0.054**	.
		(0.228)	.	(0.022)	.
	Deviation from Mean:	-0.254	-0.225	-0.023	-0.017
		(0.200)	(0.237)	(0.019)	(0.022)
SCHOOLING:					
Months of school		0.105***	0.110***	-0.001**	-0.001
		(0.005)	(0.006)	(0.001)	(0.001)
School fees	Mean:	0.576	.	0.060	.
		(0.507)	.	(0.049)	.
	Deviation from Mean:	0.504	0.671	0.023	0.037
		(0.962)	(1.011)	(0.091)	(0.096)
Coeducational school	Mean:	0.015	.	-0.015	.
		(0.788)	.	(0.076)	.
	Deviation from Mean:	0.169	-0.110	0.051	0.021
		(2.170)	(2.295)	(0.206)	(0.217)
PARENTAL EDUCATION					
Mother's education					
No Qualifications	Mean:	-1.165***	.	-0.110***	.
		(0.378)	.	(0.036)	.
	Deviation from Mean:	-1.176	0.128	-0.125	-0.001
		(0.885)	(1.173)	(0.084)	(0.111)
NVQ Level 1	Mean:	-1.212***	.	-0.117***	.
		(0.396)	.	(0.038)	.
	Deviation from Mean:	0.894	3.406**	0.081	0.319**
		(1.015)	(1.337)	(0.097)	(0.126)
NVQ Level 2	Mean:	0.109	.	0.011	.
		(0.275)	.	(0.026)	.
	Deviation from Mean:	-0.490	0.258	-0.044	0.025
		(0.633)	(0.809)	(0.060)	(0.077)
NVQ Level 3 #		...	...	...	...
NVQ Level 4	Mean:	0.937***	.	0.090***	.
		(0.276)	.	(0.027)	.
	Deviation from Mean:	-0.731	-0.150	-0.072	-0.018
		(0.645)	(0.824)	(0.062)	(0.078)
NVQ Level 5	Mean:	1.388***	.	0.132***	.
		(0.456)	.	(0.044)	.
	Deviation from Mean:	-0.987	-0.736	-0.086	-0.065
		(0.759)	(0.948)	(0.072)	(0.090)
Overseas Qualification	Mean:	-1.580***	.	-0.152***	.
		(0.607)	.	(0.058)	.
	Deviation from Mean:	0.475	1.317	0.064	0.160
		(1.186)	(1.487)	(0.113)	(0.141)

		ARE (1) Raw PC Scores	FE (2) Raw PC Scores	ARE (3) Std. PC Scores	FE (4) Std. PC Scores
Partner's education					
No Qualifications	Mean:	-1.575***	.	-0.147***	.
		(0.415)	.	(0.040)	.
	Deviation from Mean:	0.822	1.486	0.079	0.146*
		(0.718)	(0.933)	(0.068)	(0.088)
NVQ Level 1	Mean:	-1.094**	.	-0.102**	.
		(0.481)	.	(0.046)	.
	Deviation from Mean:	0.975	2.201*	0.085	0.204*
		(0.893)	(1.133)	(0.085)	(0.107)
NVQ Level 2	Mean:	-0.448	.	-0.040	.
		(0.313)	.	(0.030)	.
	Deviation from Mean:	0.401	1.042	0.035	0.097
		(0.591)	(0.739)	(0.056)	(0.070)
NVQ Level 3 #		…	…	…	…
NVQ Level 4	Mean:	1.118***	.	0.107***	.
		(0.311)	.	(0.030)	.
	Deviation from Mean:	-0.384	0.185	-0.043	0.014
		(0.620)	(0.774)	(0.059)	(0.073)
NVQ Level 5	Mean:	0.726	.	0.070	.
		(0.446)	.	(0.043)	.
	Deviation from Mean:	-0.529	0.096	-0.058	0.002
		(0.697)	(0.854)	(0.066)	(0.081)
Overseas Qualification	Mean:	1.186*	.	0.115**	.
		(0.609)	.	(0.059)	.
	Deviation from Mean:	-1.454	-1.695	-0.141	-0.158
		(0.992)	(1.251)	(0.095)	(0.118)
FAMILY STRUCTURE					
Married		-0.053	-0.657	-0.001	-0.084
		(0.489)	(1.597)	(0.047)	(0.151)
Mother has a resident partner		0.081	2.137	0.014	0.219
		(0.454)	(1.571)	(0.044)	(0.149)
Partner is the natural father		0.943**	0.973	0.089**	0.092
		(0.385)	(1.255)	(0.037)	(0.119)
Number of siblings		-0.190**	-0.185	-0.019**	-0.017
		(0.083)	(0.248)	(0.008)	(0.023)
HEALTH					
Child has a longstanding illness	Mean:	-2.069***	.	-0.200***	.
		(0.280)	.	(0.027)	.
	Deviation from Mean:	-0.085	0.008	-0.008	0.001
		(0.237)	(0.273)	(0.023)	(0.026)
Mother's general health					
Excellent		-0.011	0.165	-0.001	0.017
		(0.165)	(0.236)	(0.016)	(0.022)
Very good / Good #		…	…	…	…
Fair / Poor		0.053	0.329	0.003	0.027
		(0.214)	(0.313)	(0.020)	(0.030)
Mother has a longstanding illness		-0.086	-0.143	-0.006	-0.013
		(0.198)	(0.297)	(0.019)	(0.028)
Mother has depression		-0.046	-0.389	-0.005	-0.035
		(0.172)	(0.552)	(0.017)	(0.052)
Partner's general health					
Excellent		0.089	0.122	0.008	0.011
		(0.178)	(0.246)	(0.017)	(0.023)
Very good / Good #		…	…	…	…
Fair / Poor		-0.370	-0.082	-0.035	-0.009
		(0.246)	(0.328)	(0.024)	(0.031)
Partner has a longstanding illness		0.066	-0.117	0.006	-0.011
		(0.187)	(0.271)	(0.018)	(0.026)

	ARE (1) Raw PC Scores	FE (2) Raw PC Scores	ARE (3) Std. PC Scores	FE (4) Std. PC Scores
MATERNAL EMPLOYMENT				
Full time	-0.085	0.066	-0.008	-0.000
	(0.212)	(0.357)	(0.020)	(0.034)
Part time	-0.140	-0.268	-0.014	-0.028
	(0.172)	(0.275)	(0.016)	(0.026)
Not working #	...	...	...	...
MONEY RELATED FACTORS				
Type of Housing tenure				
Own / Mortgage	0.575**	0.646	0.054**	0.060
	(0.244)	(0.565)	(0.023)	(0.053)
Rent / Other #	...	...	...	...
Council rented	-0.148	-0.492	-0.020	-0.071
	(0.288)	(0.834)	(0.028)	(0.079)
Car Usage	0.750***	0.404	0.078***	0.047
	(0.255)	(0.452)	(0.024)	(0.043)
Holidays abroad	0.289*	0.208	0.029*	0.023
	(0.164)	(0.240)	(0.016)	(0.023)
HOME ATMOSPHERE				
0 - 12 Scale, 12 = calm and organised	0.076***	0.013	0.007***	0.001
	(0.027)	(0.039)	(0.003)	(0.004)
PARENTAL BEHAVIOURS				
Mother reads to child				
Daily	-0.296*	-0.182	-0.024	-0.011
	(0.171)	(0.235)	(0.016)	(0.022)
Weekly	-0.464***	-0.601***	-0.041**	-0.053**
	(0.176)	(0.229)	(0.017)	(0.022)
Occasionally #	...	...	...	...
Never	-1.041**	-0.782	-0.096**	-0.073
	(0.467)	(0.616)	(0.045)	(0.058)
Partner reads to child				
Daily	-0.164	-0.222	-0.013	-0.015
	(0.218)	(0.295)	(0.021)	(0.028)
Weekly	-0.137	-0.136	-0.010	-0.007
	(0.170)	(0.222)	(0.016)	(0.021)
Occasionally #	...	...	...	...
Never	-0.398	-0.092	-0.037	-0.012
	(0.345)	(0.447)	(0.033)	(0.042)
Frequency of library visits				
Never	-0.423***	-0.034	-0.041***	-0.006
	(0.147)	(0.215)	(0.014)	(0.020)
Once a month to once a year	-0.178	-0.373	-0.017	-0.034
	(0.229)	(0.312)	(0.022)	(0.030)
Daily to at least once a week #	...	...	...	...
Parter's time spent with child				
Plenty	-0.851	0.236	-0.090	0.017
	(0.883)	(1.140)	(0.084)	(0.108)
Just enough #	...	...	...	...
Not enough	0.531**	0.356	0.048**	0.030
	(0.241)	(0.311)	(0.023)	(0.029)
Father plays games with child				
Daily	-0.165	0.275	-0.014	0.029
	(0.225)	(0.285)	(0.021)	(0.027)
Several times a week #	...	...	...	...
Less than several times a week	0.178	0.369*	0.015	0.033*
	(0.163)	(0.207)	(0.016)	(0.020)
Mother smacks child when naughty	-0.030	0.132	-0.002	0.012
	(0.142)	(0.223)	(0.014)	(0.021)
Mother tells child off when naughty	-0.322	-0.084	-0.032	-0.010
	(0.207)	(0.290)	(0.020)	(0.027)

		ARE (1) Raw PC Scores	FE (2) Raw PC Scores	ARE (3) Std. PC Scores	FE (4) Std. PC Scores
Regular Bedtimes					
Never	Mean:	-2.246***	.	-0.215***	.
		(0.546)	.	(0.053)	.
	Deviation from Mean:	0.477	0.567	0.040	0.047
		(0.412)	(0.496)	(0.039)	(0.047)
Sometimes	Mean:	-0.944*	.	-0.088*	.
		(0.514)	.	(0.049)	.
	Deviation from Mean:	0.433	0.314	0.041	0.029
		(0.320)	(0.380)	(0.031)	(0.036)
Always	Mean:	0.043	.	0.004	.
		(0.263)	.	(0.025)	.
	Deviation from Mean:	0.029	0.067	0.005	0.010
		(0.172)	(0.194)	(0.016)	(0.018)
Hours of TV child watches per day					
None		-0.482	0.140	-0.051	0.007
		(0.470)	(0.624)	(0.045)	(0.059)
Less than one hour		-0.002	0.168	0.001	0.017
		(0.166)	(0.224)	(0.016)	(0.021)
One to three hours #					
More than three hours		-0.191	0.041	-0.021	-0.001
		(0.181)	(0.243)	(0.017)	(0.023)
SHOCKS					
Family moved home since last wave		-0.484**	-0.163	-0.045**	-0.017
		(0.200)	(0.264)	(0.019)	(0.025)
NEIGHBOURHOOD FACTORS					
Urban	Mean:	0.213	.	0.019	.
		(0.261)	.	(0.025)	.
	Deviation from Mean:	-0.541	-0.856	-0.047	-0.075
		(0.695)	(0.824)	(0.066)	(0.078)
IMD Score Group					
Low	Mean:	-0.381	.	-0.047*	.
		(0.249)	.	(0.024)	.
	Deviation from Mean:	0.341	0.499	0.019	0.034
		(0.615)	(0.759)	(0.059)	(0.072)
Middle #					
High	Mean:	0.379	.	0.031	.
		(0.259)	.	(0.025)	.
	Deviation from Mean:	0.397	0.160	0.033	0.010
		(0.608)	(0.711)	(0.058)	(0.067)
TIME INVARIANT FACTORS					
SCHOOLING					
Teacher tenure		0.025*	.	0.002*	.
		(0.013)	.	(0.001)	.
Class size		0.048*	.	0.005*	.
		(0.026)	.	(0.002)	.
EARLY FACTORS					
Birthweight		1.072***	.	0.102***	.
		(0.174)	.	(0.017)	.
Days of gestation		0.020***	.	0.002***	.
		(0.008)	.	(0.001)	.
Child was in a special care unit at birth		-0.106	.	-0.011	.
		(0.309)	.	(0.030)	.
Parents attended antenatal classes		0.150	.	0.012	.
		(0.181)	.	(0.017)	.
Mother breastfed		0.894***	.	0.084***	.
		(0.193)	.	(0.019)	.

	ARE (1) Raw PC Scores	FE (2) Raw PC Scores	ARE (3) Std. PC Scores	FE (4) Std. PC Scores
GENDER				
Male	-1.359***	.	-0.133***	.
	(0.161)	.	(0.016)	.
MONTH OF BIRTH				
Jan	0.245	.	0.026	.
	(0.361)	.	(0.035)	.
February	0.500	.	0.051	.
	(0.383)	.	(0.037)	.
March	0.322	.	0.042	.
	(0.371)	.	(0.036)	.
April	1.238***	.	0.131***	.
	(0.380)	.	(0.037)	.
May	1.535***	.	0.160***	.
	(0.371)	.	(0.036)	.
June	0.971***	.	0.107***	.
	(0.373)	.	(0.036)	.
July	0.937**	.	0.097***	.
	(0.378)	.	(0.036)	.
August	1.076***	.	0.110***	.
	(0.377)	.	(0.036)	.
September	0.187	.	0.006	.
	(0.365)	.	(0.035)	.
October	0.049	.	-0.005	.
	(0.368)	.	(0.035)	.
November	0.731**	.	0.064*	.
	(0.364)	.	(0.035)	.
December #	…	…	…	…
ETHNICITY				
White #	…	…	…	…
Black	-3.083***	.	-0.298***	.
	(0.539)	.	(0.052)	.
Asian	-1.910***	.	-0.180***	.
	(0.357)	.	(0.034)	.
Other	0.254	.	0.029	.
	(0.458)	.	(0.044)	.
CONSTANT	33.557***	48.347***	-1.518***	-0.116
	(2.564)	(1.345)	(0.247)	(0.127)
sigma_u				
_cons	7.021***		0.681***	
	(0.078)		(0.007)	
sigma_e				
_cons	6.916***		0.657***	
	(0.052)		(0.005)	
N	21,490	21,490	21,490	21,490
r2		0.080		0.011

Standard errors in parentheses
* p<0.100, ** p<0.050, *** p<0.010

The first variable of interest is family income and the results indicate a significant positive between-effect but no within-effect. The insignificance of the within-effect is likely to be a result of the lack of within-variation for this variable. Family income was relatively stable for most families between the two waves, with a correlation coefficient of 0.7 between the logged family income measures at ages 5 and 7. There is, however, substantial variation between the incomes of different families. The result on the mean family income carries the same weight as the OLS result above – it indicates that there is an independent effect even when a broad range of other factors are controlled for, but it cannot be interpreted causally. The splitting out of family income into between and within effects was unfortunately necessary, as a Hausman test comparing fixed and random effects models with a single family income variable returned a chi-squared statistic of 104.22 and a p-value of 0.02 – below the required level for the ARE model to be accepted. In these specifications, family income showed a small, negative but insignificant effect in the fixed effects model and a small, positive, insignificant effect in the ARE model. However, these results should not be given too much weight as the models did not pass the relevant specification tests.

Secondly, months of school shows a positive, statistically significant effect when using the raw scores and a zero effect using the standardised scores. The positive effect using the raw scores is due to the fact that the mean of the second test was higher than the first (53.4 compared to 50.9) and months of school increases automatically over time by construction. For this reason, I consider the result using the standardised scores to be more convincing, and this indicates no important effect of quantity of schooling at these early stages of the child's education.

Thirdly, taking a look at the school and teacher quality variables, school fees and attending a coeducational school are both statistically insignificant. Looking at the bottom of the table where the time-invariant factors are reported, teacher tenure has a positive and statistically significant effect, but so does class size, and in both cases, these effects are extremely small. The overall impression in regards to the effect of school quality from this data is that the measured proxies are unimportant. This is in line with other studies that have used a similar approach (e.g. see Todd and Wolpin, 2007 who use child and sibling fixed effects). Rather than indicating that school quality is unimportant for children's cognitive development, it may be that these measures are simply poor proxies for the true effectiveness of the schools and teachers (Hanushek, 1986).

Regarding the other factors included as controls, making use of the between variation in the data as has been done here leads to much more interesting results than the results of the fixed effects models alone. Firstly, there is a positive and significant effect of the mother's partner being the child's natural father. Whilst the coefficient in the fixed effects model is 0.973 for the raw scores and is statistically insignificant, the coefficient in the augmented random effects model is similar at 0.943, but is statistically significant at the 1% level. This result could reflect various influences; one aspect could be the stability the family has enjoyed since it means there has been no change in the child's two parental figures since birth and furthermore, it is likely the natural father is more concerned for the child's development than another party, and this would find expression in various behaviours and decisions. Secondly, the number of siblings is negative and insignificant in the fixed effects models, but statistically significant (and of a similar magnitude) in the ARE specifications. This may reflect parental resource allocation, as parents with more children have less time to spend on each individually. Home atmosphere is also positive and statistically significant in the ARE specifications (whilst in the fixed effects specifications it is positive but insignificant). Although the coefficient is quite small, this is an important finding which backs up the results found in Dearden *et al* (2011b) and other papers on the importance of the home learning environment.

Furthermore, money related factors can also be seen to have a significant effect on children's development, with owning or mortgaging a house, being able to use a car and going on holidays abroad all returning statistically significant coefficients once the between-variation in the data is taken into account. This may indicate that the importance of family background is in fact related to money *per se,* a question which has been debated in many studies. Living in an owned/mortgaged home may provide stability to the family, which is further supported by the fact that the coefficient on having moved since the last wave has a negative and statistically significant coefficient.

The role of the parents' behaviours and attitudes is also important. Never taking the child to the library has a negative and statistically significant effect. This negative impact can be seen in the fixed effects models, but only becomes statistically significant once the between variation is taken into account in the augmented random effects models. The frequency of the mother reading to the child is somewhat less intuitive, as there are negative signs on "daily" and "weekly" as well as on never (with "occasionally" being the base category). This may simply be due to the fact that more families read to their child daily at age 5 than at age 7, while on the whole the test scores were higher at age 7. The father's attitude to how much time they spend with the child also returns an interesting result, with a positive coefficient on "not enough". Although a lack of quality father-child time would be expected to have a negative result, the positive result in this case could arise because it reveals the father's attitude to the importance of spending time with their child. Having a father who considers this important would have various other positive effects on the child's development, which may explain this positive coefficient. Regular bedtimes show a large between effect but an insignificant within effect. The consistency of the between effect is not explicitly checked in the Hausman tests but it indicates that regular bedtimes do have a role to play, since the coefficient on "never" is large and negative and the coefficient on "sometimes" is also negative and statistically significant.

The results of these models also confirm the importance of the early factors which were observed in the OLS models above. The impact of these factors is clear, with positive and statistically significant coefficients on birthweight, days of gestation and breastfeeding. However, since they can only be observed at one time (around the child's birth), they can only be included as controls in the random effects framework and the effects cannot be given a causal interpretation.

Finally, it is also interesting that some variables for which we might have expected there to be a significant result actually do not turn out this way. For example, the mother's labour force engagement is insignificant, as is the IMD score group of the child's neighbourhood. On the other hand, traditionally important factors such as parent's education and the child's ethnicity and health return the expected results here and the coefficients are generally large in magnitude.

4.5.2.4 Summary of Results from Panel Models

Throughout this section, we have seen that there are various data issues which make it difficult to get a clear set of robust results. The inconsistency of the random effects models (arising from endogeneity) and the lack of within-variation which affects the fixed effects models (especially when only two periods of data are used for the pattern construction scores) are the primary issues. However, using an augmented random effects approach has proven effective in combatting these issues. Such an approach makes it possible to take into account the highly informative between-subject variation in the data, whilst still insuring consistency by testing the results against coefficients from a fixed-effects model using the Hausman test. Using this approach has shown which factors have a key impact on children's cognitive development in the early years of school.

Family income has a positive effect, and whilst this could only be observed in the between-effect, not the within-effect, (such that is was not tested in the Hausman test), the finding that money in itself is important was further substantiated by the statistical significance on the variables for owning or mortgaging the family home, car usage and taking holidays abroad. These variables relate to that family's ability to invest in goods and activities which may be beneficial for the child's development or which indicate a lack of financial hardship. The school variables, relating to quantity and quality of schooling, on the whole did not show substantial results. This may be because the proxies used were not powerful enough. It would be good to follow this up using data which contains school and teacher identifiers for a larger sample (and over a longer period) to explore the effect of school quality defined more broadly. Some of the time-invariant factors also showed significant effects. Although these functioned as controls and were not explicitly included in the Hausman test, it is nonetheless interesting to note that birthweight, breastfeeding, and days of gestation all had positive and statistically significant coefficients. Despite the broad range of factors that are included as controls, these birth-related factors could nonetheless still reflect other family characteristics rather than having a direct impact in their own right. For this reason, I would place more weight on the factors that could specifically be tested using the Hausman test and which demonstrated significant results. These include the partner being the child's natural father and parental behaviours such as taking the child to the library, as well as home atmosphere and continuing to live in the same residence over time. The implications of these findings will be discussed further in the following section.

4.6 Conclusion

This chapter has explored the impact of various factors on children's cognitive development in the first two years of school, using very recent data on children born in the new millennium and innovative panel data techniques. Using the Millennium Cohort Study not only provides up-to-date findings for a current policy environment, it also boasts a large sample size and a longitudinal structure which make it possible to use baseline ability measures from a comparable test and more robust estimation techniques than can be obtained from simple OLS regressions. Nonetheless, several data issues remain: notably, endogeneity (or the inability to 'mop-up' all individual heterogeneity that is correlated with the variables of interest) and the lack of within-variation in key variables. I addressed this second problem by introducing an augmented random effects model which makes use of both within and between-subject variation and where variables which appear to have different between and within effects enter as means and deviations from means separately. The consistency of results from this model is tested by comparing it to a fixed effects model using the well-known Hausman test.

The first question of interest was the direct effect of income. The strong correlation between family income and children's test scores is well documented in the literature, but a question still remains as to whether the money itself is important or whether family income rather proxies other characteristics which are beneficial for the children's development. Whilst I acknowledge the difficulties in overcoming the endogeneity of family income and do not claim to establish a causal effect, this research nevertheless adds to current findings in this literature. I found that family income had a positive, statistically significant effect in the simple OLS regressions which controlled for a broad array of other factors. When using the raw pattern construction scores at age 7 as the dependent variable, logged, equivalised family income had a coefficient of 2.23 in a model where the baseline test score (at age 5) was the only other covariate. Once all the other covariates were included, the coefficient dropped to 0.93 but was still statistically significant. Given the breadth of other covariates included, this is an interesting finding, and aligns with the results found in Gregg *et al* (2007) and Dooley and Stewart (2004). The other money related variables (i.e. car usage, holidays abroad and type of housing tenure) were all positive but statistically insignificant in these specifications. Turning to the panel data results, the fixed effects models have insignificant coefficients on family income, most likely due to a lack of within-variation in family incomes over the two waves. In the augmented random effects model, the between-effect is split out from the within-effect and we can see that although the within-effect remains insignificant, the between-effect is positive and statistically significant. This mirrors the finding from the OLS results. Although the approach taken does not give an estimate of the causal impact of money *per se,* it does reinforce the direct importance of family income, on the one hand, whilst also demonstrating the interconnections between family income and a broad range of other family characteristics. The statistical significance of the other money-related factors (type of housing tenure, car usage and holidays abroad) in the augmented random effects models further consolidates this finding.

In terms of schooling, I examined variables on quantity of schooling (months of school attended), school quality (fee-paying and single-sex schools and class size) and teacher quality (years of experience). The school quantity variable (months of school) showed very mixed results, with negative effects in the OLS models, a positive effect using raw scores and an insignificant effect using standardised scores in the fixed effects models, and a positive effect using raw scores and a negative but extremely small effect using standardised scores in the augmented random effects models. This variable was difficult to construct with precision due to a lack of information on holidays and time off school and had the characteristic that it increased for every child by construction. Since the mean of the second pattern construction test was higher than on the first test, this explains the positive effect of this variable in specifications which used the raw pattern construction scores as a dependent variable in contrast to negative or very small coefficients on models using the standardised scores. In terms of economic significance, the results using the standardised scores appear to be more meaningful. As such, the overall finding is that quantity of schooling did not contribute significantly to the children's relative cognitive development between these ages.

Regarding school quality, the OLS results showed a positive effect of attending a school that charges fees, a positive but very small effect of teacher experience and insignificant results for attending a coeducational school and for class size. Since the only schooling variable with a strong positive effect was money-related (school fees), this would seem to paint education as a hindrance to rather than a facilitator of social mobility. This result did not appear in the fixed effects models (possibly also because very few children changed between fee paying and non-fee paying schools in this period), and neither did it appear in the augmented random effects model. In both cases, the coefficients were still positive but they were insignificant. Teacher tenure and class size both had very small positive effects in the augmented random effects models. Since these were only recorded at one wave, it was not possible to include them in the fixed effects framework but only as controls in the augmented random effects model. The fact that these indicators of school quality did not have substantial results does not necessarily indicate that school quality is unimportant. It has been argued that measures such as class size are poor reflections of true quality and that school and teacher fixed effects provide a better indication of the overall quality and impact of a child's school and teachers (Hanushek, 1986, 2005). Unfortunately, there were too many missing observations from the teacher surveys to facilitate such analyses using the MCS.

Finally, several other factors can be seen to be important contributors to children's development at these young ages. The results from the OLS models may be due to selection, however, the augmented random effects model provides results which are comparable to the results of a fixed effects model where the children are used as their own control to deal with individual heterogeneity that is correlated with the other covariates. The factors that have a significant effect in this model were the mother's partner being the child's natural father (positive effect), the number of siblings (negative effect), money related factors (owning/mortgaging the family home, car usage and holidays abroad – all positive), a calm and organised home atmosphere (positive effect), the mother reading to the child never or daily[21] (negative effect), never visiting the library (negative effect), the partner not having enough time with the child (which may reflect their attitude towards parenting rather than the actual amount of time spent with the child) (positive effect), and the family having moved home since the last wave (negative effect). To bring these together, stability seems to be a very important factor for the child and the parent's inputs in terms of investments and behaviours are also very important. Furthermore, the time-invariant factors included in the ARE model supported the results from the OLS models and indicated that birthweight, days of gestation and breastfeeding all have an important effect on the children's test scores at age seven. It would be useful to do further research into these factors to determine if they simply reflect parental and environmental influences or rather impact directly on later outcomes. Breastfeeding could be promoted more actively among groups where this is practiced less and the possibilities to impact on birthweight and gestation so as to contribute to later outcomes should be further explored.

This chapter has made a contribution to the existing literature in this area in several ways. Firstly, it is the first study I am aware of to use the fourth wave of the MCS to explore school-related factors. Since the survey for the fourth wave was carried out in 2008, the findings above relate to a very current school environment for UK children. Secondly, it presents an innovative approach to dealing with a highly prevalent empirical problem, addressing endogeneity and a lack of within-variation in key variables by means of an augmented random effects models where the between and within effects of certain variables are allowed to differ where appropriate. Thirdly, the implementation of this approach has generated insights into

[21] As discussed above, this counter intuitive result may arise because more families read to their children daily at age 5 rather than age 7, but the overall performance in the pattern construction test was higher at age 7.

which factors are most important for children's development in the first few years of school. The development of children in their early years has been of increasing importance as a policy focus. The policy implications of these findings will be explored in the final chapter of the thesis.

5 Trajectories of Development and Regression to the Mean

5.1 Introduction

Chapter 3 examined the gap in university participation rates between children from more and less advantaged families and established that this is not driven by differences in their degree of debt aversion. In fact, there is a body of evidence which points to the gap in educational outcomes starting much earlier in life. Tests from very early ages already show a substantial gap in the test scores of children from well-off and from disadvantaged families (for example age 3 in Dearden *et al*, 2011). The previous chapter examined possible factors driving early years achievement, focusing on family income, schooling and other factors. A further important question is the rate of children's development at these young ages, and specifically, whether children's cognitive development trajectories are dependent on their families' socioeconomic position. In this chapter, I examine whether the *rate* of cognitive development up to age 7 differs for children from more or less advantaged families.

Whilst it has been established that there is a gap in the early cognitive test scores of children from different family backgrounds, the question is whether this gap widens as they get older. One highly influential paper to address this question is Feinstein (2003), who found that by the age of 10, children from low-income families who had initially been classified as high ability had actually been overtaken by children from high-income families who had initially been classified as low ability. Naturally, there is great interest in the relative progress of bright children from poorer families, and this finding has become extremely well-known among academics and policy makers alike. In fact, the central diagram from the paper was included in the government's first Child Poverty strategy document (Department for Education, 2011) and can often be seen in other presentations and policy documents. However, recent work (especially a paper by Jerrim and Vignoles, 2011[22]) has raised the question of whether this finding is merely an expression of a well-known statistical artefact called regression to the mean

[22] I reference the working paper of 2011 through this chapter since it is longer and more detailed. The published paper came out in 2013 and is also included in the bibliography.

(RTM). Blanden, Katz and Redmond (2012) have called for more work to be done in this area, building on the work of Jerrim and Vignoles, "to distinguish children's true developmental trajectories from RTM effects" (p159).

RTM can be expressed simply as the fact that an extreme event is likely to be followed by a less extreme event and causes issues with interpretation of change by making natural variation in repeated data look like real change (Barnett *et al*, 2005). Regarding test scores, it means that individuals who score particularly well (or badly) on an initial examination will most likely see their score in a follow up test falling closer to the mean score than their original result, since test scores express a combination of ability (which is permanent) and luck (which is transitory). The phenomenon is likely to affect children's test scores more than it would adult's scores because the stochastic component in their scores is very significant. Young children are strongly influenced by external factors and their own mood and health such that their test scores will consist of a true measure of their ability plus a significant error component. Since children from richer families have been shown to have a higher mean score than children from poorer families on cognitive ability tests at early ages, a high score is more likely to be an outlier for a poor child while a low score is more likely to be an outlier for a child from a rich family. If children are divided into ability groups based on their initial scores and their family income, regression to the mean predicts that rich children who initially perform less well will score closer to the mean (i.e. higher) on a subsequent test, while children initially classed as high ability from a poor background will most likely score closer to their mean (i.e. lower) on a subsequent test. If we observe this pattern in the data, we therefore need to be very careful before we give it a substantive interpretation, as we may in fact be falling into the 'regression trap' and simply misinterpreting RTM as a real difference in the rates of development.

This chapter uses various methods to account for RTM in order to discover whether there is truly a substantive difference in the rates of cognitive development of young children, using data from the Millennium Cohort Study, a recent longitudinal dataset with information on nearly 19,000 children born in the UK in the new millennium and their families. The main methods I use in this chapter are the use of an auxiliary test to divide the children into ability groups rather than the baseline score; and including the baseline as a covariate in a value-added style model to account for RTM explicitly. I find that children's test scores measured at multiple points of time are indeed strongly affected by RTM, but that family income nonetheless has a large role to play in their cognitive development. There is clear evidence that children from poor families who are initially classed as high ability do drop behind their peers from advantaged homes, even once the RTM effect has been accounted for.

This chapter makes certain important contributions to the existing literature. Firstly, it provides a statistical breakdown of the RTM patterns in the MCS data, highlighting differences in how this effect operates for subgroups within the cohort. Secondly, it provides a robust estimation of children's true developmental trajectories at these ages by using regression analysis as well as graphical analysis, which clarifies whether or not the development gradients of various groups are statistically different from zero, after RTM has been accounted for. And thirdly, it provides a demonstration of how using a value-added functional form (conditional model) addresses RTM and gives an estimate of the impact of family income on children's cognitive development in a way that is robust to this phenomenon. The findings provide further support for a policy focus on bright children from disadvantaged backgrounds.

The next section reviews the current literature, examining RTM and rates of cognitive development. Sections three and four describe the data and methodology, section five presents the key findings and section six concludes.

5.2 Literature Review

5.2.1 Regression to the Mean

The concept of regression towards the mean was first developed in the late 19th century by the biologist Francis Galton and presented in his 1886 paper "Regression towards Mediocrity in Hereditary Stature". He observed that the heights of children tend to fall closer to the mean than their parent's heights, for example, that children of particularly tall parents tend to be shorter than them by a certain fraction of the difference between their parents' height and the mean height, and vice versa for children of short parents. Galton developed this idea over several years using experiments and gathering data on various phenomena. Although his suggestion of what lies behind regression to the mean has since been shown to be incorrect (he thought that it had to do with inheritance of characteristics from the grandparents' generation and further back), the discovery of this idea was a major contribution to statistics and has been useful in many fields. The development of regression analysis as we know it today also has its roots in this work.

Regarding another important historical contribution of this concept, Friedman (1992) writes that 'the regression fallacy was the seed out of which [his] permanent income hypothesis grew' (p2130). There appeared to be a paradoxical conflict between the results of budget studies and data on the incomes of individuals over time in that people's marginal propensity to consume appeared from the budget studies to lie above the average propensity, while this was not apparent in the time series data. The solution to this conundrum came through realising that individuals were usually grouped according to income in one period while consumption was averaged over time. Those classified with a low income appeared to have higher marginal rates of consumption; however, the permanent income of these individuals was often higher than the observed low measure, which was why their propensity to consume appeared high. On the other hand, those with high measured income had lower marginal rates of consumption because they were often classed as such due to an unusually high reported income whereas their permanent income was actually lower. Friedman's separation of income into permanent and transitory components thus arose out of this paradox (Friedman, 1992).

An understanding of the tendency of outliers to regress towards the mean is very helpful in avoiding the trap of giving a substantive interpretation to trends that are actually just statistical artefacts. The economic literature (and indeed studies from many fields) contains numerous examples of this mistake. Perhaps the best known example is a book written by Horace Secrist in 1933 and entitled "The triumph of mediocrity in business". Secrist argued that the profits of businesses tend towards the average over time, and ‘demonstrated’ this extensively through many tables and charts. He viewed this as an important economic phenomenon and a possible cause of the Great Depression, however, his book was sharply criticised by Harold Hotelling who wrote that `the seeming convergence is a statistical fallacy, resulting from the method of grouping. These diagrams really prove nothing more than that the ratios in question have a tendency to wander about’ (Hotelling, 1933, quoted in Stigler (1997)). Secrist’s book had been proofed by numerous well-known statisticians before publication and even after Hotelling’s review, was referred to in other studies, which shows how easy it is even for well versed statisticians to fall into what has become known as the ‘regression trap’. A more recent example of this is Camacho-Cuena *et al* (2004), who explored subjects’ willingness to pay (WTP) for improved recyclability of a certain good. They write that “At the population level, we find that median contributions in the experiment and stated hypothetical values do not significantly differ from each other. However, for subjects with high and low declarations, some systematic deviations from declared values are obtained (downwards for the former and upwards for the latter).” (p315). By grouping the respondents according to their initial response and measuring the change from this point, the authors are inadvertently falling into the regression trap but interpret their findings substantively. In the case of overdeclaration, they interpret this as “misjudgement by a subject of the proportion of *homo economicus* in his own utility function and behaviour” (p. 327), while underdeclaration is explained through an additional assumption that “subjects are averse to the possibility of deceiving themselves in a direction which is usually associated with opportunistic behaviour” (p.327). A much simpler (and more accurate) explanation is that the variation within the individuals’ responses is giving rise to regression to the mean.

At least one of the authors subsequently noticed his mistake, going on to write a further paper (Garcia-Gallego *et al* (2011)), which clearly demonstrates the potential for RTM effects to mistakenly be given a substantive interpretation and refers to the paper described above as an example of this. The authors start by providing several other examples of papers where this has happened, and then describe their own experimental set-up and data generating process. Their focus is on the stochastic component of choice. Having made the point that RTM can be observed in situations where there is within subject variation, their experiment involves participants making several choices between multiple lotteries (at least one of their choices is randomly selected and paid out). There are seven variations of the basic idea, divided into two main groups. In one group, each person is independent and has no information about the choices of other participants; while in the other group, the participants are informed about the choices other participants made before them. In particular, they are informed what the mode choice of the other participants was for the previous part of the session, before they moved on to making further decisions. In analysing the choices that were made, the authors show that if the participants with information about the mode choice are divided into three groups – those who were below the mode in the previous part, those who were at the mode and those who were above it – there is a very clear pattern of movement towards the mode, with those who were below it moving upwards, those who were above it moving downwards and those who were around it not showing a clear pattern of change. This can be interpreted as the participants responding to the information they were given about the choices other people had made, i.e. that participants tend to move towards the choices others make, when they are informed about this. However, if the same analysis is performed on the group which didn’t have any information about other participants choices, the same pattern can be observed: those who were grouped as being below the mode moved upwards, those above it moved downwards and those at it stayed around the same level – even though they didn’t have any information about what the mode choice had been. This basically nullifies the initial finding about the effect of social information on choice behaviour, and demonstrates once again that it is possible to give a substantive interpretation to something that is in fact an expression of stochastic variation within subjects’ choices.

Authors who have recognised the implications of this phenomenon for their own work have used a variety of methods for dealing with it. For example, Friedman and Schwarz (1982; quoted in Friedman, 1992) allowed for the regression effect by reversing independent and dependent variables and systematically reporting the results from regressions run in both directions as upper and lower limits of the computed parameters. Becker and Meyer (2012), in their paper on football team's strategies, rather than including current rank as an indicator of overall performance, include fixed effects for each team and season to capture a team's average performance, and include current rank as what they describe as 'an elegant and unequivocal way' to control for RTM effects. They find evidence of significant regression-to-the-mean effects. Dixon and Rollin (2012) focus on the dynamics of firm size and use the average size over the period rather than the initial or final value to avoid the regression trap which is very common in literature in this area of research. In the epidemiological field, Twisk and Proper (2004) show that the effect of a counselling intervention on health outcomes appears very differently when the baseline measurement is only included in so far as the dependent variable is the absolute change over time, and that due to RTM, change should rather be measured using the baseline as a covariate. Ederer (1972) suggests using one baseline measurement to divide subjects into groups and then calculating change from a different baseline measurement. Furthermore, Barnett *et al* (2005) emphasise planning the study carefully from the outset in order to avoid RTM (e.g. including an appropriate control group), and also suggest several methods of adjusting for it once the data has been collected, such as classifying participants into groups on the basis of numerous measures, explicitly calculating RTM and adjusting for it statistically, and including the baseline as a covariate in an ANCOVA setup. Similarly, including the baseline measure as a covariate in a regression framework is a common suggestion for dealing with this problem within the epidemiological literature. Jerrim and Vignoles (2011) pick up on the suggestion made by Ederer (1972) and also discuss the importance of focusing on a single skill over time since combining several tests can artificially decrease the correlation between the ability measures over time and increase the RTM effect. Some of these approaches will be further expanded upon in regards to the empirical question in the methodology section below.

Finally, it is also possible that the trends do have a substantive reason, which remains even after RTM effects have been accounted for. For example, Denke and Frantz (1993) describe this possibility in regards to the measurement of the effectiveness of a cholesterol-lowering diet on hypercholesterolemia. They have two measures of pre-treatment cholesterol levels and one post treatment measure, which they name P_1, P_2 and T_1 respectively. They define two measures of change, the first ($T_1 - P_1$) based on the initial baseline measurement and the second ($T_1 - P_2$) based on the second baseline measurement. They show that if the population is divided into quintiles using P_1, the first measure of change ($T_1 - P_1$) displays a clear pattern of RTM in addition to the effect of diet. However, the second measure of change, i.e. ($T_1 - P_2$), makes it possible to isolate the true effect of the diet, having removed the RTM effect. Using the second measure of change to eliminate the RTM effect, they find that there is a significant substantive effect of diet on cholesterol levels and even that the strength of this effect depends on the initial level, in that subjects with high cholesterol levels were more responsive to diet.

5.2.2 RTM and Children's Cognitive Development

One highly influential paper to compare the rates of development of young children from various socio-economic groups is Feinstein (2003), using data from the BCS. This question is addressed by firstly using principal component analysis to develop an ability index at each age where test scores are available (22 months, 42 months, 5 years and 10 years). Test scores from the various cognitive ability assessments undertaken at each age were combined into a single index for each age using this methodology. The children were then broken up into groups according to their ability index at age 22 months and their family background. Tracking the development of these groups over time shows that children from a high SES family who initially did poorly had a tendency to improve rapidly, while children from a low SES background who initially did very well had a tendency to drop back. In fact, high-ability children from disadvantaged backgrounds were overtaken by low-ability children from high SES families by age 10. This finding in particular has become well known among academics and policy makers and has been highly influential in terms of encouraging a focus on bright young children from poor families before and in the first few years of school.

One methodological issue not raised specifically in his paper (but raised more recently in a paper by Jerrim and Vignoles, 2011) is the possibility that the trends described are simply RTM effects, rather than indications of true differences in the rate of development of children from different family backgrounds. Looking at one excerpt from the paper, Feinstein writes that “The children of educated or wealthy parents who scored poorly in the early tests had a tendency to catch up, whereas children of worse-off parents who scored poorly were extremely unlikely to catch-up and are shown to be an at-risk group”. He thus gives the trends a substantive interpretation; however, there is a danger that the improvement of children from high SES families who initially scored poorly is merely an expression of regression to the mean, and the same for the dramatic drop in the scores of children from low SES families who initially did very well. For this to be the case there would have to be a significant difference in their initial group means, which can in fact be observed (e.g. see Figure 1 of Feinstein, 2003).

Jerrim and Vignoles (2011) provide a thorough explanation of how RTM effects could be the real reason behind this finding. They provide a detailed mathematical model and demonstrate their arguments using simulated data. The final sections of their paper use data from the ALSPAC and MCS datasets to demonstrate the effects they had described with “real world” data. They show that using various methods to deal with RTM leads to very different patterns in the trajectories of children’s cognitive development over these ages. Although the early parts of the paper are very detailed and thorough, their analysis of the MCS data is restricted to graphical analysis. In this chapter, I delve more deeply into the RTM effect in the MCS dataset using regression analysis and other techniques to estimate the true developmental trajectories more robustly.

More recently still, Blanden *et al* (2012) have also examined children’s cognitive development trajectories using data from the MCS. They created an ability index for the latest three waves in a similar way to Feinstein (2003). Using the same groups as he did, they trace out the relative change in the scores of children from different ability groups and family backgrounds (using parental education). Although they comment briefly on the RTM effects visible in the graphs they produce, they do not attempt to deal with RTM, but simply identify it as a component of the trends they observe and recommend that further work be carried out in this area, building on the work of Jerrim and Vignoles. This chapter provides more detailed analysis in this area and seeks to identify whether bright children from disadvantaged homes do in fact drop behind their peers from more advantaged homes, once the RTM effect has been taken out of the picture.

5.3 Theoretical Framework: Defining Regression to the Mean

Regression to the mean is a statistical phenomenon that occurs whenever data is measured with some natural variation, i.e. when the correlation between two variables or between multiple measurements of a single variable is less than perfect (Campbell and Kenny, 1999). It occurs because values are observed with random error. RTM states that when observing repeated measurements in the same subject, extreme observations are likely to fall closer to the subject's true mean when they are measured again (Barnett *et al*, 2005).

The RTM effect for a sub-sample depends on the strength of correlation between the two measurements (i.e. the ratio of between-subject variation to the total variation in the sub-sample) and the distance between the population mean and the cut-off point used to define the sub-sample. It can be estimated using the following formula (Barnett *et al*, 2005; Garcia-Gallego, 2011):

$$RTM\ effect = \frac{\sigma_w^2}{\sqrt{\sigma_w^2+\sigma_b^2}} G(z) = \sigma_t(1-\rho)G(z) \qquad (5.1)$$

where $\sigma_t^2 = \sigma_w^2 + \sigma_b^2$ is the total variance, $\sigma_w^2 = (1-\rho)\sigma_t^2$ and $\sigma_b^2 = \rho\sigma_t^2$ are, respectively, within-subject and between-subject variance and ρ is the correlation between the two measurements. $G(z) = f(z)/F(z)$, with $z = (c - \mu)/\sigma_t$ if the subsample is selected using c as a lower bound and $z = (\mu - c)/\sigma_t$ if the subsample is selected using c as an upper bound. $f(z)$ and $F(z)$ are, respectively, the probability density function and the cumulative distribution function of the standard normal distribution and μ is the mean of the sample. This formula will be used later to estimate the RTM effect for various subgroups within the dataset used in this chapter, which is introduced in the following section.

5.4 Data

5.4.1 The Millennium Cohort Study

This chapter uses the Millennium Cohort Study, a recent large-scale longitudinal dataset, and includes data from the first four waves. The first wave was run between June 2001 and September 2002 in England and Wales and between September 2001 and January 2003 in Scotland and Northern Ireland, interviewing families of nearly 19,000 children aged around 9 months. Children were selected using Child Benefit records and were born in all months of the year and across the UK. The sample was designed to reflect the total population, although certain sub-samples, such as children from disadvantaged backgrounds or ethnic minorities, were intentionally over-sampled. This makes it possible to examine issues related to these groups more robustly. However, weights are also provided which align the sample to the whole population. Fieldwork for the fourth wave of the study was concluded in December 2008, with over 13,800 families with over 14,000 cohort children taking part. There was very little attrition between waves 3 and 4, as ninety per cent of families who had taken part in all of the previous MCS surveys (ages 9 months and 3 and 5 years) also participated at age 7.

In terms of its suitability for dealing with the issue of RTM, the MCS has three key advantages. Firstly, the MCS includes several assessments that were carried out at more than one wave. Pattern construction assessments were carried out at age 5 and age 7, and the naming vocabulary subset of the British Ability Scales was carried out at age 3 and 5. This is an advantage compared to the data from the earlier longitudinal survey, the British Cohort Study (BCS), used in Feinstein (2003). In that paper, he constructed an ability index for each age because the cognitive assessment variables at each age were substantively distinct from the measures at the other ages. However, the MCS makes it possible to examine at the development of a single skill over time. Secondly, the children underwent multiple assessments at age 3 (namely the Bracken School Readiness Test and the Naming Vocabulary component of the British Ability Scales) and at age 5 (namely Pattern Construction and Picture Similarity tests). Jerrim and Vignoles (2011) discuss how one way of dealing with RTM caused by selection is to divide up the sample using a certain assessment and measure progress from a different assessment. The presence of two different assessments at ages 3 and 5 in the MCS makes this possible. Finally, the MCS also contains family income measures and a rich array of variables on parental behaviours, child characteristics and other possible mediating factors to cognitive development, making it possible to control for these factors in a regression framework.

5.4.2 Sample Selection

The MCS employs a sophisticated stratified cluster sampling strategy with finite population sampling and varying probabilities of selection. The population was stratified to over-represent residents of areas with high proportions of ethnic minorities (in England), areas of high child poverty, and the three smaller countries of the UK. The datasets provide weights that align the sample to the population of the whole UK or the relevant country within it, and furthermore also account for any attrition that occurred at each wave. All regression based analysis in this chapter uses these weights.

My sample is restricted further as I drop twins and triplets so that any within-family correlation does not affect the final outcomes. To deal with issues of missing data, I include missing dummies for most variables. Thus in the regressions including various controls, no observations are lost due to missing data. There is one key exception to this however, as I remove from the data all the children who do not have a test score recorded for all relevant tests (i.e. both pattern construction tests and picture similarity). Fortunately, this only affects 3.34% of the sample. The cognitive assessments had a very high participation rate, with the vast majority of cohort children taking part (Chaplin Gray et al, 2010).

5.4.3 Key variables

5.4.3.1 Test scores

The following table provides a summary of the cognitive assessments that were carried out at each wave (no cognitive assessments were included in the wave 1 survey as the children were still too young).

Table 5-1: MCS Cognitive Assessments, waves 2 to 4

Sub-Test	MCS2 (Age 3)	MCS3 (Age 5)	MCS4 (Age 7)	Task	Ability/Process
School Readiness					
Bracken School Readiness	√			Tests knowledge and understanding of basic concepts	6 sub-tests including colours, letters numbers/counting, sizes, comparisons and shapes
Ability Scales					
Naming Vocabulary	√	√		The child is shown a series of pictures of objects and is asked to name them.	Expressive Verbal Ability
Pattern Construction		√	√	The child is asked to replicate a design using patterned squares.	Spatial Problem Solving
Picture Similarities		√		The child is shown a row of four pictures and is asked to identify a further congruent picture.	Non-Verbal Reasoning
Achievement Scales					
Word Reading			√	The child is asked to read a series of words presented on a card.	Educational Knowledge of Reading

Source: Adapted from Connelly (2013), Tables 1 and 3

In this chapter, I focus on Pattern Construction and Picture Similarity (the reasons for this are described in the methodology section). The Pattern Construction assessment, taken from the British Ability Scales, assesses children's non-verbal reasoning and spatial visualisation, and can also be used to observe dexterity and coordination, as well as traits like perseverance and determination. It was carried out at waves 3 and 4 and as such, provides a consistent picture of the children's development in these skills between ages 5 and 7. Picture similarity is a test of children's problem solving abilities. Children are shown a row of 4 pictures on a page and asked to place a card with a fifth picture under the picture most similar to it (Hansen *et al*, 2012). Results are also checked using the Naming Vocabulary tests from waves 2 and 3 and Bracken School Readiness at wave 2. For all of these assessments, the MCS includes a variety of scores, including raw scores, percentage scores, age standardised scores and normative scores. I use standardised t-scores for all tests.

5.4.3.2 Family Income

In this chapter I use OECD equivalised family income, which is available as a derived variable for each of the four waves. While Violato *et al* (2011) used imputation techniques to derive a continuous income variable from the data that was available in bands, these derived variables have now been made available as part of the MCS dataset. The OECD equivalence scale provides a method of accounting for the size of the family. A value of one is assigned to the first household member while each additional adult is assigned a value of 0.7 and children a value of 0.5. This also removes the need carry out separate analyses for lone-parent households and two-parent households, as per Violato *et al* (2011).

Table 5-2: Descriptive statistics

	Mean	Std. Dev.	Min	Max	Obs
Log of equivalised family income, 9 months	5.57	0.68	2.67	7.16	7002
Standardised pattern construction, age 5	0	1	-3.17	2.99	7087
Standardised pattern construction, age 7	0	1	-3.03	2.49	7087
Standardised picture similarity, age 5	0	1	-3.60	2.44	7087
Standardised naming vocabulary, age 3	0	1	-2.51	2.64	6686
Standardised naming vocabulary, age 5	0	1	-3.00	2.28	7086
Standardised bracken school readiness, age 3	0	1	-2.80	2.65	6335

Table 5.2 (above) provides standard descriptive statistics for the logged income variable (from wave 1) and the key test scores, all standardised to a mean of zero and a standard deviation of 1. Descriptive statistics split by high and low family income groups are included in the data section of the previous chapter.

The following table (5.3, below) shows the raw numbers in each family income group and each ability group. The full sample is divided into quartiles according to OECD equivalised family income at wave 1 (9 months of age). Almost all analysis in the subsequent chapters focuses on high and low income children. For this reason, the sample was divided into quartiles rather than thirds, with the middle two income quartiles being combined to create the middle income group. The ability groups are defined by splitting the full sample into three equal groups, firstly according to the baseline pattern construction test score, and secondly according to the auxiliary test – picture similarity, both of which were carried out at age 5.

Table 5-3: Raw Numbers and Row Percentages of Children by Family Income Group and Ability Group

		Ability (defined by Pattern Construction, age 5)			
		Low	*Medium*	*High*	***Total***
Equivalised Family Income	*Low*	939	846	549	**2,334**
		(40.23)	(36.25)	(23.52)	**(100)**
	Middle	622	897	815	**2,334**
		(26.65)	(38.43)	(34.92)	**(100)**
	High	463	866	1,005	**2,334**
		(19.84)	(37.1)	(43.06)	**(100)**
	Total	**2,024**	**2,609**	**2,369**	**7,002**
		(28.91)	**(37.26)**	**(33.83)**	**(100)**

** Row percentages in brackets*

		Ability (defined by Picture Similarity, age 5)			
		Low	*Medium*	*High*	***Total***
Equivalised Family Income	*Low*	945	721	668	**2,334**
		(40.49)	(30.89)	(28.62)	**(100)**
	Middle	721	796	817	**2,334**
		(30.89)	(34.10)	(35.00)	**(100)**
	High	527	841	966	**2,334**
		(22.58)	(36.03)	(41.39)	**(100)**
	Total	**2,193**	**2,358**	**2,451**	**7,002**
		(31.32)	**(33.68)**	**(35.00)**	**(100)**

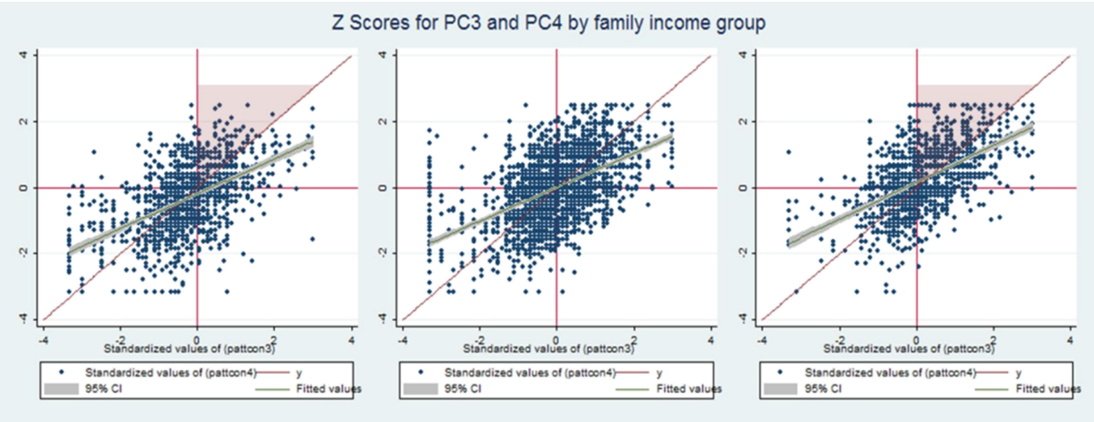
** Row percentages in brackets*

This table shows that children from low income families are more likely to be defined as low ability according to either test, and vice versa for children from high income families. The top section shows that when children are divided into ability groups by their baseline pattern construction score, 40% of low income children fall into the low ability group, compared to 20% of high family income children, while 24% of low income children fall into the high ability group compared to 43% of high family income children. A very similar pattern is observed when the picture similarity test is used to divide children into ability groups.

5.4.4 Family Income and RTM

Now looking graphically at the contrast in scores between the higher and lower family income groups, especially in terms of their movement over time and the patterns of RTM in the data, figure 5.1 below shows scatter plots of standardised pattern construction scores at ages 5 and 7 by family income group, where the income groups are quartiles, determined using OECD equivalised family income. The graphs on the left and right show the top and bottom income quartiles, while the centre graph contains data on the two middle quartiles. The x and y axis are shown in red to help identify children who scored above or below average on each test. The 45 degree line is also drawn in red to show children who improved or fell back from one test to the next. Anyone scoring above and to the left of this line did better in the second test. If all the dots fell on the 45 degree line, there would be perfect correlation between the initial score and the follow up. Deviation from this indicates RTM. Therefore, the gradient of the line of best fit indicates the extent of RTM, which is greater the flatter the line is. In the graphs below, the line of best fit is less steep than the 45 degree line in each case. The two most interesting aspects of this set of graphs are the dramatic contrast between the high and low income groups in terms of the proportion of children scoring above or below average and the evidence of RTM.

Figure 5-1: Scatter Plots of Baseline and Follow-up Pattern Construction Scores



The leftmost graph, for the low income group, shows that most children scored below average on the first test but of these, most did better in the second test; a few scored above average on the first test and most of these scored worse on the second test. The middle graph, for the mid income group, also shows that those who scored above average on the first test were more likely to do less well on the second test and vice versa. For the high income group (right hand side graph), most children scored above average on the first test and almost all of these also scored above average on the second test, though some less well than the first time; some scored slightly below average on the first test (though not as low as the low income group) and most of these did better on the second test. Thus the graphs show clear differences between income groups in the baseline scores and tendency to change, as well as evidence of RTM for all groups. It is particularly interesting to look at the two coloured triangles, as this shows the children from each income group who scored above average on the first test and maintained this or improved further on the second test. For the low income group, only 7% fall within this triangle, while for the high income group, 23% of the sample can be seen there.

I now use the formula for RTM effects presented in section 5.1.3. This is reproduced below for the reader’s convenience

$$RTM\ effect = \frac{\sigma_w^2}{\sqrt{\sigma_w^2+\sigma_b^2}} G(z) = \sigma_t(1-\rho)G(z) \qquad (5.1)$$

Where $\sigma_t^2 = \sigma_w^2 + \sigma_b^2$ is the total variance, $\sigma_w^2 = (1-\rho)\sigma_t^2$ and $\sigma_b^2 = \rho\sigma_t^2$ are, respectively, within-subject and between-subject variance and ρ is the correlation between the two measurements. $G(z) = f(z)/F(z)$, with $z = (c - \mu)/\sigma_t$ if the subsample is selected using c as a lower bound and $z = (\mu - c)/\sigma_t$ if the subsample is selected using c as an upper bound. $f(z)$ and $F(z)$ are, respectively, the probability density function and the cumulative distribution function of the standard normal distribution and μ is the mean of the sample.

I firstly define two high ability groups; the first consists of those scoring above 54 in the first test – this is the "high ability" group used in the rest of the chapter and is approximately the top tercile. The second consists of those scoring above 60 in the first test, which is the mean score plus one standard deviation. I then further divide these groups into high, middle and low family income groups, and report results for the high and low income families.

Results are summarised in table 5.4 below. These results confirm the prior expectation that high achievers from poor families display a larger RTM effect than children from richer families; and secondly that the RTM effect is greater for both groups when the cut-off score is more extreme, i.e. further from the mean. In this dataset, the fact that the children from poorer families display a larger RTM effect does not only have to do with the fact that their mean score is further from the cut-off than is the mean score of the children from more advantaged families, but is also because of the variation in the respective sub-samples, with high ability children from poor families showing greater within and between variation. The RTM effect I have calculated here is the expected change in the subsample's mean for purely statistical reasons (Garcia-Gallego *et al*, 2011). In the following sections, I will present various methods to account for this effect so the "real" trajectories of the various subgroups can be compared more accurately.

Table 5-4: Estimated RTM effects: High Achievers from High and Low Income Families

Total Observations: 11,222				
High Ability Sample:	*Scored above 54 on the first test*		*Scored above 60 on the first test*	
Family Income group:	*High*	*Low*	*High*	*Low*
Observations	1,865	1,241	798	625
Population mean	54.4	49.5	54.4	49.5
Cut-off point	55	55	61	61
Within-variation among high achievers	3.93	4.18	3.90	4.59
Between-variation among high achievers	6.62	6.86	6.16	6.67
Total variation in sub-sample	7.53	7.81	7.10	7.79
Correlation between tests	0.77	0.77	0.75	0.73
z = (c-u)/ot	0.08	0.70	0.93	1.47
f(z)	0.40	0.31	0.26	0.14
F(z)	0.47	0.24	0.18	0.07
G(z)	0.85	1.29	1.46	1.91
RTM effect	**1.70**	**2.81**	**3.05**	**4.98**

This section has introduced the data set I use and the key variables of the analysis, as well as some of the key trends in the data. There is clearly a difference in the mean scores of children from well-off families compared to those from less advantaged backgrounds as measured by family income. Furthermore, the data displays clear patterns of regression to the mean caused by variation within individual's scores between survey waves. Furthermore, it also indicates that children from poor families are more likely to regress downward towards the mean if they start with a high score than children from rich families, and vice-versa. The next section will discuss my methodology, in particular different ways of accounting for this phenomenon.

5.5 Methodology: Dealing with RTM

This chapter has the aim of determining if the influence of income outweighs ability (i.e. whether low-ability, high family-income children overtake high-ability, low family-income children) in a way that is robust to the presence of RTM. Several strategies for dealing with the issue of RTM are employed: focusing on comparable tests of the same skill over time; dividing the children into ability groups based on an auxiliary test; and including the baseline measure as a covariate in OLS models. These three methods are described in detail below.

5.5.1 Method 1: Comparable Assessments across Periods

RTM can occur due to non-comparability of assessments since if tests are used that differ in scale or content, this will artificially reduce the correlation between an individual's test scores over time. For example, if children were classified into a high ability group based on a maths test given in the first period, but the test in the second period focused more on language, some of the children who were classified as high ability initially would have much more average scores on the second test, simply because the ability measure is no longer focusing on their strongest skill (Ladd and Lauen, 2010). It is therefore important to use tests that measure the same skill in consecutive periods.

With this in mind, there are several options using the MCS data, namely

1) Create an ability index by combining various tests using principle component analysis
2) Use vocabulary related tests across three periods – naming vocabulary in waves 2 and 3 and word reading in wave 4
3) Restrict the analysis to two waves using naming vocabulary in waves 2 and 3 or pattern construction in waves 3 and 4

Although option (1) was employed by Feinstein (2003) and Blanden, Katz and Redmond (2012), this approach may in fact have compounded the effects of RTM because the correlation between waves is artificially reduced by combining different tests in each period, as argued by Jerrim and Vignoles (2011). These authors therefore employed option (2), arguing that the naming vocabulary and word reading tests provide a comparable measure of language skills at the three ages. However, (as they also mention), these two tests are somewhat different in that naming vocabulary tests expressive language skills whilst word reading tests receptive language skills. Their scale is also different as naming vocabulary is scored between 20 and 80 whilst word reading is scored between 55 and 145 and word reading also has a greater variance than the naming vocabulary tests. I have therefore decided to restrict the analysis to two waves in this chapter. I have chosen to focus on pattern construction, using picture similarity at wave three as the auxiliary test (discussed further below), since these are the most recent measures. However, I also validate the analysis by using naming vocabulary at waves 2 and 3 with the bracken school readiness score as the auxiliary ability measure at wave 2. Using comparable tests for each wave of data eliminates RTM caused by non-comparability of assessments, which can be a key source of RTM as greater variation within individuals leads to a lower overall correlation in test scores across the relevant waves.

5.5.2 Method 2: Ability Groups based on an Auxiliary Test

Using an auxiliary test helps deal with a second source of RTM, namely selection, which arises if a test is used to classify children into low or high ability groups, but this score is not a perfect measure of their true ability. There is a random element in all the children's scores and their result on a particular day will reflect their true ability as well as this random component. Children may therefore be classified as high ability partly due to good fortune, but would then be unlikely to experience this in the same measure when reassessed, leading to a regression towards the mean in their test scores. Furthermore, if there are two groups being compared that have different means but a single-cut off point is used to classify high achievers, the development of the two groups' scores may differ because the cut-off point lies further from the mean of one group than the other and its members are less likely to meet it (and be classified as high ability) on two consecutive assessments. Particularly in the group with the lower true mean, people will have been classified as high-ability incorrectly in the sense that their true ability is not actually that high and they only achieved a high score due to random variation. The further the cut-off point from the group mean, the greater the RTM effect, which helps explain why the low SES group seems to be falling behind (Jerrim and Vignoles, 2011). The most well-known way of dealing with this type of RTM is to use the average of a series of tests carried out over a period of time (e.g. see Davis, 1976) to determine the classification into groups. However, as this is not possible in this case due to data limitations, I rely on an alternative option, namely dividing the children into ability groups using one test, and measuring their development from a different test.

This method was first suggested in an epidemiological context, as it is quite common within epidemiology for groups to be divided according to a baseline measure and for change to be calculated from this same measure. This can often give the impression that an extreme group has experienced significant improvement, while in fact it is just an expression of RTM. The reasoning behind this method is provided in Ederer (1972), who shows that classifying groups according to one measurement and measuring change from another can reduce or even eliminate the RTM effect. I present his approach below, and then apply it to the MCS data.

Firstly, if we consider paired measurements x_1 and x_2, the regression coefficient for x_2 on x_1 is given by $b_{21} = r_{21}\frac{s_2}{s_1}$ where $r_{21}$is the coefficient of correlation between x_1 and x_2 and s_1 and s_2 are the standard deviations. The slope (b_{21}) of the regression line will be less than one in the presence of regression to the mean.

It is possible to deal with RTM by classifying on an auxiliary test because RTM takes places between the first and second measurements (Jerrim and Vignoles, 2011). In order to explore the continued divergence in scores beyond the second time period, we can explore the trivariate distribution of x_1, x_2 and x_3 – test scores captured at time periods t_1, t_2 and t_3. Of interest are the changes from x_2 to x_3 after classifying on x_1. The following values for x_2 and x_3 are obtained if we classify on x_1 (assuming bivariate normality between $x_1$and x_2 and between x_2 and x_3):

$$x_2 = a_2 + b_{21}x_1 \tag{5.2}$$

$$x_3 = a_3 + b_{31}x_1 \tag{5.3}$$

Measuring the change from x_2 obtained after having classified on x_1 is equivalent to solving the first equation for x_1 and substituting the solution into the second equation, which gives:

$$x_3 = a_3 + \frac{b_{31}}{b_{21}}(x_2 - a_2) \tag{5.4}$$

This makes the regression coefficient for x_3 on x_2, having classified on x_1,

$$b_{32(1)} = \frac{b_{31}}{b_{21}} = \frac{r_{31}s_3/s_1}{r_{21}s_2/s_1} = \frac{r_{31}s_3}{r_{21}s_2} \qquad (5.5)$$

We thus have $b_{32} = r_{32}\frac{s_3}{s_2}$ and $b_{32(1)} = \frac{r_{31}s_3}{r_{21}s_2}$. A reduction in the regression effect in the change from t_2 to t_3 obtained by changing the classification point from t_2 to t_1 implies that $b_{32} < b_{32(1)}$ making $r_{32} < r_{31}/r_{21}$ a necessary condition for the reduction of the regression effect; whilst the elimination of the effect implies that $b_{32} < b_{32(1)} = 1$, for which $s_3r_{31} = s_2r_{21}$ is a necessary condition.

Applying this to the MCS data, Table 5.5 below presents correlation coefficients and standard errors for the three tests, and calculates the relevant regression coefficients. It is important to mention that rather than there being several measurements of the same variable on different occasions, there is a baseline and a follow-up measure of the same variable (pattern construction scores at age 5 and 7) and another test score at age 5, namely the children's scores on the picture similarity test taken on the same day as the first pattern construction test. Most studies that divide the groups according to one test and measure change from another use tests which are all measuring the same thing, whereas that is not an option in this case. Fortunately however, this doesn't seem to be a problem, as the table below indicates that this method is able to remove the regression effect entirely in this case. This is shown by the fact that $\mathrm{b}_{32(1)} = 1$, which, as described above, is the necessary condition for the elimination of the regression effect.

The discussion above demonstrated that $r_{32} < r_{31}/r_{21}$is a necessary condition for the RTM effect to be reduced – that condition is fulfilled with this data since $r_{32} = 0.54 < \frac{r_{31}}{r_{21}} = 0.90$. Furthermore, the necessary condition for the RTM effect to be eliminated is $s_3r_{31} = s_2r_{21}$, which is fulfilled here almost exactly since s_3r_{31} = 3.06 and s_2r_{21} = 3.04. This leads to a coefficient of exactly one for the change between x_2 and x_3 after classifying on x_1 . This shows that dividing the groups using the picture similarity test score and measuring the change between the two pattern construction tests makes it possible to completely eliminate the RTM effect from the measure of change in this case. This is especially encouraging as one concern is that since the two tests at age 5 were carried out on the same day, factors unrelated to the child's true underlying ability (such as their health on that particular day) may have influenced both tests making the random component correlated across waves and leading to residual RTM effects remaining even when the auxiliary test is used. It is encouraging that this does not seem to be an issue in this case, judging by the fact that the figures above, calculated from the MCS data, fulfil the theoretical condition stipulated in Ederer's analysis.

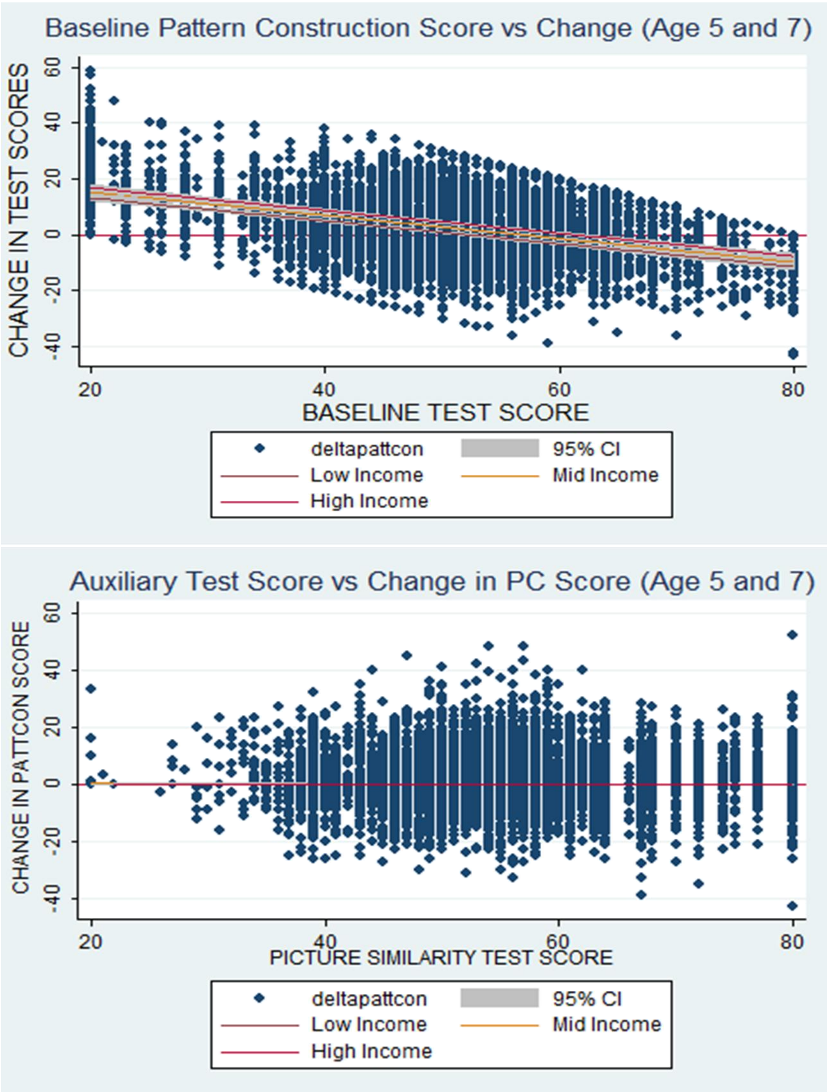
Table 5-5: Using an auxiliary test to reduce or eliminate RTM effects – Picture Similarity and Pattern Construction figures

Standard Errors		Correlations			
s_1=	10.04	r_{21}=	0.32		
s_2=	9.58	r_{31}=	0.29		
s_3=	10.72	r_{32}=	0.54		
Results					
r_{32}=	0.54	s_3r_{31}=	3.06	b_{32}=	0.60
$r_{31/r21}$=	0.90	s_2r_{21}=	3.04	$b_{32(1)}$=	1.00

(1 = picture similarity at age 5; 2 = pattern construction at age 5; 3 = pattern construction at age 7)

The effectiveness of this procedure is further demonstrated by the graphs below which demonstrate the extent of RTM in the MCS data and also the effect of using a different test as a baseline measure to classify children into groups initially. The graph on top shows the change in test score against the baseline. There is a strong indication of RTM as the graph shows that the higher a person's score was at wave 2, the more likely it was for them to perform less well at age 5, while almost all those that scored poorly on the first test did better the second time. Campbell and Kenny (1999) note that a negative correlation between change and baseline such as this is an inevitable consequence of RTM.

Figure 5-2: Change in Pattern Construction Test Scores against Different Baseline Tests



The lower graph shows how this can be dealt with using a different test as the baseline. Graphing the change in the pattern construction scores against the age 5 scores of the picture similarity test shows a very different pattern, where it seems that the link has been broken between the initial test score and the change in the two waves. This further confirms the effectiveness in dealing with RTM of using picture similarity test scores to divide the children into ability groups whilst measuring their development using the change in pattern construction scores between ages 5 and 7.

5.5.3 Method 3: Including the Baseline Measure as Covariate

Numerous papers explore the factors which affect children's cognitive outcomes at a particular point in time, (e.g. see Gregg *et al*, 2007; Blau, 1999; McCulloch and Joshi, 2002, Violato *et al*, 2011). In these papers, various cognitive outcome measures (often from different periods) are examined in separate regressions but there is no lagged score included as a covariate. By focusing on children's outcomes at a single point in time, these papers abstract from issues relating to the change in children's test scores (i.e. the rate of their cognitive development), such as the issue of RTM. However, the question of children's relative *rates* of cognitive development is extremely important. Furthermore, most policy debates revolve around the impact of certain factors (especially family income) on development. For this reason, it is imperative to have a robust framework where the impact of these factors on the *rate* of development can be examined. This section provides an alternative approach where rather than the children being divided into groups depending on their family income and early ability, family income is included as a covariate alongside other factors, allowing us to judge its impact conditional on other factors such as ethnicity and parental education.

In econometrics, a commonly used specification is the value-added functional form. In this specification, the dependent variable is the follow-up measure or the gain score (i.e. the absolute change) and the baseline measure is included as a covariate, along with other covariates. To my knowledge, this functional form has not been discussed in the economics literature in relation to RTM. It is used more frequently in this way within epidemiology, where several papers recommend ANOVA as a possible means for compensating for RTM effects (e.g. Barnett *et al*, 2005)[23]. This section presents this functional form as a way of dealing with RTM, making it a simple but useful approach in econometric analysis. It starts with a criticism of using the change score as the dependent variable with no control for the baseline when RTM is present and shows how this can lead to biased estimates of other covariates. It then presents an argument for dealing with

[23] ANOVA and regression are very similar mathematically and operate according to a similar principle, both belonging to the general linear model.

RTM by including the baseline score as a covariate and discusses other relevant aspects of this approach.

Where a baseline score is available and we are interested in examining the change in children's scores over time, the most obvious dependent variable would simply be the absolute change between two periods, i.e.

$$\Delta Y = y_{2i} - y_{1i} \tag{5.6}$$

where y_2 is the variable measured at time period 2, and y_1 is the measure at time period 1.

We would thus estimate: $y_{2i} - y_{1i} = a + bX_i + u_i$ (5.7)

In fact, using this measure of change as the dependent variable places a very restrictive assumption on the functional form, as it is the same as estimating

$$y_{2i} = a + b_1 y_{1i} + b_2 X_i + u_i \tag{5.8}$$

under the assumption that b_1 = 1.

Since $b_1 = r_{21}\frac{s_1}{s_2}$

where r_{21} is the correlation between y_1 and y_2, and s_1 and s_2 are the standard deviations, b_1 will only equal 1 if there is perfect correlation between y_1 and y_2 or in the rare cases where the greater variation in the baseline measurement exactly offsets the imperfect correlation. RTM can be expressed as imperfect correlation between the two measures, therefore whenever RTM is present it is highly unlikely that b_1 will equal 1. This means that using a change score as the dependent variable without including the baseline measure as a covariate will generally lead to incorrect estimates when the data displays RTM.

Furthermore, if b_1 is not estimated but rather fixed at 1 in that y_1 is included on the left-hand side of the equation as part of the absolute change, y_1 can be seen as an omitted variable. If y_1 is correlated with any of the variables in X, omitting it will cause the parameter estimates on those variables to be biased. For example, if there is a correlation between family income and baseline scores, the parameter estimates on family income will be biased by the omission of the baseline measure as a covariate. The strong correlation between family income and baseline ability in the MCS data make this an important issue in estimating the effect of family income on children's development over time.

Using the value-added functional form (also known as the conditional model), equation 5.8, can deal with RTM by explicitly modelling the correlation between the baseline measure and the measure of change. It is therefore recommended by Plewis (1985) and Twisk (2002). The relationship between the change score and the baseline is captured by the coefficient b_1, thereby removing this as a source of bias from the other coefficients in the model, contained in the vector b_2. Twisk (2002) writes that in this model, change is defined relative to the baseline score and that this relativity is expressed by the regression coefficient, such that "this model 'corrects' for RTM" (p186).

The value-added functional form, including a lagged outcome as a covariate, has been much discussed in the econometric literature (e.g. see Hanushek, 1986, for a discussion of the advantages of this specification). Todd and Wolpin (2007) show that 'strict value-added models that include lagged test scores and current inputs impose strong assumptions on the pattern of the coefficients associated with the inputs' (p99), especially in regards to the fact that the impact of (observed and unobserved) inputs must decay geometrically over time. However, they also find that these assumptions are less strict if historical information on inputs is also included, as per Cunha and Heckman (2003) and the specification adopted below, which also uses historical inputs.

In the econometric literature, the lagged test score is generally interpreted as a proxy for all unobserved individual heterogeneity, whereas in the value-added type model in this chapter, the lagged dependent variable has a different function, i.e. to provide a measure of change (development) that is robust to RTM. This aspect is emphasised within the epidemiological literature but as far as I am aware has not been widely discussed in an econometric context.

As Plewis (1985) and Twisk (2002) both show, if the baseline is included as a covariate, it is possible to use either the follow-up measure or the absolute change as the dependent variable, as the model above (equation 5.8) is mathematically equivalent to

$$y_{2i} - y_{1i} = a^* + b_1^* y_1 + b_2^* X + u^* \tag{5.9}$$

where $a^* = a$, $b_1{}^* = (b_1 - 1)$ and $b_2{}^* = b_2$

Importantly, since $b_2^* = b_2$, the parameter values on covariates in a value-added type model can be interpreted as measuring the impact of that factor on the *change* in test scores over time. This means that when the baseline measure is included as a covariate, the other covariates indicate the effect of each factor on the child's cognitive development, measured as change in standardised test scores over time.

Finally, another model that deals similarly with the issue of RTM uses as its dependent variable the residuals from a regression of y_2 on y_1. This works the same way as the conditional model to purge the correlation between the change in test scores and the baseline measure from the model. Results from this model will generally be very similar to results from the conditional model. I present results for both variants of this approach in the results section below.

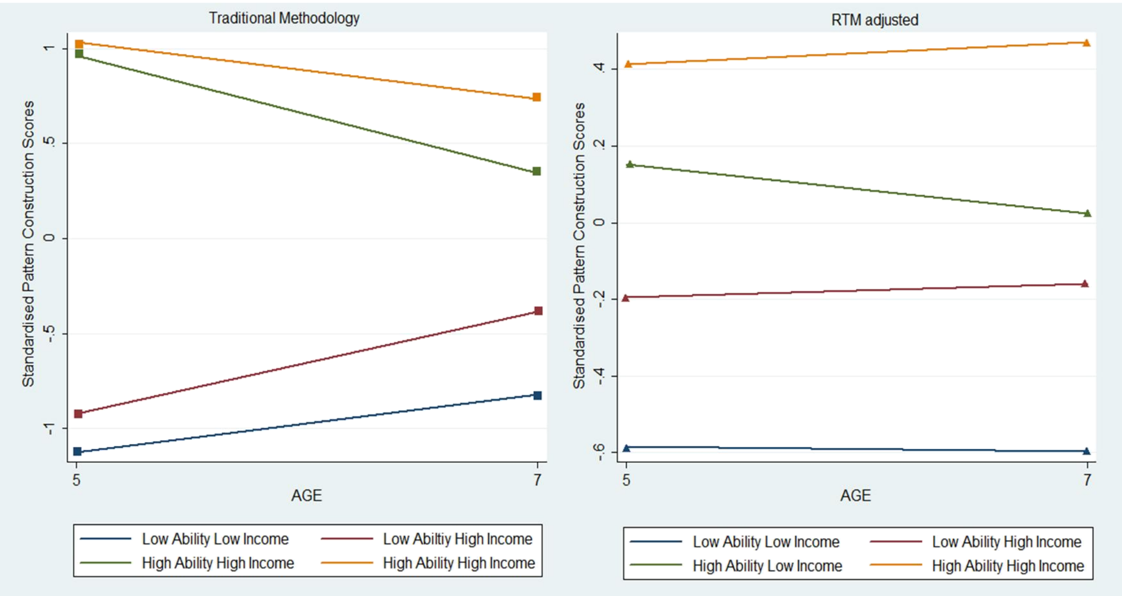
5.6 Results

The results section is divided into two parts, the first part introduces the element of family income by analysing the progression of groups divided according to this factor (and baseline ability) and examines whether or not these groups show different rates of development over time, while the second section includes family income as an explanatory variable in regression based models, allowing us to measure the effect of family income conditional on further explanatory variables.

5.6.1 Development Gradients of Children from Different Income and Ability Groups

My first approach to examining the question of the role of family income is to examine the rates of change in cognitive outcomes between children from various family income and ability groups. Similar to the approach adopted by Feinstein (2003), children are divided into groups based on their family background (in this case measured by equivalised family income at age 9 months) and their performance in a cognitive test. Rather than constructing an ability index using principle component analysis as Feinstein did, I focus on a single test – primarily, pattern construction. As discussed above, this test assesses children's non-verbal reasoning and spatial visualisation, and can also be used to observe dexterity and coordination, as well as traits like perseverance and determination. It was undertaken by the cohort children at ages 5 and 7. Children are thus firstly divided into ability groups according to their family income and their standardised pattern construction score at age 5 (their baseline score). At the same time, an alternative grouping is constructed which uses an auxiliary test to account for the issue of RTM, namely the picture similarity test score. In this case, children are divided into ability groups according to their family income and their standardised picture similarity score at age 5.

Figure 5-3: Developmental Gradients of Family Income - Ability Groups



I firstly present a graphical comparison of the trajectories of the various family income and ability groups using both methodologies (figure 5.3). This is analogous to the graph contained in Jerrim and Vignoles (2011) using naming vocabulary test scores from ages 3 and 5. The graphs below present the standardised pattern construction scores at ages 5 and 7, with ability groups defined using the baseline score for the graph on the left and an auxiliary test (picture similarity) for the graph on the right.

The graph on the left shows a clear pattern of RTM, with the high ability groups displaying negative gradients and the low ability groups rising upwards towards the mean. If we look at the graph on the right, however, the lines are much flatter, since the RTM effect has been removed. The high income, high ability group's line now even slopes slightly upwards, whilst the high ability, low income group's line still slopes downwards, though much less steeply than before. The lines of the low ability groups both appear to be essentially flat.

These graphs show that the pattern seen in Feinstein (2003) and other analyses such as Blanden and Machin (2007), is largely the result of strong RTM patterns in the data. Once this is accounted for, the results look very different, which is also the conclusion reached by Jerrim and Vignoles (2011). However, although accounting for RTM has reduced the gradient of the high ability, low income group, it is still negative in the graph on the right. This indicates that a more robust analysis should be undertaken to determine whether or not bright children from disadvantaged families are indeed dropping behind. Whilst the analysis of the MCS data in Jerrim and Vignoles (2011) stops at the presentation of a graph similar to the above, in this chapter, I take this one step further and estimate the slope of the gradients to determine if they are in fact flat, or if any slopes are statistically significantly different from zero once the RTM effect has been removed.

My next step is therefore to estimate these gradients using a regression-based approach. I run two separate regressions using these alternative groupings. Both regressions use pooled cross section data for each cohort member over the two waves and clustered standard errors. The dependent variable is the standardised pattern construction scores from ages 5 and 7, and the explanatory variables include a time dummy to indicate the survey wave, group dummies for the nine family income – ability groups, and interaction terms between the time dummy and the group dummies. The group dummies themselves indicate where each group starts relative to the others (e.g. the low income-low ability group has a low initial starting point), while the interaction terms indicate the rate of development between the two waves. This allows us to check if different income-ability groups have different rates of development over this timespan. Most importantly, the second regression uses groups that were divided according to the auxiliary test, rather than the baseline score. Having accounted for RTM effects in this way, it thus allows us to examine whether there is still a difference in the rates of development. This would then justify greater confidence in giving this a substantive interpretation. These results are reported in Table 5.6 below.

Table 5-6: Rates of Development for the Income-Ability Groups

	(1)		(2)	
Dependent Variable:	Std. Pattern Construction		Std. Pattern Construction	
Ability groups divided by:	Pattern Construction (age		Picture Similarity (age 5)	
time	0.056*	(0.026)	0.041	(0.032)
Low Ability, Low Income (LALY)	-1.424***	(0.057)	-0.627***	(0.079)
Low Ability Average Income (LAAY)	-1.488***	(0.066)	-0.307***	(0.083)
Low Ability, High Income (LAHY)	-1.496***	(0.075)	-0.176	(0.090)
Average Ability, Low Income (AALY)	0.098*	(0.042)	-0.108	(0.079)
Average Ability, Average Income (AAAY)#	…		…	
Average Ability, High Income (AAHY)	-0.087*	(0.041)	0.171*	(0.078)
High Ability, Low Income (HALY)	1.681***	(0.059)	0.266**	(0.088)
High Ability, Average Income (HAAY)	1.491***	(0.049)	0.421***	(0.076)
High Ability, High Income (HAHY)	1.441***	(0.046)	0.484***	(0.074)
LALY*time	0.255***	(0.041)	-0.051	(0.045)
LAAY*time	0.432***	(0.047)	0.005	(0.048)
LAHY*time	0.515***	(0.053)	-0.036	(0.053)
AALY*time	-0.135***	(0.038)	-0.081	(0.048)
AAAY*time#	…		…	
AAHY*time	0.086*	(0.037)	0.038	(0.045)
HALY*time	-0.675***	(0.045)	-0.157**	(0.050)
HAAY*time	-0.472***	(0.039)	-0.104*	(0.045)
HAHY*time	-0.345***	(0.036)	-0.014	(0.043)
constant	-0.090**	(0.029)	-0.021	(0.055)
N	14,174		14,174	
r2	0.497		0.127	

Standard errors in parentheses

Reference case

* p<0.10, ** p<0.05, *** p<0.010

As can be seen in the table above, in both regressions, the low ability groups start with a below average score and the high ability groups with an above average score. Especially in column two, it is apparent that that low ability - low income children started off lower than their low ability –high income counterparts, while high ability - high income children started even higher than their high ability – low income counterparts.

Focusing on the interaction terms, in column one, there is strong evidence of RTM. The low ability groups all improve rapidly. Of these, the high income – low ability group improves fastest, with a coefficient of 0.515, while the low ability – low income group also improves, but somewhat slower, with a coefficient of 0.255. The high ability groups confirm the pattern of RTM, as they all drop downwards towards the mean. The high ability – low income group drops fastest, with a coefficient of -0.675, while the high ability – high income group has a coefficient of -0.345. This lends support to the argument that more of the low income children who were classified as high ability achieved this due to the random element in their scores rather than true ability, compared to the high income, high ability children.

Turning now to the second model where the groups have been divided in such a way as to account for the issue of RTM (i.e. based on the auxiliary test), the low ability groups all have interaction terms which are not statistically significantly different from zero. Their relative rate of development is essentially flat over this period, which indicates that the negative gradient we can see in column 1 is entirely due to RTM effects. On the other hand, the high ability groups display an interesting pattern: we can see that the high ability – high income group's coefficient is also insignificant at any usual significance level, but that the high ability low income group has a statistically significant negative coefficient of -0.157.

That is the key finding of this section, i.e. that while the high ability, high income group's line is flat once RTM is controlled for, the high ability - low income group still has a downward sloping gradient. This gives confidence in asserting that bright children from disadvantaged families do indeed display a slower rate of development and that this finding is not merely a statistical artefact. Comparing the coefficients for this group from the two specifications, without controlling for RTM, the coefficient is -0.675, while once this has been controlled for, it falls to -0.157 in the second specification. RTM is clearly a very large part of the story and is operating for all income-ability groups. However, the strong significance of this coefficient in the second specification indicates that family income also has a substantive impact on the rate of development as measured at these ages.

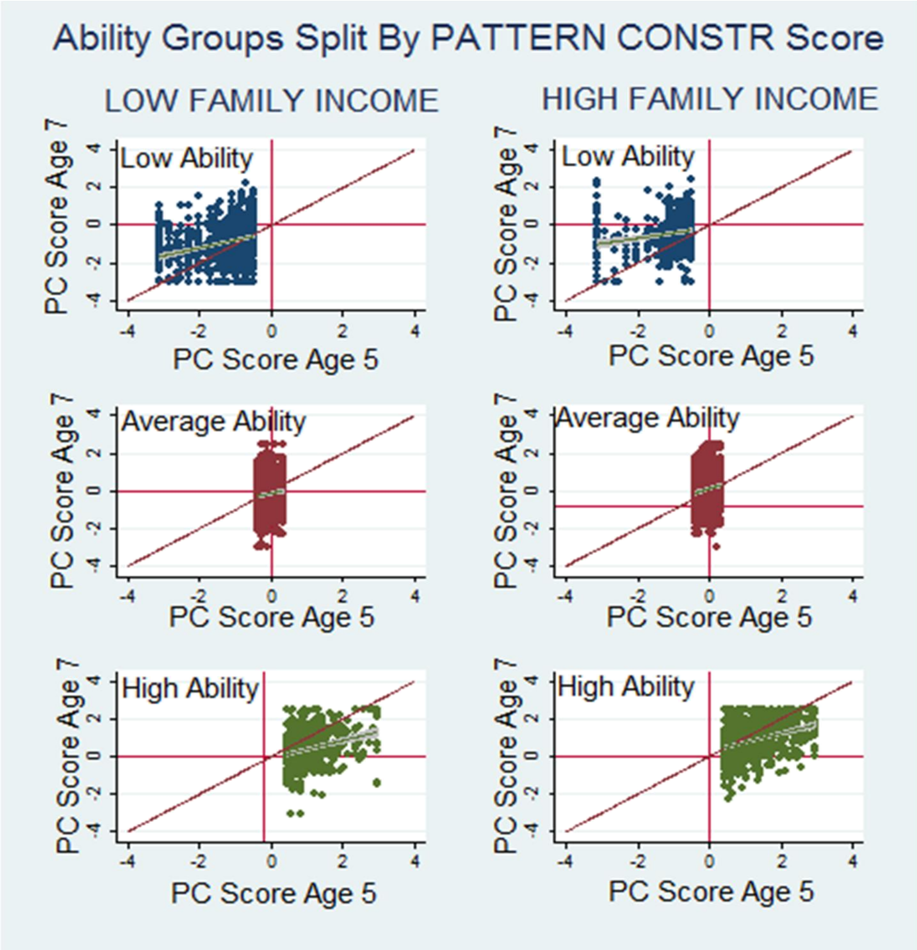
The second model has a lower R-squared than the first model. In this context, where the model only includes dummies for the various income-ability groups and the interactions of these dummy variables with the time variable, the lower R-squared has the same meaning as the smaller parameter values, namely that income has less of an impact than is otherwise thought from models that use traditional methodology. However, more than 12% of variation is explained in this model, which shows there is still an important role for family income. It is also important to note that this approach rests on the assumption that the variance remains constant between the two tests. For this reason, the standardised test scores were used (i.e. where the standard deviation of the scores for each test had been standardised to 1).

The number of cognitive assessments carried out as part of the MCS survey makes it possible to test the robustness of this finding. In particular, I have explored various combinations of the possible auxiliary tests, outcome tests and ages and found that while this result is not universal, it appears to be robust, as it holds true in the majority of specifications. The results for the standardised naming vocabulary tests divided by the baseline and the bracken school readiness test (as per Jerrim and Vignoles, 2011) also follow the above pattern (see appendix B). This is important as it allows us to generalise this result, rather than it being confined to a single measure of cognitive ability at ages 5 and 7.

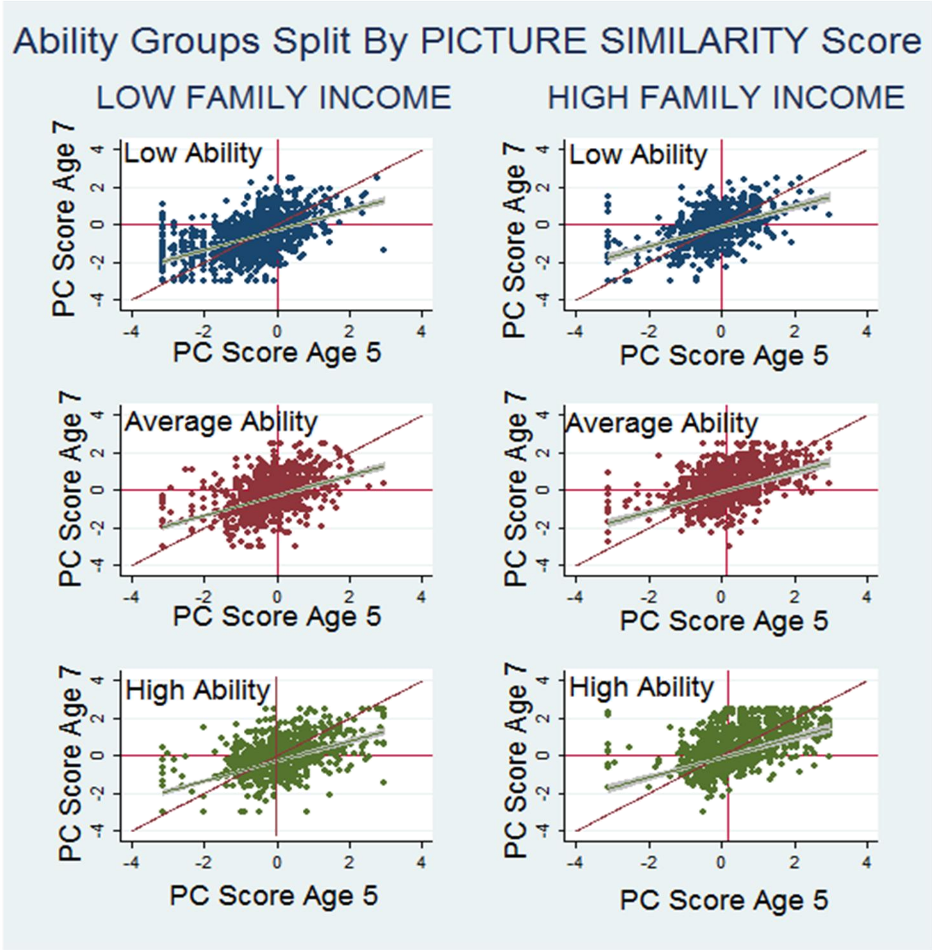
In order to look in a more detailed manner at what is driving the result for the pattern construction test above, Figure 5.4 below provides scatter plots for the high and low income groups, divided into ability groups defined by the baseline score (left hand graph) and the auxiliary score (right hand graph). Firstly, these graphs demonstrate substantive differences in the distribution of test scores between the high and low family income groups. For example, 40% of low income children are classified as low ability using pattern construction scores, compared to just 20% of the high income

Figure 5-4, Panels A and B: Breakdown of Pattern Construction Scores by Income and Ability Groups

Panel A:



Panel B:



children. This leads to a concentration of low income children in the top left-hand graph of Panel A, with an even greater concentration of these children (83%) sitting in the bottom left-hand quadrant (i.e. scoring below average on both tests). In the same vein, 43% of high income children were classified as high ability using the baseline measure, compared to only 24% of low income children, and 84% of these high ability - high income children scored above average on both tests, compared to 72% of the high ability - low income children. Furthermore, the straight lines on the edges of the distributions show the cohort members who scored the highest and lowest possible scores on each test. Low income children were much more likely to have the lowest possible scores, while more high income children achieved the maximum possible score on either test. Only eight low income children achieved the maximum possible score on the second test, compared to 35 high income children.

Secondly, the results from the analysis above in Table 5.5 can be further explained using these figures. In Panel A, we can see that in the bottom left graph (the HALY group), the great majority of the dots (78%) fall below the 45 degree line (almost none of the poor children initially classified as bright is able to maintain or improve upon their score in the second test); while in the top right graph (the LAHY group), the great majority of the dots (71%) fall above the 45 degree line (almost none of the children from well-off families initially classed as low ability fails to improve their score on the second test). When the alternative method is used in Panel B, the dots fall much more evenly on either side of the line, which shows that the alternative criterion for dividing the children into ability groups effectively combats this RTM effect. For the LAHY group, only 48% of dots sit above the 45 degree line once the groups are defined according to the alternative test. As we saw above, the coefficient on the interaction term for this group became insignificant once the alternative grouping method was applied.

The only group to retain a statistically significant coefficient was the high ability low income group, which showed a significant decline, even after the alternative classification method was employed. Looking at the panels above again, we can see that the dots in the bottom left graph of Panel B fall much more evenly around the 45 degree line than they do in the bottom left graph of panel A. In fact, the proportion of dots falling below the line has decreased from 78% to 55%. Nonetheless, the line of best fit in the graph for this group is still flatter than any other in Panel B. The contrast to the gradient of the line of best fit for the high ability – high income group is particularly marked. This demonstrates that the standardised test scores of the HALY group were less strongly correlated between occasions than those of any other group, i.e. that although the children from well-off families maintained their good position over time, the children from less advantaged families failed to do the same.

These findings indicate that high income children not only start at a higher baseline score, but are also improving relative to their peers from disadvantaged households, whilst low income children who are genuinely high ability (and not misclassified due to random error) score well initially but struggle to maintain this standard, relative to their high income peers. Given that the two tests (pattern construction and picture similarity) were taken on the same day, there may be reasons for RTM not being fully accounted for by this method. However, Table 5.5 above addresses this question using the formulas provided by Ederer (1972) and finds that the relevant coefficient is equal to unity, meaning that RTM is fully accounted for by using the picture similarity test as the auxiliary test. Furthermore, the method used seems to have totally removed the RTM effects among low ability children. These two points give confidence in asserting that a substantive interpretation of this finding is indeed appropriate.

In summary, this section has demonstrated that RTM is a key factor behind the changes in scores between baseline and follow-up, that its effect differs in strength at either end of the ability spectrum depending on family income, and that it can be dealt with effectively by splitting the children into ability groups according to an auxiliary test rather than the baseline test.

Using this methodology indicates that there are substantive differences between high and low income groups for both high and low ability levels, not only in terms of the baseline score, but also in terms of their rate of development over time. On average, high ability children from advantaged homes develop faster than high ability children from disadvantages homes. Examining similar results for naming vocabulary between ages 3 and 5 confirms this overall picture – that although RTM is highly prevalent in the change in the children's test scores between waves, a child's family income group has a genuine effect both on their baseline score and their development over time.

5.6.2 The Effect of Family Income on Children's Rates of Cognitive Development

Another way of dealing with RTM, as discussed in the methodology section above, is by using conditional models where the test score in the second period (or, equivalently, the change in test scores) is conditional on the test score from the first period. This method 'corrects' for RTM because RTM is the tendency for there to be a less than perfect correlation between the second measure and the baseline. Including the baseline measure explicitly in the model removes this source of bias. The functional form of these models is the same as in "value-added" models where the baseline score is included as a proxy for individual heterogeneity

The table below (Table 5.7) shows the effect of income on test scores under four different specifications, one using the absolute change as the dependent variable and not including the baseline measure as a covariate, as well as three conditional models. The first two conditional models have as the dependent variables the follow-up measure and the absolute change and account for RTM by including the baseline score as a covariate (these two are mathematically equivalent). The final model accounts for RTM by using as the dependent variable the residuals from a regression of the baseline measure on the follow-up measure.

. The first model, where the dependent variable is the absolute change in scores, shows a statistically insignificant and very small effect of family income. In the methodology section, I argued that this model is misspecified. The effect of income is not apparent because the model does not account for RTM. This will be explained more fully below. Models (2) to (4) all show a statistically significant effect for income, as the coefficients on the low family income dummies are all significant. It can be seen that models (2) and (3) are mathematically equivalent as all the coefficients are exactly the same, except for the coefficients on the baseline test score variable which differ by exactly one. The fourth model uses the residuals from a regression of the baseline measure on the follow-up measure as the dependent variable and has very similar coefficients on the family income dummies to models (2) and (3). The R-squared value is significantly lower because the baseline score is accounted for in a different way, rather than being included in the model as a covariate. In a set of parallel specifications where no control variables were included beyond the income groups and the baseline measure, models (2) to (4) showed strongly significant results for both the low family income and high family income dummies. However, the coefficients on these variables were not significant at any reasonable significance level in model (1).

Table 5-7: Effect of Income under Different Specifications (Pattern Construction, age 5 and 7)

	(1)	(2)	(3)	(4)
	y_2-y_1	y_2	y_2-y_1	$\hat{u}$
Low Family Income Group	-0.043	-0.096**	-0.096**	-0.091**
	(0.036)	(0.030)	(0.030)	(0.030)
Mid Family Income group #	-	-	-	-
High Family Income Group	0.014	0.047	0.047	0.045
	(0.030)	(0.029)	(0.029)	(0.028)
Baseline Pattern Construction		0.524***	-0.476***	
		(0.013)	(0.013)	
Controls	YES	YES	YES	YES
Constant	-0.006	-0.186	-0.186	-0.180
	(0.139)	(0.113)	(0.113)	(0.113)
N	7,002	7,002	7,002	7,002
R^2	0.04	0.36	0.27	0.06

Standard errors in parentheses; # - Reference Category

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

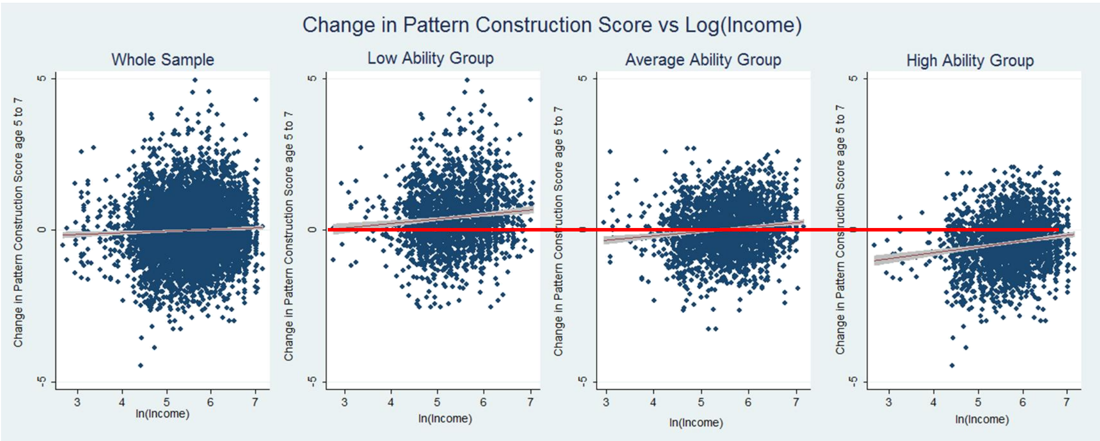
Dependent variables: standardised pattern construction scores

Income groups: Top and bottom tertiles of OECD equivalised income

Controls: family structure, parents labour market engagement and education, child gender, ethnicity, month of birth, birthweight, health, pre-school, family moved house

The reason for the insignificance of the income variables in the first specification can be seen from the graphs below in Figure 5.5, which are scatter plots of change in pattern construction test scores against logged family income, firstly for the whole sample and then for three groups divided according to baseline pattern construction score.

Figure 5-5: Change in Pattern Construction Score against Logged Family Income, Whole Sample and Ability Groups



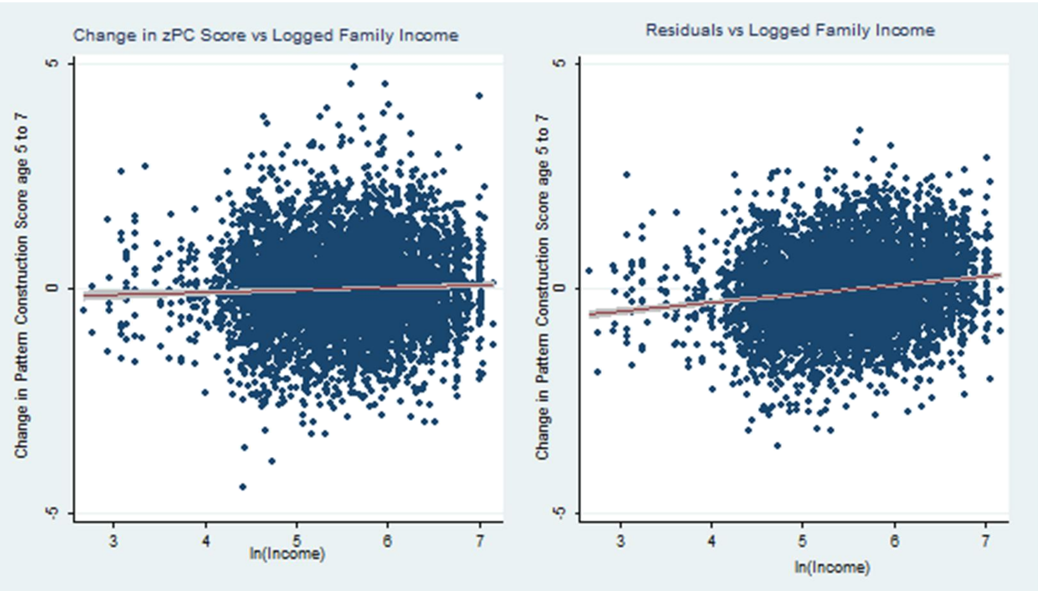
Although fitting a line of best fit to each of the three sub-groups shows a positive relationship between family income and change in test scores in each group, the line of best fit for the whole sample (which is equivalent to the slope estimate from the first model in the table above) is approximately flat. What these graphs demonstrate is the extent of RTM in the data and the strong relationship between family income and baseline score. The combination of these two factors results in the apparent independence of family income and change in test scores in the full sample.

To be more specific, in the graph of low initial ability children, we see that most data points show a positive change in test scores (they lie above the x axis due to RTM) and also that the points are concentrated around a mean log income of 5.3; in the mid initial ability group, the scores fall slightly further right, with a mean logged income of 5.6, and that in terms of absolute change in scores they fall fairly evenly around zero, as those close to the mean of the distribution had no strong tendency to increase or decrease their scores; the third group, those with a high baseline score, have a mean log income of 5.8 and have most data points below the x axis, also due to RTM.

Breaking the sample into even smaller groups confirms this pattern, as the main body of scatter points in each graph moves further and further rightward and downward as the baseline ability group increases, while each graph shows a positive relationship between family income and change in test scores. These two effects just about cancel each other out in the full sample, such that the line of best fit between log income and change in test scores is essentially flat and the point estimate on logged income in a regression is very close to zero (0.06). This demonstrates how important it is to take account of each child's baseline ability score when estimating the effect of family income on the change in their scores over time.

Models (2) to (4) in Table 5.6 all try to do this, taking account of RTM by including the baseline measure as a covariate or by using a residual as the dependent variable. Residual change is graphed against logged family income in Figure 5.6 below to provide a comparison with the first model. We can see a dramatic change in the income gradient. This confirms the importance of family income as a factor influencing the rate of children's cognitive development, even once RTM has been accounted for by using a conditional model where the relationship between baseline and follow-up scores is modelled explicitly.

Figure 5-6: Absolute and Residual Change in Pattern Construction Scores against Logged Family Income



5.7 Conclusion

This chapter has explored the impact of family income on the trajectories of cognitive development of children from different family backgrounds. While various studies have identified substantial gaps in achievement at particular ages, the question of development in terms of the rate of change in cognitive achievement over time is still an open question. Examining change in individuals' scores over time introduces various methodological issues, and in this chapter I have focused on one of these, namely the issue of regression to the mean. Jerrim and Vignoles (2011) raises the question of whether the different rates of development between children from different family background and ability groups, as first identified in Feinstein (2003), may merely be the product of RTM, rather than evidence of substantive differences in the true development of these groups. Blanden *et al* (2012) calls for further work to be done in this area to distinguish true differences in children's developmental trajectories from RTM effects. This chapter provides more detail on the RTM patterns in the MCS data, uses various methods to account for this and seeks to provide a more robust view of children's true developmental trajectories up to age 7.

My approach was firstly to focus on the development of a single skill over time to eliminate regression effects due to non-comparability, and secondly to use an auxiliary test to separate the children into their respective ability groups and measure change from a separate test (as per Ederer, 1972, and Jerrim and Vignoles, 2011). We saw that while this is effective in dealing with the issue of RTM, there is still evidence of a decrease over time for the high ability - low income group, while the other groups are steady once this method has been applied. I argue that rather than this decline being residual RTM, a substantive interpretation is appropriate, namely that the benefits accruing to young children in higher family income households not only help them to score better originally, but also help them to maintain this position, while the fact that children from low incomes drop back is also a product of their low family income, possibly due to a lack of environmental factors which are necessary to encourage children's further development and help them keep up with their peers from well-off families.

My second method for dealing with the issue of RTM introduced another, quite simple, approach which is often used in epidemiology but has not been discussed in the econometrics literature in this context. This is namely to use a conditional model (or value-added functional form) where the baseline score is included as a covariate. It is necessary to use this functional form when examining the effects of family income on the change in children's test scores over time, as my results show that the negative correlation between baseline score and the follow up score (i.e. RTM) is balanced out by the positive correlation between family income and baseline score, such that family income appears unimportant when a gain score is used as the dependent variable in a regression and the baseline is not included as a covariate. Once the baseline score is included as a covariate however, the effect of family income can be seen to be substantial and statistically significant.

My results using these various methods all point in the same direction, demonstrating that although the test scores of children do include a large random component such that RTM is a key element of the change in these scores over time, family income nonetheless has an important role to play. The group of high achieving children from poor families was the only group to show a decline in performance after RTM had been controlled for in the way the ability groups were divided. Furthermore, the dummy variables for low family income were statistically significant in regressions showing the rate of development over time. Whilst the importance of dealing with RTM in order to reach a reliable conclusion has been demonstrated in this chapter, it is clear that family income does in fact dominate the ability effect in terms of rates of development, and that this is not just a statistical artefact. These results highlight the importance of a continued government policy focus on bright young children from poor families.

James Heckman, a well-known US economist and Nobel Prize laureate, has argued that governments should invest heavily in disadvantaged young children, as this is one of the rare public policy initiatives 'that promotes fairness and social justice and at the same time promotes productivity in the economy and in society at large' (Heckman, 2006: p. 2). Policies which support and encourage bright children from poor backgrounds are thus important not only from a social justice perspective, but also from the point of view of efficiency in the use of limited government resources. Policies which have been implemented in the UK which focus specifically on this group, such as the Young Gifted and Talented programme, will be discussed in the conclusion together with recommendations for how these can be developed further.

6 Conclusion

6.1 Overview

In the UK, a strong link between parental income and children's educational and cognitive outcomes has long been established (Blanden and Gregg, 2004). Various aspects of this relationship have been examined in this thesis. The high degree of intergenerational transfer of advantage has implications for social mobility. Whilst the issue of social mobility has been increasingly prominent in the political arena, the role of education in social mobility remains ambiguous – does it function as "the great social leveller" or rather enable the privileged "to consolidate their position in society" (Major, 2012, p155)? Whilst this question has not been explored extensively in the literature, there is some indication that education has been working as a force for maintaining the status quo. Blanden and Machin (2004) show that the relationship between family income and both participation in full time education at age 19 and degree attainment at age 23, actually strengthened as university participation expanded in the 1980s and 1990s. Galindo-Rueda and Vignoles (2005) also found that the influence of family background on university participation is growing and show that the decline in the importance of ability relative to the influence of family background is partly due to the fact that low ability children with high economic status experienced the largest increases in educational attainment in recent years. Whilst education has the potential to play an important role in facilitating social mobility, it can also serve to strengthen existing inequalities and even hinder mobility if it becomes a way of securing success for those who are rich but not especially able, and excluding the clever poor.

The aim of the thesis has been to explore some the avenues through which income/social background influences educational outcomes, as this can provide insight into the barriers that those from poorer families face when accessing education. This thesis has focused on family income as a measure of social background, although socio-economic class was also used as a measure of family background in chapter three. Blanden and Gregg (2013) explores possible reasons why social mobility in terms of income seems to have fallen between 1958 and 1970, while social mobility in terms of class remained constant. They find evidence that this has to do with changes in the permanent component of income that is unrelated to social class. In my own results in chapter three, I find very similar results for the effect of debt aversion on university participation, whether the sample is broken down by family income or by father's socio-economic class. I therefore refer to "family background" in general, without differentiating explicitly between family income and family socio-economic class. Three specific aspects of the relationship between family background and children's educational outcomes were explored in detail in the previous chapters. The implications of these findings will now be unpacked further, especially in relation to the issue of securing access to higher education for those from disadvantaged family backgrounds.

6.2 Debt Aversion and University Participation

In Chapter 3, I undertook an analysis of what determines the university participation decision, with a particular focus on the effect of debt aversion on this decision. Participation in higher education is an important avenue for progression for those from poorer families, however, it is possible that greater concerns about indebtedness act as a barrier to participation for this group. Although the student financial support system includes measures to support students from low-income backgrounds, debt aversion may act as a greater barrier for this group because a poor student taking on debt that equates to two or more years of family income may be put off compared to somebody for whom the fees are *relatively* much lower; and more directly, because we can expect richer students to end studies with less debt.

The results suggest firstly that debt aversion acts as a barrier to university participation for all social groups. In logistic regressions with university participation as the dependent variable, the odds ratios on the debt aversion variables were well below unity and statistically significant. I ran separate regressions for each gender and also for different measures of debt aversion (a value-based measure using the statement "owing money is always wrong" and a risk-based measure using the statement "once you get into debt it is often very difficult to get out of it"), and found a clear, consistent pattern that debt aversion has a negative impact on university participation, controlling for a wide range of other factors. The value-based debt aversion measure was statistically significant for both genders and the risk-based measure was significant for females. The size of the effect is also quite large, reducing the participation probability by as much as 20 percentage points in some cases. Given the literature on the relative unimportance of short-term credit constraints (Carneiro and Heckman, 2003; Dearden *et al*, 2004), this is an important result, and confirms the findings of Callender and Jackson (2005), that debt attitudes are an important factor affecting the university participation decision.

One possible policy approach to addressing this issue relates to the information that is available to potential students. Barr (2010) discusses how information on student finance could be used more effectively to counteract low participation due to concerns about debt. Discussing the changes that were implemented in 2006, he highlights the need to educate people, firstly that studying is free to students (since it is graduates who pay); secondly that repayment operates as a payroll tax, meaning that student debt is very different from credit card debt, and thirdly that the total amount concerned is small when compared to the income tax payments and national insurance contributions graduates will make over their working lives. Information of this kind may help students overcome their concerns about debt, especially if a clear distinction is made between student loans and other financial responsibilities such as credit card debt. A recent National Union of Students report on student financial support in further and higher education (Heynat and Davies, 2012) highlights the complexity of the financial support system and the barriers this can create. Quoting Mangan *et al* (2010) they discuss the fact that a large proportion of potential students who would likely qualify for a bursary or grant (based on their household income) did not think in fact that they would, and that there was a reluctance to actively search for information regarding finances. For the bursary system in particular, criteria are often complex and vary greatly between institutions. For this reason, a case has been made for a national bursary system, as this would be much simpler and more transparent for students (Chester and Bekhradnia, 2008). Adnett (2006) and Adnett and Tlupova (2008) also highlight how the complexity of the system can act as a barrier to participation, noting that "this decentralised approach to providing targeted support to students from low-income families places a complex decision-making burden on those who typically are the least-informed and the least likely to possess the necessary skills" (2006, p307). These papers highlight how information can be used as a tool to overcome the barriers posed by debt aversion.

Programs such as AimHigher appear to have had an important role to play in this regard. For example, a majority of students surveyed for one evaluative report (Passy and Morris, 2010) reported that "they learned through Aimhigher that the level of potential debt was manageable" (p32). AimHigher was closed in 2011, partly due to the general cuts in government funding arising from the need for austerity after the global financial crisis, and possibly partly in response to reports of the limited effectiveness of the program (Emmerson *et al*, 2006). However, the AimHigher program was very diverse and evaluation was not effectively built in to the program design from the outset (Wylie, date unknown). It seems that findings relating to its ineffectiveness have more to do with the difficulty of identifying (in an econometric sense) a significant, positive effect; while substantial qualitative evidence for its effectiveness in a more personal and individual way seems to have been given little weight. Despite questions as to its cost-effectiveness, the program seems to have had an important role to play and I would recommend that it be re-established in the future, especially now that the increase in undergraduate fees means understanding the funding system is even more important for young people weighing up their options in regards to higher education.

The second major finding of chapter 3 was that the effect of debt aversion did not differ by family background. Although the initial descriptive statistics showed that young people from lower family income groups (and lower social classes) were more likely to be debt averse, analysis of the effect of debt aversion on university participation showed quite consistent effects for all family income groups (and socio-economic class groups). This was analysed using various methodologies, including interaction effects, sub-samples and a decomposition analysis. The only possible caveat to this was a slight suggestion that among females, the effect may be somewhat stronger for girls from low income families. Nonetheless, the overall picture was clear – debt aversion has an effect on university participation across the board, not more or less so for young people from disadvantaged backgrounds.

This stands in contrast to the findings of Callender and Jackson (2005), who found a clearer effect of debt aversion among young people from disadvantaged families. They found that debt aversion had a negative effect on university participation intention for their whole sample and for young people from the lowest social class group in particular, but found inconclusive evidence of this among young people from the middle and upper classes specifically. That is the major difference to my findings as I find a significant effect across the board. I would argue that this difference is due to the fact that two quite different systems of student finance were in operation when the surveys for each respective investigation were carried out. For the Callender and Jackson (2005) paper, young people were interviewed in 2002, when the system involved upfront fees and a different approach to student financial support. Although students from poor families would have received an exemption for fees, they would still have accumulated debt during their degrees as there were no maintenance grants available, but rather subsidised loans for living costs. On the other hand, it is understandable that debt was not a major issue for students from higher income families as their fees were paid up front and they were not eligible for the maximum amount of maintenance loans (Callender and Kemp, 2000), meaning their level of indebtedness at the end of their studies would have been lower than that of students from the lowest family income groups. By contrast, under the system that was in place when the LSYPE pupils were surveyed (the data used in my analysis), fees were higher (set at a maximum of £3,000 per annum rather than £1,000 per annum) and were to be repaid after graduation. Furthermore, whilst maintenance loans were available for all students, these were supplemented with maintenance grants for students from disadvantaged backgrounds. This means that debt had become a factor for students of all family backgrounds and helps explain why I found the debt aversion variables to be statistically significant for all family income groups in my analysis.

The student finance system has now changed again with fees having been increased to a maximum of £9000 per year and further changes to maintenance loans and grants as of the academic year 2012/13. These changes will lead to a substantial increase in the level of indebtedness of students on graduation. The results of my research indicate that this may have an impact on participation rates. Initial figures from a report from the Higher Education Funding Council for England (HEFCE, 2013) on the impact of the 2012 reforms indicate that fewer students than usual deferred their studies in 2011/12 (presumably to avoid the fee increase), which lead to an increase in applications in that year and a decrease in 2012/13 when the higher fee regime was implemented. It will not be possible to gauge the effect on the long-term trend of participation rates until more time has passed.

Apart from deciding not to participate in university at all, other possible reactions to the increase in fees include delaying participation or choosing a university which makes it possible to live at home or where there are good opportunities for part-time work, though this may lead to compromises on the choice of course (Heynat and Davies, 2012). Another effect may be that more students start studying abroad, for example in continental Europe where fees are generally much lower and more courses are starting to be taught in English (Wilkins *et al*, 2013). Another important element of the current situation facing young people as they make decisions regarding higher education is that the increase in fees has come at a time when youth unemployment rates are very high. Although this may also increase the demand for education, on the other hand, the difficulties in securing graduate employment at the end of one's studies, coupled with the prospect of high student debts, brings the overall return to investing in a degree into question. Estimates of the returns to a degree (e.g. Chevalier and Walker, 2001; Conlon and Patrignani, 2011; Walker and Zhu, 2011) indicate that historically, there have been substantial returns. However, this differs significantly by degree subject, with medicine and dentistry (Chevalier and Walker, 2001) as well as law, economics and management (Walker and Zhu, 2011) offering the highest returns, whilst subjects such as modern foreign languages offer much lower private returns. This may mean that students' choices concerning their degree subject may also be affected by the increase in fee levels as financial considerations become more important.

Both Callender and Jackson (2005) and my own research have demonstrated that debt aversion acts as a barrier to university participation, with my research showing that debt aversion affects actual participation (rather than just participation intention) and the fact that the effect now applies to young people across the board. However, it is nonetheless clear that the role of prior attainment is even more significant. Although debt aversion impacts on students with the necessary qualifications to participate in higher education, the achievement of these qualifications seems to be the major factor determining differential university participation rates between family income groups. Barr (2010) makes this point very strongly, demonstrating that entry into higher education depends on A-level points, which depend on GCSE results, which in turn depend heavily on family background. For this reason, the second and third empirical chapters of this thesis took a step back from the university participation decision at age 18 to explore factors affecting early educational attainment. These will now be discussed in more detail.

6.3 Factors Affecting Children's Cognitive Development

Chapter four focuses on the factors which affect children's cognitive development between ages 5 and 7 – the first few years of school. The analysis was carried out using data from the Millennium Cohort Study, and thus provides a very rich and up-to-date view of the factors affecting children's cognitive development in the UK in recent years. The measure of cognitive development I focused on was pattern construction, which tests children's non-verbal reasoning and spatial visualisation. This was chosen as measures were available for the same test at age 5 and age 7, and furthermore since it was considered to be a more pure reflection of 'intelligence' whereas language based tests (such as the naming vocabulary tests available at ages 3 and 5) make it more difficult to distinguish ability and the influence of family background. Three sets of explanatory variables were considered, namely family income, school-related factors and a third, more general, group of 'other factors'. Methodologically, the approach taken was to use an augmented random effects (ARE) model so that both within-subject and between-subject variation could be exploited, whilst assessing the consistency of these results by comparison to a fixed effects model using the Hausman test. This approach showed some interesting results, giving confidence in asserting that certain variables have a direct, independent effect on children's cognitive development at this stage of their lives.

The influence of family income has been a major topic in the relevant literature to date (e.g. see Mayer, 1997; Shea, 2000; Violato *et al*, 2011), much of which has been concerned with dealing with the problem of the endogeneity of family income. This arises as income is correlated with almost every other conceivable influencing factor. Existing papers have taken various approaches to dealing with this issue, and there is no clear consensus as to whether family income *per se* causally affects children's development, although I would argue that the weight of evidence lies on the side of a positive response to this question. My own approach in this chapter has been heavily influenced by the lack of within-variation in families' incomes over the waves examined. This lack of within-variation led to insignificant coefficients in the fixed effects models and meant that income had to enter separately as means and deviations from means in the ARE model. It is difficult to argue that the results provide evidence of a direct, causal effect of family income, however, the positive and significant coefficients in the OLS models and the ARE models do lend support to the findings of other papers which have demonstrated a direct effect of family income on children's cognitive outcomes (Mayer, 1997; Dooley and Stewart, 2004).

The models estimated in chapter four control for a wide array of other factors and as such, give confidence in asserting that family income is in itself an important influencing factor contributing to children's cognitive development in the first few years of school. Furthermore, the ARE model showed positive and statistically significant coefficients on the other money related factors, namely car usage, type of housing tenure (owning or mortgaging a house) and taking holidays abroad. In addition, there was also a positive and statistically significant coefficient on the school fees variable, although this measure was only available at one time point. All of this serves to confirm further that family income does in fact have an important, independent role to play. This lends support for policies such as Child Benefit, which is currently available to everyone who is responsible for a child and is normally resident in the UK, and which consists of a weekly payment of £20.30 a week for the eldest child and £13.40 a week each for any other children. Cash benefits such as this can support a family's income allowing them to invest in items that are useful for their child, according to the guardian's own discretion. A 'High Income Child Benefit Charge' exists for parents earning over £50,000, and cancels out the amount of Child Benefit received. This helps to ensure that the Child Benefit is targeted at families who need it most.

Regarding the impact of schooling and school quality, the results were much more ambiguous, which may in part be due to data deficiencies. Although the MCS included an important innovation in terms of linking school and teacher surveys into the individual household surveys, unfortunately the response rates on these were not high enough to facilitate the inclusion of school or teacher fixed effects. Hanushek (1986, 2005) has argued strongly that school quality is difficult to capture in proxy variables such as class size, expenditure or the qualification level of the teachers and recommends the use of school fixed effects instead. Since this was not possible with the MCS data, the inconclusive results achieved on the variables included may serve to further strengthen Hanushek's argument, rather than indicating that school quality or quantity of schooling are truly unimportant.

A key contribution of the analysis in chapter three is to identify specific factors which are important for children's early development. In particular, certain factors had a positive but statistically insignificant coefficient in the fixed effects model, but when the between-subject variation in these factors was considered using the ARE approach, they became statistically significant and maintained their sign and approximate size. Specifically, these variables included the partner being the child's natural father, the home learning environment and the money related factors mentioned above. In the same way, the negative coefficients on the number of siblings and on never taking one's child to the library which were observed in the fixed effects model also became statistically significant once the between-variation in these variables was included in the ARE framework.

The importance of these variables is reflected in some current government policies such as the UK Government Child Poverty Strategy (Department for Education, 2010). One of the three major areas of this Strategy is a focus on family life (e.g. support for relationships). The results above suggest that the presence of the natural father and the atmosphere of the home were both important contributors to a child's development, which lends support to this approach. Furthermore, women without a partner were significantly more likely to be in a lower family income group (more than 60% of women without a husband or resident partner are in the lowest income quartile). This lends further support to a focus on healthy families, especially as a second aim of the Strategy is financial independence rather than reliance on government benefits. The analysis also demonstrated the importance of the stability of the child's environment, for example through the negative effect of having moved home since the last wave and in the positive effect of the parents owning or mortgaging the home. This could provide justification for increased government support for young families trying to buy a home. The importance of the library variable reflects parenting behaviours, on the one hand, but may also be taken as support for continued funding for local libraries themselves.

It could be argued that family relationships and a stable home environment are not really the government's responsibility. Indeed, the UK Government Child Poverty Strategy states that "Promoting good parenting is not primarily a job for the Government" (p38). Instead, it argues that what is required is "a much wider culture change towards recognising the importance of parenting, and how society can support mothers and fathers to give their children the best start in life" (*ibid*). Although that seems somewhat vague, it is made more concrete by support for family counselling services and the development of the Sure Start program which integrates professional, neighbourhood and family support systems. Although an initial evaluation of the program (Belsky *et al*, 2006) demonstrated less positive effects than had been hoped, a second evaluation (Melhuish *et al*, 2008) showed improvements, demonstrating that parents in Sure Start Local Program areas used more services, engaged in more supportive parenting, and had more socially competent children. In particular, having studied 14 outcomes, researchers found beneficial effects associated with the programmes for five of these: children showed better social development, more positive social behaviour, greater independence; and families showed less negative parenting and provided a better home-learning environment[24] (Melhuish *et al*, 2008).

Another variable that showed a significant, positive result in the ARE models was breastfeeding, along with days of gestation and birthweight. Although these variables couldn't be checked against a fixed effects model for consistency since they can only be measured at one wave, this finding nonetheless lends support to papers such as Doyle and Denny (2010) and Fitzsimons and Vera-Hernández (2012) which use instrumental variable techniques to establish a significant positive effect of breastfeeding on cognitive development. Sure Start Centres now have a stronger health focus than in the past, and also play an active role in encouraging breastfeeding, for example through peer support programs. The centres appear to be an important support for families and children. There are currently 3,055 main Sure Start Children's Centres and a further 501 additional support sites in England. Although an Early Intervention Grant was created as part of the 2010 Spending Review to ensure that sufficient funds were available to support the continued provision of these services, in conjunction with Local Authorities, there have nonetheless been reports of the closure of an estimated 400 centres, due to funding cuts since the current government came to power (Butler, 2013). Continued political support and funding for these centres is important, and should be strengthened by the growing evidence base for the importance of the early years in setting children up for success in life. My own findings in chapter four lend further support to this and to the importance of integrating professional health and educational support with strong family structures.

[24] The full list of outcomes examined included children's immunisations, accidents, language development, positive and negative social behaviours, and independence; parenting risk; home-learning environment; father's involvement; maternal smoking, body-mass index, and life satisfaction; family's service use; and mother's rating of area

6.4 Socio-Economic Differences in the Trajectories of Children's Cognitive Development

In chapter five, I examined whether the rate of cognitive development up to age 7 differs for children from more or less advantaged families. Although it has been established that gaps emerge early in the cognitive test scores of children from different socio-economic backgrounds, it is important to examine whether these increase, remain stable, or even fall when the children start school.

The claim that bright children from poor families are overtaken by their peers from well-off families who initially scored below average (e.g. see Feinstein, 2003) has recently been disputed as being merely a product of regression to the mean (Jerrim and Vignoles, 2011). This issue was examined in detail in chapter five using various methodologies. By estimating the variation in scores due to RTM, I show that the RTM effect is greater for children from poorer families, whose mean score was further from the cut-off point used to divide children into ability groups. I also demonstrated how using an alternative test to determine these ability groups can help solve the problem of RTM and lead to accurate estimates of true change over time (based on Ederer, 1972 and Jerrim and Vignoles, 2011).

Estimating change over time for various family income and ability groups using this methodology, I found that the high-ability, high-income group's coefficient was insignificant at any usual significance level, but that the high-ability, low-income group had a statistically significant negative coefficient of -0.157. This meant that while the high-ability, high-income group's trajectory was flat once RTM was controlled for, the high-ability, low-income group had a downward sloping gradient. Estimating the terms in this way alongside a graphical analysis gives confidence in asserting that bright children from disadvantaged families do indeed drop back behind their peers and that this finding is not merely a statistical artefact.

I also showed that using a value-added functional form is imperative when RTM is present and found that the coefficient on the low family income group dummy variable was statistically significant in regressions where the rate of development over time was modelled in this way. Overall, the results of this chapter showed that while RTM is indeed a significant element of the variation in children’s test scores, there is nonetheless a clear indication that children from poor families who score well initially, do drop behind their peers from more advantaged families. This provides further justification for a policy focus on bright children from poor families.

The US economist and Nobel prize winner James Heckman has written extensively on the benefits of investing in early childhood education (Heckman et al, 2013; Heckman et al 2010; Cunha et al 2010; Doyle et al, 2009) and has summarised his message in what he calls the Heckman Equation: Invest + Develop + Sustain = Gain. The message is that governments need to invest in educational and development resources for disadvantaged families, to nurture the early development of cognitive and social skills in children from birth to age five, and to sustain early development with effective education through to adulthood. The aim of all this is not only the direct benefit of the children concerned, but for the society as a whole to ‘gain a more capable, productive and valuable workforce that pays dividends for generations to come’ (Heckman, 2013). In this vein, a new federal act has recently been introduced in the United States entitled “A Strong Start for America’s Children” (H.R. 3461), which is a major policy initiative providing for quality pre-school and other services for young children from disadvantaged families. Such policy initiatives are justified not only from a social justice perspective, but in terms of the benefits that accrue to society though having a healthier, better skilled workforce and the costs that are avoided, for example through reduced crime.

The findings of chapter five confirm how important it is to support children from an early age so they do not drop behind their peers. It has recently been recommended by Graham Allen and Frank Field that the pre-school years be referred to as “foundation years” to highlight their importance in laying a firm foundation for the child’s schooling and future life, and this has now been adopted in government documents (Department for Education, 2012). Although more efforts have been directed to the early years of a child’s life in recent years, there is still scope for vast improvements in this area and the government is currently developing a new ‘vision’ for the foundation years. It is important to foster bright children from disadvantaged backgrounds from a young age to compensate as far as possible for the comparatively smaller amount of inputs they receive at home.

One more specific policy issue relevant for the UK is the effectiveness of the Young, Gifted and Talented program, which aims to identify high achievers and provide them with additional challenges to extend them both inside and outside the classroom. Although it was more developed in the past, the program is now very dependent on the individual school and not well supported by centralised government resources. The Gifted and Talented scheme of individual schools is assessed by Ofsted (the Office for Standards in Education, Children's Services and Skills), but improvements are still dependent on the internal resources and priorities of the school. This is an area where government could increase the support it provides so that schools can identify and challenge their brightest pupils more effectively.

6.5 Limitations of the Analysis

One limitation of the analysis in this thesis relates to the identification of causal effects. Family background has been the dimension along which inequality has been measured in all three empirical chapters. As such, endogeneity is naturally a significant issue in this study, since family income is correlated with many unobservables which impact on educational outcomes. Furthermore, other factors of interest included in the models, notably debt aversion, may also be endogenous. Various approaches have been adopted in the thesis to address this issue, including the use of panel data models where the time-invariant component of unobserved individual heterogeneity can be cancelled out, as well as the use of control variables to 'mop up' as much of the unobserved individual heterogeneity as possible. Nonetheless, there still remains some question as to how close the results achieved come to the true causal results of the factors examined. For example, in the ARE model in chapter 4, the family income variable unfortunately had to be split into the mean and the deviation from the mean for the Hausman test to accept the consistency of the model. Had it not been necessary to do this, it would have been much clearer that a statistically significant result on the family income variable would have been evidence of a direct, causal impact of family income on children's cognitive development in the first few years of school.

A more robust approach would have been to use instrumental variables or a differences-in-differences approach. For future work, the identification of a suitable instrument for family income for use with this data would be a substantial development. One possibility for applying a differences-in-differences approach to examine the effect of family and other income on participation in post-compulsory education could be to use the natural experiment arising from the removal of the EMA. Since this was removed in England in 2011 but not removed in Wales, it would be possible to find a city in England and a city in Wales with comparable characteristics and a comparable trajectory of participation rates for post-compulsory education before the removal of the EMA, and to apply a differences-in-differences approach to establish the causal impact of the change in income available to pupils on participation in post-compulsory education. This approach would require administrative data to be made available to the researcher as well as linkages between datasets, such as the Individual Learner Record and the National Pupil Database; however, the results would be very interesting and would be a more robust example of the estimation of causal effects.

A further limitation to the analysis in this thesis is the issue of missing data. Both data sets used, the LSYPE and the MCS, had significant amounts of missing data on key variables, notably family income in the LSYPE and teacher and school data in the MCS. This has implications for the results presented, since in the worst case, missing data can cause bias in the parameter estimates. In particular, the missing family income data in the LSYPE may be MNAR – which is a cause for concern. In the future, an important development of the analysis would be to use maximum likelihood or multiple imputation to find appropriate values for the missing observations where family income is missing in the LSYPE data. This would improve the reliability of the results attained. For the MCS data, it is unfortunate that so much school and teacher data is missing due to nonresponse on the teacher surveys, as this prevented the effective estimation of school fixed effects. One further issue related to missing data in this analysis is the impact of the large number of single parent households. For these households, data on the education and other characteristics of the child's other parent was necessarily missing. Although this kind of missingness is more benign in some sense, as it does not lead to biased parameter estimates, it nonetheless represents a loss of potential information.

Finally, as well as these two main issues that affect the thesis as a whole, there are also chapter specific limitations. The introductory chapter presented human capital theory as the framework for the analysis, however, the empirical chapters have included elements which indicate the limitations of this framework. Other theoretical perspectives, such as Bourdieu's work on cultural capital, or perspectives such as household decision making analysis, would help to rationalise the breadth of factors which have been shown to impact on children's educational outcomes.

For the debt aversion and university participation chapter, it is important to note that the results relate to a period before the recent substantial policy change which saw undergraduate fees increase to up to £9000 per annum. Especially given the finding that Callender and Jackson's (2003) results from a still earlier policy environment seem to be no longer valid for the higher income group, it would be important for future analysis to use data which relates to the current situation. Nonetheless, the implications of the findings in chapter four are still important, as the effects of debt aversion are likely to be only more severe in a policy environment with higher fees.

Regarding the chapter on factors affecting cognitive development, a future development could be to apply principle component analysis to examine the linkages and possible underlying structure behind many of the factors examined. For the trajectories chapter, a limitation of the analysis is the fact that only two time periods could be used – if data were available measuring a single skill over a longer time period, this would facilitate a substantially more robust assessment of these trends. Unfortunately however, pattern construction and picture similarity assessments have not been included in the design of the fifth wave of the survey. This demonstrates the difficulties in measuring a single skill over time, since as children develop, the most relevant skills to be tested also change.

Finally, two issues which are of key importance to the issue of inequalities in educational outcomes by family background, but which have not been addressed in this these, relate to educational quality (such as participation not just in university in general but in high quality institutions) and peer effects, which have also been shown to have important implications for children's cognitive development (Sacerdote, 2001). These two issues represent fruitful potential areas for future research.

6.6 Family Income and Children's Outcomes: Tying the Threads Together

Through the various strands of this thesis, we have been able to consider the question of whether education acts as a facilitator or hindrance to social mobility. Although education can provide a way out for young people from disadvantaged backgrounds, it can also act as a hindrance to mobility if it strengthens existing inequalities. This means that one of the key issues is access to education. The first element of this which was examined in the thesis is access to higher education, where university participation rates by family background were examined.

Although the results of the analysis in chapter three demonstrated that debt aversion does act as a barrier to participation, it was clear that the different participation rates between family income groups are not driven by this factor. The major cause of the gap in participation rates seems rather to be the fact that young people from different family backgrounds differ greatly in their achievement at school. For example, in the LSYPE data used in chapter three, less than a third of the males from disadvantaged backgrounds were taking two or more A-levels, compared to more than half of the males from advantaged backgrounds. This finding has implications for the way higher education is funded. Since government funds are limited, there is potentially a trade-off between subsidising higher education and investing more heavily in education before and during the school years. Reducing the cost of higher education to the individual student may be of limited effectiveness in increasing participation if the reasons for non-participation are, first and foremost, related to school attainment rather than the cost of studying.

A more effective way of achieving increased participation rates among non-traditional student groups may be to focus on raising ambitions and achievement during the school years. Naturally, this must be accompanied by mechanisms which maintain the accessibility of the system to qualified candidates, such as the current funding system where university participation is free at the point of entry and fees are repaid out of earnings after graduation, alongside increased information relating to grants and bursaries, the mechanisms of the funding system, and the expected returns to various degrees.

Since the gap in educational outcomes opens up well before age 18, I decided to explore earlier influences. Chapters 4 and 5 thus focused on outcomes at ages 5 and 7, the first few years of formal schooling. I found that children from disadvantaged families who score well initially do drop behind their peers from well-off backgrounds, and that this is a substantive finding and not merely a reflection of regression to the mean. Furthermore, factors which were shown to be important for children's cognitive development at these young ages included family income (and other money related factors such as car usage), family structure (such as the presence of the natural father and the number of siblings), the home learning environment, parental behaviours (such as taking the child to the library) and stability (such as not moving home and living in a home that was owned or mortgaged). It is thus clear that the environment young children grow up in has a strong influence on their educational outcomes.

The analysis also included variables surrounding or even previous to the child's birth, including breastfeeding, birthweight and days of gestation. These variables were statistically significant, despite the large range of other background characteristics controlled for, which means that having started to look at gaps in university participation at age 18, we have now come further and further back in time to factors surrounding the birth of the child. This finding supports other recent research, such as Carneiro and Heckman (2002) and Restuccia and Urrutia (2004). This second paper investigated the major sources of persistence and inequality in earnings across generations in order to identify effective mechanisms for increasing social mobility, and found that increasing public resources devoted to early education would have a greater impact than increasing resources devoted to college subsidies. Based on findings like this, governments in the UK, the US and other countries are now starting to invest more in the early years, in particular in programs relating to health and education for the first few years of a child's life. Some programs even start before birth, educating expectant mothers (and fathers) about early childhood health issues and good parenting practices.

The best approach appears to be found in programs that start early and continue to support children as they progress through school. Barr (2010) identifies three key sets of policies for increasing university participation as being 1) fostering early child development (e.g. through Sure-Start) 2) action to improve primary and secondary education outcomes and 3) policies to encourage staying on at age 16. Although this is very general, it highlights the need to start early and continue with young people as they grow up. More specifically, in terms of its outreach agenda, HEFCE has reported that outreach is most effective when it is delivered as a progressive, sustained programme of activity and engagement over time, and that outreach programs need to begin at primary level and reach young people at different stages of their educational career (HEFCE, 2013).

One very successful program in the Unites States is the Harlem Children's Zone, which also follows this framework. Focusing on an area of 100 of the most deprived blocks in Harlem, New York, the program starts with pre-birth classes for families, continues with high-quality pre-school, specially supported primary and secondary schools, a strong support system for college applications, and further support throughout the college years. All elements of the program are interconnected, so that young people do not fall through the net and early gains are further capitalised upon in later stages of the child's education. Since it is a neighbourhood program, it emphasises the children's whole environment, and integrates a wide range of services relating to health, education and social issues. The program boasts very positive results including improved school-readiness for four year olds, 100% of third graders being on grade level in maths (well above the New York State average), and 90% of their high school seniors being accepted into college (Fryer, 2011).

Naturally, such programs require a substantial financial commitment from government, or private sources. However, the return on these investments has been estimated as being very high. As mentioned briefly above, the economist James Heckman has strongly advocated investments in early education, and has estimated the return on such investments to be as high as 10%. Due to the high incarceration rates in the United States, programs which serve young children who would otherwise have had a high likelihood of future incarceration present large savings to government funds. Incarceration rates are much lower in the UK, but there is nonetheless a parallel argument to be made, as, in 2013, 47% of the UK prison population held no academic qualifications, compared to 15% for whole working age population (Berman and Dar, 2013). There are also sizeable exchequer benefits from the increased employment rates and higher wage levels of better qualified individuals. In terms of returns to higher education, the net exchequer benefit to a degree (compared to someone holding two A-levels), has been estimated at £102,000 for men and £59,000 for women, whilst the associated rate of return to the Exchequer from the funding of these qualifications stands at 11.4% for men and 9.6% for women (Conlon and Patrigiani, 2011). There are also other social benefits of a highly qualified and skilled workforce, including improved health outcomes, and education-related spillovers, whereby the labour market outcomes of those with lower levels of qualification attainment are improved by there being a greater proportion of more highly qualified workers in the labour force (Conlon and Patrigiani, 2011). Finally, globalisation serves to further increase the need for a highly educated and skilled workforce due to pressures to maintain international competitiveness (Leitch, 2005).

The UK still demonstrates large educational attainment gaps between young people from different family backgrounds, despite many years of policies designed to address this issue. Understanding the barriers facing children from disadvantaged backgrounds can help facilitate improved education attainment and lead to greater social mobility. This thesis has highlighted several key issues – firstly, the fact that debt aversion poses a barrier to university participation to young people from all social backgrounds. Improved information regarding higher education funding mechanisms was suggested as a possible approach to addressing this issue.

We also saw that gaps in educational attainment open up very early, and also that children from poor families who score well on early tests do have a tendency to drop behind their peers from higher income families. This means it is important to start to support such children early and in a sustained way, so that early gains can be made and further capitalised upon, not allowing such students to drop behind.

Finally, analysing the specific factors that are important for children's early development highlighted the importance of family and the home learning environment, as well as stability, and the role of money itself. Programs such as Sure Start which integrate family and professional services and try to encourage children's development from the very early years should be further supported and even increased, as is currently happening in the US. It is also important that programs which start early continue to follow through. Several UK programs (such as HEFCE's outreach activity) have highlighted the importance of sustained, long-term programs which continue with children throughout school. Continued support for non-traditional students in terms of awareness of higher education, the application process and support throughout the university years would be an important mechanism for encouraging success in higher education.

The success of these students in the labour market also depends on the opportunities that are opened up to them, although analysis of such issues lies beyond the scope of this research. Social mobility is a major aim of the current coalition government. There is potential for education to play an important, positive role in achieving these aims, however, if this is to be realised, it is important to ensure that children from disadvantaged backgrounds are given a strong start to their educational career, such that opportunities for higher education are not closed to them from the outset. If this remains the case, education will continue to act as a force for maintaining current inequalities and stifling social mobility in the future.

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Appendix A:
Effects of Debt Aversion on University Participation, Males (1-3) and Females (4-6)

	(1) atuni	(2) atuni	(3) atuni	(4) atuni	(5) atuni	(6) atuni
alwayswrong						
Strongly Agree		0.353***			0.375***	
		(0.075)			(0.079)	
Agree		0.409***			0.371***	
		(0.063)			(0.055)	
Disagree		0.857			0.764**	
		(0.115)			(0.099)	
Missing		0.566**			0.598**	
		(0.161)			(0.130)	
*base category Strongly Disagree						
hardout						
Strongly Agree			0.937			0.347***
			(0.265)			(0.113)
Agree			1.511			0.469**
			(0.405)			(0.149)
Disagree			1.969**			0.708
			(0.538)			(0.230)
Missing			2.463***			0.605
			(0.790)			(0.227)
*base category Strongly Disagree						
Family Income Groups						
2: £10,400 to £25,999	1.188	1.151	1.165	1.409**	1.372**	1.376**
	(0.211)	(0.202)	(0.208)	(0.223)	(0.217)	(0.217)
3: £26,000 to £41,599	1.591**	1.506**	1.540**	1.605***	1.591***	1.566***
	(0.287)	(0.268)	(0.280)	(0.275)	(0.273)	(0.267)
4: £41,600 and above	1.949***	1.850***	1.861***	1.771***	1.725***	1.718***
	(0.353)	(0.330)	(0.340)	(0.303)	(0.297)	(0.293)
Missing	1.564**	1.505**	1.541**	1.305	1.300	1.306
	(0.287)	(0.274)	(0.284)	(0.224)	(0.223)	(0.224)
*base category, up to £10,399						
Key Stage 2 Test Scores						
2	2.216*	2.213*	2.186	1.253	1.197	1.252
	(1.044)	(1.051)	(1.040)	(0.433)	(0.420)	(0.435)
3	3.508***	3.399***	3.465***	2.826***	2.743***	2.840***
	(1.511)	(1.474)	(1.505)	(0.922)	(0.907)	(0.934)
4	6.779***	6.526***	6.719***	3.805***	3.509***	3.745***
	(2.849)	(2.758)	(2.840)	(1.222)	(1.139)	(1.217)
5	8.283***	8.066***	8.157***	6.383***	5.945***	6.181***
	(3.476)	(3.402)	(3.459)	(2.004)	(1.886)	(1.963)
6	13.599***	12.646***	13.151***	5.896***	5.268***	5.640***
	(5.626)	(5.270)	(5.503)	(1.839)	(1.663)	(1.776)
7	15.073***	13.471***	14.643***	8.226***	7.072***	7.811***
	(6.230)	(5.610)	(6.114)	(2.545)	(2.214)	(2.441)
8	21.869***	19.437***	21.379***	14.881***	12.708***	14.119***
	(8.984)	(8.037)	(8.862)	(4.600)	(3.973)	(4.410)
9	30.212***	26.389***	28.630***	18.646***	15.277***	17.670***
	(12.384)	(10.891)	(11.844)	(5.792)	(4.801)	(5.536)
10	60.560***	49.064***	56.350***	26.367***	21.700***	25.079***
	(24.959)	(20.312)	(23.426)	(8.227)	(6.854)	(7.919)
Missing	17.327***	15.900***	17.344***	6.959***	6.338***	6.890***
	(7.380)	(6.817)	(7.454)	(2.402)	(2.232)	(2.394)
*quartiles, base category lowest scores						

Ethnicity						
mixed	0.749	0.711	0.739	1.485*	1.483	1.486
	(0.178)	(0.177)	(0.186)	(0.351)	(0.355)	(0.358)
indian	4.394***	4.399***	4.152***	5.867***	5.894***	5.789***
	(0.869)	(0.881)	(0.842)	(1.221)	(1.254)	(1.219)
pakistani	2.787***	2.788***	2.746***	3.645***	3.712***	3.751***
	(0.574)	(0.569)	(0.568)	(0.677)	(0.679)	(0.707)
bangladeshi	3.432***	3.664***	3.608***	4.792***	4.977***	4.860***
	(0.857)	(0.950)	(0.902)	(0.963)	(0.990)	(0.985)
black caribbean	1.276	1.250	1.284	2.209**	2.206**	2.155**
	(0.323)	(0.324)	(0.325)	(0.685)	(0.684)	(0.681)
black african	2.609***	2.491***	2.578***	5.661***	5.928***	5.510***
	(0.740)	(0.741)	(0.741)	(1.740)	(1.815)	(1.754)
otheth	1.510	1.580	1.511	3.908***	3.794***	3.720***
	(0.520)	(0.555)	(0.522)	(1.043)	(1.025)	(0.987)
*base category white						
Long-standing health problem or disability						
Yes	0.887	0.888	0.904	0.816	0.826	0.837
	(0.154)	(0.159)	(0.157)	(0.129)	(0.133)	(0.133)
Missing	0.979	1.128	0.992	1.351	1.366	1.244
	(0.419)	(0.522)	(0.444)	(0.547)	(0.557)	(0.522)
Siblings						
1	0.838	0.780	0.820	1.005	0.985	0.956
	(0.132)	(0.125)	(0.131)	(0.146)	(0.143)	(0.140)
2	0.680**	0.642***	0.671**	0.778*	0.757*	0.742*
	(0.112)	(0.107)	(0.112)	(0.118)	(0.116)	(0.114)
3	0.616***	0.596***	0.602***	0.758	0.725*	0.720*
	(0.116)	(0.113)	(0.114)	(0.128)	(0.124)	(0.123)
4 or more	0.557***	0.553***	0.551***	0.420***	0.408***	0.405***
	(0.117)	(0.117)	(0.118)	(0.082)	(0.079)	(0.080)
Missing	0.589	0.555	0.615	1.232	1.377	1.190
	(0.270)	(0.269)	(0.282)	(0.523)	(0.574)	(0.489)
Non traditional family						
Yes	0.650***	0.649***	0.647***	0.675***	0.682***	0.692***
	(0.086)	(0.087)	(0.087)	(0.086)	(0.088)	(0.089)
Missing	0.543**	0.511**	0.520**	0.547**	0.556**	0.535**
	(0.156)	(0.151)	(0.150)	(0.143)	(0.147)	(0.146)
Father has a degree						
Yes	1.996***	1.903***	1.963***	1.562***	1.549***	1.548***
	(0.257)	(0.250)	(0.255)	(0.200)	(0.202)	(0.199)
Missing	0.961	0.993	0.978	0.891	0.880	0.873
	(0.132)	(0.138)	(0.135)	(0.119)	(0.120)	(0.119)
Mother has a degree						
Yes	1.374**	1.329**	1.364**	1.248*	1.210	1.234*
	(0.171)	(0.169)	(0.171)	(0.159)	(0.155)	(0.158)
Missing	0.738	0.737	0.718	0.629**	0.628**	0.656**
	(0.150)	(0.152)	(0.147)	(0.122)	(0.125)	(0.128)
Urban indicator						
Yes	0.792**	0.794**	0.783**	0.869	0.854	0.879
	(0.084)	(0.085)	(0.084)	(0.087)	(0.087)	(0.088)
Missing	1.417	1.480	1.396	0.000***	0.000***	0.000***
	(0.566)	(0.591)	(0.561)	(0.000)	(0.000)	(0.000)

Region						
NorthEast	0.797	0.757	0.795	1.112	1.105	1.104
	(0.185)	(0.177)	(0.188)	(0.232)	(0.233)	(0.233)
NorthWest	0.742*	0.734*	0.736*	1.298	1.291	1.281
	(0.119)	(0.120)	(0.119)	(0.210)	(0.212)	(0.208)
YorkandH	0.660**	0.675**	0.657**	1.201	1.152	1.180
	(0.121)	(0.125)	(0.121)	(0.205)	(0.197)	(0.203)
EastMid	0.537***	0.550***	0.514***	1.032	1.050	1.027
	(0.101)	(0.104)	(0.098)	(0.182)	(0.187)	(0.180)
WestMid	0.530***	0.523***	0.534***	1.048	1.042	1.045
	(0.093)	(0.092)	(0.094)	(0.178)	(0.178)	(0.178)
EastofEng	0.589***	0.571***	0.568***	0.796	0.769	0.783
	(0.103)	(0.100)	(0.100)	(0.135)	(0.132)	(0.134)
SthEast	0.501***	0.494***	0.495***	0.898	0.888	0.873
	(0.082)	(0.081)	(0.081)	(0.145)	(0.145)	(0.141)
SthWest	0.398***	0.387***	0.404***	0.856	0.792	0.813
	(0.081)	(0.079)	(0.083)	(0.161)	(0.150)	(0.152)
* base category, London						
Oberservations	4920	4920	4920	4869	4869	4869
R-squared	0.234	0.249	0.242	0.201	0.215	0.209

Exponentiated coefficients; Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Appendix B:
Rates of Development for Income-Ability Groups (Validation using alternative tests)

	(1)		(2)	
Dependent Variable:	Naming Vocabulary		Naming Vocabulary	
Ability groups divided by:	Naming Vocabulary (age 3)		Bracken School Readiness (age 3)	
time	0.058**	(0.024)	-0.025	(0.026)
Low Ability, Low Income (LALY)	-1.203***	(0.025)	-1.045***	(0.038)
Low Ability Average Income (LAAY)	-0.975***	(0.021)	-0.709***	(0.035)
Low Ability, High Income (LAHY)	-0.903***	(0.030)	-0.566***	(0.067)
Average Ability, Low Income (AALY)	-0.100***	(0.016)	-0.283***	(0.046)
Average Ability, Average Income (AAAY)#				
Average Ability, High Income (AAHY)	-0.037**	(0.016)	0.057	(0.040)
High Ability, Low Income (HALY)	1.061***	(0.033)	0.252***	(0.063)
High Ability, Average Income (HAAY)	1.086***	(0.019)	0.536***	(0.036)
High Ability, High Income (HAHY)	1.146***	(0.024)	0.562***	(0.039)
LALY*time	0.261***	(0.040)	0.071*	(0.041)
LAAY*time	0.491***	(0.040)	0.122***	(0.041)
LAHY*time	0.761***	(0.065)	0.127	(0.077)
AALY*time	-0.085*	(0.044)	0.008	(0.052)
AAAY*time#				
AAHY*time	0.272***	(0.047)	0.152***	(0.048)
HALY*time	-0.796***	(0.057)	-0.126*	(0.068)
HAAY*time	-0.538***	(0.034)	-0.130***	(0.040)
HAHY*time	-0.371***	(0.038)	0.052	(0.044)
constant	-0.108***	(0.012)	0.105***	(0.023)
N	11,986		11,986	
r2	0.528		0.284	

Standard errors in parentheses
Reference case
* p<0.10, ** p<0.05, *** p<0.010

Appendix C: Examples of STATA Output

Raw Output for Table 3.4 (Columns 1 to 6)

```
. **** Males
. logit atuni i.famincgrps  i.key2 mixed indian pakistani bangladeshi blcaribbean blafrican ///
> otheth i.hlthprobdisab i.urban i.siblings i.brokenhome i.fathdegree i.mothdegree NorthEast NorthWest Yorkand
> H ///
> EastMid WestMid EastofEng SthEast SthWest RegMiss [pweight = w6finwt_cross] if male ==1, or

note: RegMiss omitted because of collinearity
Iteration 0:   log pseudolikelihood = -2774.7585
Iteration 1:   log pseudolikelihood = -2190.5882
Iteration 2:   log pseudolikelihood = -2128.3216
Iteration 3:   log pseudolikelihood = -2124.8936
Iteration 4:   log pseudolikelihood = -2124.8556
Iteration 5:   log pseudolikelihood = -2124.8556

Logistic regression                               Number of obs   =       4920
                                                  Wald chi2(44)   =     724.34
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -2124.8556                 Pseudo R2       =     0.2342

------------------------------------------------------------------------------
             |               Robust
       atuni | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  famincgrps |
          2  |   1.187566   .2107541     0.97   0.333     .8386823    1.681583
          3  |   1.590686   .2869752     2.57   0.010     1.116913    2.265424
          4  |   1.949478   .3530222     3.69   0.000     1.367031    2.780089
        999  |   1.564113   .2866978     2.44   0.015     1.092056    2.240222
             |
        key2 |
          1  |   2.216411   1.044366     1.69   0.091     .8801704    5.581279
          2  |   3.508022   1.510561     2.91   0.004     1.508458    8.158141
          3  |   6.779403   2.849496     4.55   0.000     2.974522    15.45132
          4  |    8.28349   3.475697     5.04   0.000      3.63961    18.85262
          5  |    13.5991   5.625839     6.31   0.000     6.044706    30.59465
          6  |   15.07335   6.230488     6.56   0.000     6.704556    33.88826
          7  |    21.8686   8.984079     7.51   0.000      9.77529    48.92293
          8  |   30.21232   12.38393     8.31   0.000     13.52943    67.46658
          9  |   60.55969    24.9591     9.96   0.000     27.00033    135.8308
        999  |   17.32674   7.380312     6.70   0.000     7.518791    39.92873
             |
       mixed |   .7489349   .1784887    -1.21   0.225     .4694431    1.194828
      indian |   4.393731   .8694008     7.48   0.000     2.981286     6.47535
   pakistani |   2.786632   .5736633     4.98   0.000      1.86144    4.171673
 bangladeshi |   3.432458   .8572705     4.94   0.000     2.103847    5.600107
 blcaribbean |   1.276237   .3233256     0.96   0.336     .7767571    2.096897
   blafrican |   2.609015   .7400851     3.38   0.001     1.496308    4.549171
      otheth |   1.509672   .5202767     1.20   0.232     .7683053    2.966411
             |
hlthprobdi~b |
          1  |   .8866818   .1536849    -0.69   0.488     .6312953    1.245383
        999  |   .9794403   .4186264    -0.05   0.961     .4238016    2.263567
             |
       urban |
          1  |     .79243   .0842632    -2.19   0.029     .6433514    .9760533
        999  |   1.417179    .565762     0.87   0.382     .6480532    3.099124
             |
    siblings |
          1  |   .8379626   .1317975    -1.12   0.261     .6156656    1.140524
          2  |   .6802134   .1119939    -2.34   0.019     .4926051    .9392722
          3  |   .6159177   .1155037    -2.58   0.010     .4264774     .889507
          4  |   .5571091   .1172069    -2.78   0.005     .3688595     .841433
        999  |    .589458    .269562    -1.16   0.248     .2405438     1.44448
             |
  brokenhome |
          1  |   .6501754   .0860709    -3.25   0.001     .5015885    .8427787
         99  |    .543193   .1563945    -2.12   0.034     .3089432    .9550577
             |
  fathdegree |
          1  |    1.99605   .2570592     5.37   0.000      1.55078    2.569168
        999  |   .9614263   .1319543    -0.29   0.774     .7346659    1.258178
             |
  mothdegree |
          1  |   1.373908   .1713399     2.55   0.011     1.075981    1.754329
        999  |    .737726   .1495158    -1.50   0.133     .4958851    1.097512
             |
   NorthEast |   .7974669   .1854115    -0.97   0.330     .5056009    1.257817
   NorthWest |   .7420872   .1193727    -1.85   0.064     .5414146    1.017138
    YorkandH |   .6602177   .1212618    -2.26   0.024      .460625    .9462956
     EastMid |   .5365069   .1005158    -3.32   0.001     .3716215    .7745506
     WestMid |   .5302583   .0931589    -3.61   0.000     .3757884    .7482239
   EastofEng |   .5890632   .1032073    -3.02   0.003     .4178558    .8304191
     SthEast |    .501046   .0818739    -4.23   0.000     .3637358    .6901906
     SthWest |   .3981678   .0810437    -4.52   0.000     .2671844    .5933638
     RegMiss |  (omitted)
------------------------------------------------------------------------------
```

```
. logit atuni ib(4).alwayswrong i.famincgrps  i.key2 mixed indian pakistani bangladeshi blcaribbean blafrican
> ///
> otheth i.hlthprobdisab i.urban i.siblings i.brokenhome i.fathdegree i.mothdegree NorthEast NorthWest Yorkand
> H ///
> EastMid WestMid EastofEng SthEast SthWest RegMiss [pweight = w6finwt_cross] if male ==1, or

note: RegMiss omitted because of collinearity
Iteration 0:   log pseudolikelihood = -2774.7585
Iteration 1:   log pseudolikelihood = -2156.3234
Iteration 2:   log pseudolikelihood = -2086.3583
Iteration 3:   log pseudolikelihood = -2082.8779
Iteration 4:   log pseudolikelihood = -2082.8384
Iteration 5:   log pseudolikelihood = -2082.8384

Logistic regression                               Number of obs   =       4920
                                                  Wald chi2(48)   =     750.08
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -2082.8384                 Pseudo R2       =     0.2494
```

atuni	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
alwayswrong						
1	.3532834	.0747927	-4.91	0.000	.2333016	.5349692
2	.4085828	.0628377	-5.82	0.000	.3022527	.5523189
3	.8566094	.1148257	-1.15	0.248	.6586916	1.113996
999	.5662432	.1614091	-2.00	0.046	.3238663	.9900115
famincgrps						
2	1.151036	.2018788	0.80	0.423	.8162021	1.62323
3	1.506163	.2678657	2.30	0.021	1.062891	2.134298
4	1.850214	.3302935	3.45	0.001	1.303972	2.625278
999	1.504712	.2742397	2.24	0.025	1.052733	2.150741
key2						
1	2.212658	1.050547	1.67	0.094	.872514	5.611205
2	3.399158	1.474415	2.82	0.005	1.45263	7.954036
3	6.526239	2.757703	4.44	0.000	2.850903	14.93976
4	8.066121	3.401856	4.95	0.000	3.529179	18.43554
5	12.64634	5.269696	6.09	0.000	5.58819	28.61925
6	13.47059	5.610345	6.24	0.000	5.95485	30.47209
7	19.43657	8.036715	7.18	0.000	8.642937	43.70972
8	26.38937	10.89051	7.93	0.000	11.75304	59.25264
9	49.06431	20.31218	9.40	0.000	21.79596	110.4474
999	15.90038	6.817399	6.45	0.000	6.861974	36.84394
mixed	.7114096	.1768591	-1.37	0.171	.4370265	1.158062
indian	4.398962	.8805961	7.40	0.000	2.971353	6.512474
pakistani	2.78776	.5685651	5.03	0.000	1.869186	4.15775
bangladeshi	3.664262	.9495184	5.01	0.000	2.205033	6.089168
blcaribbean	1.250183	.3237997	0.86	0.389	.7525071	2.076999
blafrican	2.491098	.740786	3.07	0.002	1.390805	4.461855
otheth	1.579872	.5548868	1.30	0.193	.7937082	3.144729
hlthprobdi~b						
1	.8878565	.1591447	-0.66	0.507	.6248392	1.261587
999	1.127761	.52161	0.26	0.795	.4555345	2.791986
urban						
1	.7941845	.0852677	-2.15	0.032	.6434756	.980191
999	1.479734	.5908475	0.98	0.326	.6765577	3.236403
siblings						
1	.7798686	.1249173	-1.55	0.121	.5697419	1.067492
2	.6416442	.1073251	-2.65	0.008	.4622932	.8905763
3	.5962011	.1129944	-2.73	0.006	.4112157	.8644022
4	.5529307	.1171998	-2.80	0.005	.3649633	.8377073
999	.5552873	.2686767	-1.22	0.224	.2151109	1.433419
brokenhome						
1	.6493416	.0871197	-3.22	0.001	.4991956	.844648
99	.5107787	.1506867	-2.28	0.023	.2864948	.9106447
fathdegree						
1	1.903163	.2503345	4.89	0.000	1.47066	2.46286
999	.9927521	.1383546	-0.05	0.958	.7554633	1.304573
mothdegree						
1	1.329151	.1685989	2.24	0.025	1.036578	1.704303
999	.7370075	.1520947	-1.48	0.139	.4918256	1.104416
NorthEast	.7571056	.1767641	-1.19	0.233	.479097	1.196436
NorthWest	.7338815	.120304	-1.89	0.059	.5322184	1.011957
YorkandH	.674525	.1254752	-2.12	0.034	.4684438	.971267
EastMid	.5499938	.1038674	-3.17	0.002	.3798453	.7963589
WestMid	.523487	.0921576	-3.68	0.000	.3707282	.7391901
EastofEng	.5709236	.1002316	-3.19	0.001	.4047069	.805407
SthEast	.4935024	.0810642	-4.30	0.000	.3576583	.6809421
SthWest	.386643	.0792343	-4.64	0.000	.2587464	.5777581
RegMiss	(omitted)					

```
. logit atuni ib(4).hardout i.famincgrps  i.key2 mixed indian pakistani bangladeshi blcaribbean blafrican ///
> otheth i.hlthprobdisab i.urban i.siblings i.brokenhome i.fathdegree i.mothdegree NorthEast NorthWest Yorkand
> H ///
> EastMid WestMid EastofEng SthEast SthWest RegMiss [pweight = w6finwt_cross] if male ==1, or

note: RegMiss omitted because of collinearity
Iteration 0:   log pseudolikelihood = -2774.7585
Iteration 1:   log pseudolikelihood = -2170.7707
Iteration 2:   log pseudolikelihood = -2105.5404
Iteration 3:   log pseudolikelihood = -2102.1236
Iteration 4:   log pseudolikelihood = -2102.0853
Iteration 5:   log pseudolikelihood = -2102.0852

Logistic regression                               Number of obs   =       4920
                                                  Wald chi2(48)   =     749.64
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -2102.0852                 Pseudo R2       =     0.2424

------------------------------------------------------------------------------
             |               Robust
       atuni | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     hardout |
          1  |   .9366402   .2652046    -0.23   0.817     .5377244    1.631495
          2  |   1.510669   .4049677     1.54   0.124     .8932768    2.554773
          3  |   1.969081   .5381578     2.48   0.013     1.152462    3.364344
        999  |    2.46328    .790023     2.81   0.005     1.313762    4.618608
             |
  famincgrps |
          2  |   1.164866   .2080393     0.85   0.393     .8208349     1.65309
          3  |   1.539595   .2800569     2.37   0.018      1.07788    2.199088
          4  |   1.860937    .339575     3.40   0.001     1.301393    2.661061
        999  |   1.541358   .2836948     2.35   0.019     1.074572    2.210912
             |
        key2 |
          1  |   2.185552   1.039661     1.64   0.100     .8602939     5.55233
          2  |   3.465367   1.504546     2.86   0.004     1.479742    8.115446
          3  |   6.718651   2.839962     4.51   0.000     2.934139    15.38451
          4  |   8.157131   3.458993     4.95   0.000     3.552953    18.72774
          5  |    13.1509   5.502677     6.16   0.000     5.791491    29.86209
          6  |   14.64323   6.114057     6.43   0.000     6.459974    33.19274
          7  |   21.37924   8.862175     7.39   0.000      9.48746    48.17641
          8  |   28.63042   11.84385     8.11   0.000      12.7263       64.41
          9  |   56.34966    23.4258     9.70   0.000     24.94756    127.2784
        999  |   17.34389   7.453828     6.64   0.000     7.470135    40.26843
             |
       mixed |   .7386006   .1855424    -1.21   0.228     .4514202    1.208477
      indian |   4.151662   .8424742     7.01   0.000     2.789281    6.179476
   pakistani |   2.745935   .5676594     4.89   0.000     1.831149    4.117719
 bangladeshi |   3.607823   .9017296     5.13   0.000     2.210539    5.888332
 blcaribbean |   1.283714   .3250482     0.99   0.324     .7815131     2.10863
   blafrican |   2.578133   .7409463     3.30   0.001     1.467821    4.528326
      otheth |   1.510609    .522071     1.19   0.233     .7673157    2.973924
             |
hlthprobdi~b |
          1  |   .9038448   .1574549    -0.58   0.562     .6424062     1.27168
        999  |   .9917109   .4435749    -0.02   0.985     .4127219    2.382937
             |
       urban |
          1  |    .783428   .0836053    -2.29   0.022     .6355667    .9656884
        999  |   1.395547   .5614529     0.83   0.407     .6342951     3.07042
             |
    siblings |
          1  |   .8198033   .1306795    -1.25   0.213     .5998259    1.120454
          2  |   .6712014   .1119874    -2.39   0.017     .4839863    .9308347
          3  |   .6024992   .1140179    -2.68   0.007     .4157896    .8730502
          4  |   .5511705   .1176159    -2.79   0.005     .3627818    .8373874
        999  |   .6146697   .2820065    -1.06   0.289     .2501013    1.510663
             |
  brokenhome |
          1  |     .64728   .0865193    -3.25   0.001     .4980989    .8411412
         99  |    .520477   .1498648    -2.27   0.023     .2960116    .9151543
             |
  fathdegree |
          1  |   1.963431   .2551518     5.19   0.000      1.52195    2.532975
        999  |   .9779175   .1348664    -0.16   0.871     .7462966    1.281424
             |
  mothdegree |
          1  |   1.363605   .1708541     2.48   0.013     1.066686    1.743174
        999  |   .7177233   .1473495    -1.62   0.106     .4799592    1.073272
             |
   NorthEast |   .7953109   .1875352    -0.97   0.331     .5009826    1.262558
   NorthWest |   .7362317   .1189977    -1.89   0.058     .5363325    1.010636
    YorkandH |   .6566932   .1209863    -2.28   0.022     .4576577    .9422892
     EastMid |   .5140024   .0976662    -3.50   0.000     .3541826    .7459385
     WestMid |   .5336624   .0944837    -3.55   0.000     .3771927    .7550398
   EastofEng |    .567842   .0998303    -3.22   0.001     .4023285     .801446
     SthEast |   .4954457   .0811815    -4.29   0.000     .3593536    .6830777
     SthWest |    .403853   .0828336    -4.42   0.000     .2701685    .6036871
     RegMiss |  (omitted)
------------------------------------------------------------------------------
```

```
. **** Females
. logit atuni i.famincgrps  i.key2 mixed indian pakistani bangladeshi blcaribbean blafrican ///
> otheth i.hlthprobdisab i.urban i.siblings i.brokenhome i.fathdegree i.mothdegree NorthEast NorthWest Yorkand
> H ///
> EastMid WestMid EastofEng SthEast SthWest RegMiss [pweight = w6finwt_cross] if male ==0, or

Iteration 0:   log pseudolikelihood = -2987.9646
Iteration 1:   log pseudolikelihood = -2422.6385
Iteration 2:   log pseudolikelihood =  -2387.038
Iteration 3:   log pseudolikelihood = -2386.1088
Iteration 4:   log pseudolikelihood = -2386.1038
Iteration 5:   log pseudolikelihood = -2386.1033
Iteration 6:   log pseudolikelihood = -2386.1032
Iteration 7:   log pseudolikelihood = -2386.1031

Logistic regression                               Number of obs   =       4869
                                                  Wald chi2(45)   =     882.08
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -2386.1031                 Pseudo R2       =     0.2014

------------------------------------------------------------------------------
             |               Robust
       atuni | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  famincgrps |
          2  |   1.408881   .2227919     2.17   0.030     1.033405    1.920783
          3  |   1.605268   .2753218     2.76   0.006     1.146982    2.246665
          4  |   1.770755   .3034683     3.33   0.001     1.265556    2.477625
        999  |   1.304773   .2237667     1.55   0.121      .932299    1.826059
             |
        key2 |
          1  |   1.253246   .4331474     0.65   0.514     .6365665     2.46734
          2  |   2.825691   .9220425     3.18   0.001     1.490636    5.356457
          3  |   3.804779   1.222147     4.16   0.000     2.027271    7.140802
          4  |   6.383172    2.00423     5.90   0.000     3.449616    11.81143
          5  |   5.895758   1.839311     5.69   0.000     3.198812    10.86652
          6  |   8.226109   2.545076     6.81   0.000     4.485814    15.08508
          7  |   14.88148    4.60022     8.73   0.000     8.119317    27.27551
          8  |   18.64614   5.791958     9.42   0.000     10.14342    34.27626
          9  |   26.36734   8.226735    10.49   0.000     14.30499      48.601
        999  |   6.959099   2.402013     5.62   0.000     3.537945    13.68847
             |
       mixed |   1.484768   .3510998     1.67   0.095     .9340647    2.360154
      indian |    5.86739    1.22089     8.50   0.000     3.902353    8.821926
   pakistani |   3.645361   .6773047     6.96   0.000     2.532725    5.246782
 bangladeshi |   4.791644   .9628769     7.80   0.000     3.231739    7.104488
 blcaribbean |   2.208733    .685187     2.55   0.011     1.202502    4.056958
   blafrican |     5.6609   1.739818     5.64   0.000       3.0994    10.33935
      otheth |     3.9081   1.043266     5.11   0.000     2.315995     6.59468
             |
hlthprobdi~b |
          1  |   .8160239   .1291493    -1.28   0.199     .5983924    1.112806
        999  |   1.350851   .5472176     0.74   0.458     .6106516    2.988282
             |
       urban |
          1  |   .8689389    .087306    -1.40   0.162     .7136174    1.058067
        999  |   .0000777   .0000854    -8.61   0.000     9.02e-06    .0006698
             |
    siblings |
          1  |   1.004953   .1458397     0.03   0.973     .7561689    1.335589
          2  |    .778222   .1180534    -1.65   0.098     .5780686    1.047678
          3  |   .7579232   .1284301    -1.64   0.102     .5437373     1.05648
          4  |   .4204465   .0821145    -4.44   0.000     .2867268    .6165284
        999  |   1.232439   .5226018     0.49   0.622     .5368132    2.829488
             |
  brokenhome |
          1  |   .6754279   .0858809    -3.09   0.002     .5264395    .8665817
         99  |   .5474797    .143291    -2.30   0.021     .3277815    .9144324
             |
  fathdegree |
          1  |   1.562296   .1999016     3.49   0.000     1.215763    2.007602
        999  |   .8910443   .1194291    -0.86   0.389     .6851891    1.158746
             |
  mothdegree |
          1  |   1.247851   .1585946     1.74   0.081     .9727019    1.600831
        999  |   .6287815   .1221283    -2.39   0.017     .4297054    .9200865
             |
   NorthEast |   1.111624   .2320708     0.51   0.612     .7383378    1.673636
   NorthWest |   1.298159   .2099165     1.61   0.107     .9455527    1.782255
    YorkandH |   1.201302    .205167     1.07   0.283     .8595629    1.678906
     EastMid |   1.031626   .1816754     0.18   0.860     .7305006     1.45688
     WestMid |   1.047638   .1778578     0.27   0.784     .7511086    1.461235
   EastofEng |   .7962687   .1352444    -1.34   0.180     .5708015    1.110796
     SthEast |   .8984453   .1446131    -0.67   0.506     .6553643    1.231687
     SthWest |   .8562829   .1609919    -0.83   0.409     .5923531     1.23781
     RegMiss |   35308.62   36883.23    10.02   0.000     4557.421    273553.5
------------------------------------------------------------------------------
```

```
. logit atuni ib(4).alwayswrong i.famincgrps  i.key2 mixed indian pakistani bangladeshi blcaribbean blafrican
> ///
> otheth i.hlthprobdisab i.urban i.siblings i.brokenhome i.fathdegree i.mothdegree NorthEast NorthWest Yorkand
> H ///
> EastMid WestMid EastofEng SthEast SthWest RegMiss [pweight = w6finwt_cross] if male ==0, or

Iteration 0:   log pseudolikelihood = -2987.9646
Iteration 1:   log pseudolikelihood = -2386.1056
Iteration 2:   log pseudolikelihood = -2345.7939
Iteration 3:   log pseudolikelihood = -2344.7406
Iteration 4:   log pseudolikelihood = -2344.7348
Iteration 5:   log pseudolikelihood = -2344.7342
Iteration 6:   log pseudolikelihood = -2344.7342

Logistic regression                               Number of obs   =       4869
                                                  Wald chi2(49)   =     901.56
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -2344.7342                 Pseudo R2       =     0.2153

------------------------------------------------------------------------------
             |               Robust
       atuni | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 alwayswrong |
          1  |   .3754615   .0786304    -4.68   0.000       .24906    .5660136
          2  |   .3711711   .0554349    -6.64   0.000     .2769784    .4973961
          3  |   .7644736   .0993353    -2.07   0.039     .5925947    .9862051
        999  |   .5980475    .130166    -2.36   0.018     .3903645    .9162227
             |
  famincgrps |
          2  |   1.372123   .2169829     2.00   0.045     1.006438    1.870679
          3  |   1.590693   .2731041     2.70   0.007     1.136174    2.227041
          4  |   1.724997   .2967944     3.17   0.002     1.231217    2.416806
        999  |   1.300347    .222639     1.53   0.125     .9296531    1.818854
             |
        key2 |
          1  |   1.196948    .420489     0.51   0.609     .6012395    2.382886
          2  |   2.743189   .9073016     3.05   0.002     1.434575    5.245514
          3  |   3.509042   1.138623     3.87   0.000     1.857755    6.628094
          4  |   5.945195   1.886372     5.62   0.000     3.192164    11.07253
          5  |   5.267588   1.662827     5.26   0.000     2.837343    9.779391
          6  |   7.071672   2.213517     6.25   0.000     3.829005    13.06046
          7  |   12.70818   3.972728     8.13   0.000     6.886328    23.45196
          8  |   15.27691   4.800923     8.68   0.000     8.251576    28.28357
          9  |   21.69999   6.854387     9.74   0.000     11.68396    40.30223
        999  |    6.33824   2.232419     5.24   0.000     3.178069    12.64079
             |
       mixed |    1.48262   .3549976     1.64   0.100     .9272969    2.370506
      indian |   5.893625   1.253981     8.34   0.000     3.883945    8.943178
   pakistani |   3.711945    .678873     7.17   0.000     2.593739    5.312228
 bangladeshi |   4.977111   .9898776     8.07   0.000      3.37043    7.349696
 blcaribbean |   2.206344   .6835961     2.55   0.011     1.202109    4.049513
   blafrican |   5.927616   1.815226     5.81   0.000     3.252482    10.80302
      otheth |   3.793791   1.024935     4.94   0.000     2.234148    6.442212
             |
hlthprobdi~b |
          1  |   .8262623   .1331441    -1.18   0.236     .6024973    1.133133
        999  |   1.365889   .5574841     0.76   0.445     .6137618    3.039703
             |
       urban |
          1  |     .85438   .0866715    -1.55   0.121     .7003289    1.042318
        999  |   5.43e-07   8.10e-07    -9.68   0.000     2.93e-08    .0000101
             |
    siblings |
          1  |   .9854958   .1433782    -0.10   0.920     .7409941    1.310674
          2  |    .756734   .1155869    -1.82   0.068     .5609536    1.020844
          3  |    .725172   .1240646    -1.88   0.060     .5185789    1.014068
          4  |   .4081816   .0794016    -4.61   0.000     .2787875    .5976317
        999  |   1.376769   .5736443     0.77   0.443     .6084147    3.115462
             |
  brokenhome |
          1  |   .6821521   .0883817    -2.95   0.003     .5291721    .8793575
         99  |   .5555689   .1470947    -2.22   0.026     .3306514    .9334811
             |
  fathdegree |
          1  |   1.549137   .2019206     3.36   0.001     1.199888    2.000041
        999  |   .8804705   .1196391    -0.94   0.349       .67461     1.14915
             |
  mothdegree |
          1  |   1.209905   .1550619     1.49   0.137     .9411548    1.555399
        999  |   .6280505   .1247967    -2.34   0.019      .425458    .9271127
             |
   NorthEast |   1.105085   .2326225     0.47   0.635     .7315033    1.669457
   NorthWest |    1.29104   .2118968     1.56   0.120     .9359075    1.780928
    YorkandH |   1.152307   .1970408     0.83   0.407     .8241675    1.611094
     EastMid |   1.050403   .1866907     0.28   0.782     .7414292    1.488134
     WestMid |   1.042115   .1781007     0.24   0.809     .7454919    1.456763
   EastofEng |   .7692858   .1322369    -1.53   0.127     .5492498    1.077471
     SthEast |   .8883766   .1445744    -0.73   0.467     .6457622    1.222142
     SthWest |   .7922698   .1495972    -1.23   0.218     .5472028    1.147091
     RegMiss |    4894861    7094664    10.63   0.000     285758.8    8.38e+07
------------------------------------------------------------------------------
```

```
. logit atuni ib(4).hardout i.famincgrps  i.key2 mixed indian pakistani bangladeshi blcaribbean blafrican ///
> otheth i.hlthprobdisab i.urban i.siblings i.brokenhome i.fathdegree i.mothdegree NorthEast NorthWest Yorkand
> H ///
> EastMid WestMid EastofEng SthEast SthWest RegMiss [pweight = w6finwt_cross] if male ==0, or

Iteration 0:   log pseudolikelihood = -2987.9646
Iteration 1:   log pseudolikelihood = -2400.5527
Iteration 2:   log pseudolikelihood = -2363.4596
Iteration 3:   log pseudolikelihood = -2362.4949
Iteration 4:   log pseudolikelihood = -2362.4893
Iteration 5:   log pseudolikelihood = -2362.4888
Iteration 6:   log pseudolikelihood = -2362.4887
Iteration 7:   log pseudolikelihood = -2362.4887

Logistic regression                               Number of obs   =       4869
                                                  Wald chi2(49)   =     908.98
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -2362.4887                 Pseudo R2       =     0.2093

------------------------------------------------------------------------------
             |               Robust
       atuni | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     hardout |
          1  |   .3473002    .112649    -3.26   0.001      .183913    .6558395
          2  |   .4685893   .1489247    -2.39   0.017     .2513435    .8736088
          3  |   .7077914   .2302525    -1.06   0.288     .3741105    1.339093
        999  |   .6050514   .2268571    -1.34   0.180     .2901644    1.261655
             |
  famincgrps |
          2  |   1.375906   .2169072     2.02   0.043     1.010182    1.874037
          3  |   1.565594   .2672655     2.63   0.009     1.120389    2.187708
          4  |   1.718307    .292785     3.18   0.001     1.230447    2.399597
        999  |   1.305908   .2236091     1.56   0.119     .9336037    1.826682
             |
        key2 |
          1  |   1.251608   .4348403     0.65   0.518     .6334898    2.472848
          2  |   2.840239    .934443     3.17   0.002     1.490419    5.412545
          3  |   3.745157   1.217173     4.06   0.000     1.980752    7.081251
          4  |   6.181172    1.96263     5.74   0.000     3.317412    11.51708
          5  |     5.6404   1.776075     5.49   0.000     3.042843    10.45539
          6  |    7.81092   2.441017     6.58   0.000      4.23341    14.41166
          7  |   14.11947   4.409609     8.48   0.000      7.65565    26.04081
          8  |   17.67009   5.536084     9.17   0.000     9.562145    32.65295
          9  |   25.07894   7.919262    10.20   0.000     13.50586     46.5689
        999  |   6.889801   2.394416     5.55   0.000     3.486488    13.61524
             |
       mixed |   1.485967   .3578491     1.64   0.100     .9268803     2.38229
      indian |   5.789405   1.219259     8.34   0.000     3.831505    8.747793
   pakistani |   3.751241   .7074903     7.01   0.000     2.592012    5.428915
 bangladeshi |   4.860096   .9847816     7.80   0.000     3.267152    7.229702
 blcaribbean |   2.154727   .6810068     2.43   0.015      1.15976    4.003286
   blafrican |   5.510089   1.753832     5.36   0.000     2.952743    10.28233
      otheth |   3.720217   .9870064     4.95   0.000     2.211755    6.257481
             |
hlthprobdi~b |
          1  |   .8370657   .1331578    -1.12   0.264     .6128484    1.143315
        999  |    1.24354   .5220673     0.52   0.604     .5461416    2.831484
             |
       urban |
          1  |   .8787261    .088285    -1.29   0.198     .7216622    1.069974
        999  |   .0000769   .0000848    -8.59   0.000     8.85e-06    .0006676
             |
    siblings |
          1  |   .9557591    .140176    -0.31   0.758     .7169805    1.274059
          2  |   .7420522   .1135171    -1.95   0.051     .5498193    1.001495
          3  |   .7199986   .1231997    -1.92   0.055     .5148512    1.006889
          4  |    .405495   .0798844    -4.58   0.000     .2756099    .5965903
        999  |   1.190172   .4892503     0.42   0.672     .5317429    2.663898
             |
  brokenhome |
          1  |   .6917342   .0888517    -2.87   0.004     .5377796    .8897628
         99  |   .5348487   .1458349    -2.30   0.022     .3134278    .9126923
             |
  fathdegree |
          1  |    1.54809   .1987594     3.40   0.001     1.203678     1.99105
        999  |   .8732473   .1187847    -1.00   0.319     .6688849    1.140048
             |
  mothdegree |
          1  |   1.234226   .1577041     1.65   0.100     .9607978    1.585469
        999  |   .6562826   .1278889    -2.16   0.031     .4479386    .9615312
             |
   NorthEast |   1.104278    .233263     0.47   0.639     .7299185    1.670639
   NorthWest |   1.280889   .2076377     1.53   0.127     .9322402    1.759928
    YorkandH |   1.179986   .2033048     0.96   0.337     .8418207    1.653994
     EastMid |   1.026891   .1802216     0.15   0.880     .7280086    1.448478
     WestMid |   1.045498   .1782905     0.26   0.794     .7484564    1.460428
   EastofEng |   .7830962    .133619    -1.43   0.152     .5604997    1.094094
     SthEast |   .8731382   .1410403    -0.84   0.401     .6361891    1.198339
     SthWest |   .8133615   .1524312    -1.10   0.270     .5633274    1.174374
     RegMiss |   36870.99   38581.14    10.05   0.000     4742.452    286659.7
------------------------------------------------------------------------------
```

Raw Output for Table 4.7, Columns 1 and 2 (Raw PC Scores – ARE and FE models)

```
. xtreg pattcon `panelcontrols3', mle
note: monthsofschoolmiss omitted because of collinearity
note: telloffmiss omitted because of collinearity
note: dev_regbedM omitted because of collinearity

Fitting constant-only model:
Iteration 0:   log likelihood = -79735.667
Iteration 1:   log likelihood = -79656.828
Iteration 2:   log likelihood = -79655.483
Iteration 3:   log likelihood = -79655.482

Fitting full model:
Iteration 0:   log likelihood = -78388.776
Iteration 1:   log likelihood = -78374.835
Iteration 2:   log likelihood = -78374.812
Iteration 3:   log likelihood = -78374.812

Random-effects ML regression                    Number of obs      =     21490
Group variable: newid                           Number of groups   =     12845

Random effects u_i ~ Gaussian                   Obs per group: min =         1
                                                               avg =       1.7
                                                               max =         2

                                                LR chi2(136)       =   2561.34
Log likelihood  = -78374.812                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
     pattcon |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    mn_lninc |   .5966045   .2278381     2.62   0.009       .15005    1.043159
   dev_lninc |  -.2544973   .1999154    -1.27   0.203    -.6463243    .1373296
monthsofsc~l |   .1045961   .0053528    19.54   0.000     .0941048    .1150874
monthsofsc~s |  (omitted)
mn_school~es |   .5758529   .5070711     1.14   0.256    -.4179881    1.569694
mn_school~ss |    3.88669   3.106134     1.25   0.211    -2.201222    9.974601
dev_schoo~es |   .5037572   .9621547     0.52   0.601    -1.382031    2.389546
dev_schoo~ss |  -2.679924    2.50401    -1.07   0.285    -7.587692    2.227844
mn_mixedsc~l |   .0145073   .7876781     0.02   0.985    -1.529313    1.558328
dev_mixeds~l |   .1687963   2.170221     0.08   0.938    -4.084759    4.422351
mn_mixedsc~s |  -12.76321   3.480716    -3.67   0.000    -19.58529   -5.941136
dev_mixeds~s |   .0406144   2.542286     0.02   0.987    -4.942174    5.023403
 mn_nvqNoneM |  -1.164902   .3776547    -3.08   0.002    -1.905092   -.4247129
    mn_nvq1M |  -1.211818   .3962585    -3.06   0.002    -1.988471    -.435166
    mn_nvq2M |   .1085223   .2753532     0.39   0.693    -.4311601    .6482047
    mn_nvq4M |   .9366983   .2757408     3.40   0.001     .3962562     1.47714
    mn_nvq5M |   1.387843   .4562014     3.04   0.002     .4937047    2.281981
   mn_nvqosM |  -1.580095   .6073198    -2.60   0.009    -2.770419   -.3897697
 mn_nvqNoneP |  -1.575288   .4149638    -3.80   0.000    -2.388602   -.7619743
    mn_nvq1P |  -1.094012   .4808075    -2.28   0.023    -2.036377   -.1516464
    mn_nvq2P |  -.4484567   .3128073    -1.43   0.152    -1.061548    .1646344
    mn_nvq4P |    1.11767   .3111377     3.59   0.000     .5078515    1.727489
    mn_nvq5P |   .7257968   .4464203     1.63   0.104    -.1491709    1.600764
   mn_nvqosP |   1.185825   .6094878     1.95   0.052    -.0087488      2.3804
   mn_nvqNAP |   .5047508   .4867091     1.04   0.300    -.4491816    1.458683
dev_nvqNoneM |  -1.175742   .8845057    -1.33   0.184    -2.909341    .5578574
   dev_nvq1M |   .8939998   1.014611     0.88   0.378    -1.094601    2.882601
   dev_nvq2M |  -.4903335   .6325277    -0.78   0.438    -1.730065    .7493979
   dev_nvq4M |   -.731477   .6450142    -1.13   0.257    -1.995681    .5327276
   dev_nvq5M |  -.9865692   .7591565    -1.30   0.194    -2.474489    .5013501
  dev_nvqosM |   .4747141   1.185899     0.40   0.689    -1.849606    2.799034
dev_nvqNoneP |   .8219379   .7175746     1.15   0.252    -.5844825    2.228358
   dev_nvq1P |   .9754372   .8929486     1.09   0.275    -.7747099    2.725584
   dev_nvq2P |   .4005873   .5913293     0.68   0.498    -.7583969    1.559571
   dev_nvq4P |  -.3844597     .62015    -0.62   0.535    -1.599931    .8310119
   dev_nvq5P |  -.5289761   .6968298    -0.76   0.448    -1.894737    .8367853
  dev_nvqosP |  -1.454177   .9921622    -1.47   0.143    -3.398779    .4904252
  dev_nvqNAP |   .3624693    .594851     0.61   0.542    -.8034172    1.528356
    married1 |  -.0533007   .4888343    -0.11   0.913    -1.011398     .904797
 marriedmiss |  -.8243717   2.231685    -0.37   0.712    -5.198394     3.54965
    respart1 |    .081061   .4544381     0.18   0.858    -.8096213    .9717432
 respartmiss |   .5339711   4.514484     0.12   0.906    -8.314254    9.382196
    natfath1 |   .9425062   .3849145     2.45   0.014     .1880877    1.696925
    siblings |  -.1903241   .0829543    -2.29   0.022    -.3529114   -.0277367
mn_chlsi~ess |  -2.069233    .280341    -7.38   0.000    -2.618691   -1.519774
mn_chlsi~iss |   -4.92359   7.484385    -0.66   0.511    -19.59271    9.745535
mgenhealthex |  -.0107836   .1653149    -0.07   0.948    -.3347949    .3132277
mgenhealthfp |   .0525285   .2139723     0.25   0.806    -.3668495    .4719065
mgenhealth~s |  -2.019419    6.44452    -0.31   0.754    -14.65045    10.61161
dev_chls~ess |  -.0845313   .2371134    -0.36   0.721     -.549265    .3802024
dev_chls~iss |  -1.495432   4.030916    -0.37   0.711    -9.395881    6.405018
  mlsillness |  -.0864981   .1984549    -0.44   0.663    -.4754626    .3024664
mlsillness~s |   .0449027   .2539845     0.18   0.860    -.4528978    .5427032
  depression |  -.0455567   .1721297    -0.26   0.791    -.3829246    .2918113
depression~s |  -3.612489   4.925573    -0.73   0.463    -13.26644    6.041457
pgenhealthex |   .0892645   .1784015     0.50   0.617    -.2603961     .438925
pgenhealthfp |  -.3702503   .2463944    -1.50   0.133    -.8531744    .1126738
pgenhealthNA |  -6.554555   4.857075    -1.35   0.177    -16.07425    2.965136
  plsillness |   .0659589    .187371     0.35   0.725    -.3012815    .4331994
    plsillNA |   5.136077   2.976418     1.73   0.084    -.6975942    10.96975
    parttime |  -.1400845   .1717924    -0.82   0.415    -.4767914    .1966225
    fulltime |  -.0850345   .2119333    -0.40   0.688    -.5004162    .3303472
    tenureMO |   .5753217   .2441927     2.36   0.018     .0967128    1.053931
    tenureCR |  -.1482419     .28762    -0.52   0.606    -.7119668    .4154831
  tenuremiss |   .8321778   4.617514     0.18   0.857    -8.217983    9.882339
```

car1	.7503573	.2551579	2.94	0.003	.250257	1.250458
carmiss	2.594231	1.26869	2.04	0.041	.1076438	5.080818
holiday1	.2885139	.1640452	1.76	0.079	-.0330087	.6100366
holidaymiss	6.990298	6.798875	1.03	0.304	-6.335252	20.31585
homeatmosp~e	.0755512	.0273924	2.76	0.006	.021863	.1292393
readdayM	-.2963637	.171079	-1.73	0.083	-.6316722	.0389449
readweekM	-.4643853	.1757279	-2.64	0.008	-.8088056	-.1199649
readneverM	-1.040836	.4671774	-2.23	0.026	-1.956487	-.1251854
readmissM	-.174662	6.022294	-0.03	0.977	-11.97814	11.62882
readdayP	-.1640512	.2180015	-0.75	0.452	-.5913262	.2632239
readweekP	-.1374941	.1699507	-0.81	0.419	-.4705914	.1956032
readneverP	-.3978662	.345007	-1.15	0.249	-1.074068	.2783351
readnaP	5.845108	5.230727	1.12	0.264	-4.406927	16.09714
libraryN	-.4225543	.1473899	-2.87	0.004	-.7114331	-.1336755
libraryW	-.1784667	.2286813	-0.78	0.435	-.6266738	.2697405
timeplenty	-.8511311	.8828458	-0.96	0.335	-2.581477	.8792148
timenote	.5310761	.2413043	2.20	0.028	.0581284	1.004024
timena	-3.416534	5.149023	-0.66	0.507	-13.50843	6.675365
playday	-.1648493	.2249879	-0.73	0.464	-.6058175	.2761188
playless	.1781467	.1625616	1.10	0.273	-.1404683	.4967616
playNA	-.4290128	5.396626	-0.08	0.937	-11.00621	10.14818
smack	-.0298893	.1417571	-0.21	0.833	-.3077281	.2479494
smackmiss	-1.014645	.3924776	-2.59	0.010	-1.783887	-.2454033
telloff	-.3218661	.2065814	-1.56	0.119	-.7267582	.083026
telloffmiss	(omitted)					
mn_regbedN	-2.246392	.545965	-4.11	0.000	-3.316464	-1.17632
mn_regbedS	-.9436442	.5139018	-1.84	0.066	-1.950873	.0635848
mn_regbedA	.0434117	.2626972	0.17	0.869	-.4714654	.5582888
mn_regbedM	-6.555285	9.287733	-0.71	0.480	-24.75891	11.64834
dev_regbedN	.4770847	.4124105	1.16	0.247	-.3312251	1.285395
dev_regbedS	.4325827	.3204462	1.35	0.177	-.1954803	1.060646
dev_regbedA	.0290175	.1722364	0.17	0.866	-.3085598	.3665947
dev_regbedM	(omitted)					
tvnone	-.4817971	.4698642	-1.03	0.305	-1.402714	.4391198
tvless1hr	-.0021779	.1662051	-0.01	0.990	-.3279338	.3235781
tv3plushrs	-.1910136	.1814406	-1.05	0.292	-.5466306	.1646034
moved1	-.4838216	.2004713	-2.41	0.016	-.8767382	-.090905
movedmiss	-4.459541	9.873572	-0.45	0.652	-23.81139	14.8923
mn_urban	.2133122	.2613805	0.82	0.414	-.2989842	.7256086
mn_urbanmiss	.4130414	.3041638	1.36	0.174	-.1831087	1.009191
mn_imdlow	-.3806633	.2494992	-1.53	0.127	-.8696727	.1083462
mn_imdhigh	.3789167	.2592889	1.46	0.144	-.1292803	.8871137
dev_urban	-.5409976	.6948621	-0.78	0.436	-1.902902	.820907
dev_urbanm~s	2.924928	1.208651	2.42	0.016	.5560162	5.29384
dev_imdlow	.3408477	.6151243	0.55	0.580	-.8647738	1.546469
dev_imdhigh	.3972879	.6083905	0.65	0.514	-.7951355	1.589711
teachtenure	.0250155	.0133614	1.87	0.061	-.0011723	.0512034
teachtenur~s	-.2406938	.5022291	-0.48	0.632	-1.225045	.7436572
classcount	.0480385	.025916	1.85	0.064	-.0027559	.0988328
classcount~s	.2135077	.4980307	0.43	0.668	-.7626144	1.18963
birthwgtk	1.071554	.174454	6.14	0.000	.7296308	1.413478
birthwgtmiss	-2.392604	2.904811	-0.82	0.410	-8.085928	3.300721
gestation	.0201821	.0075464	2.67	0.007	.0053915	.0349728
gestationm~s	.1845863	.8914491	0.21	0.836	-1.562622	1.931795
specialcare	-.1059728	.3089957	-0.34	0.732	-.7115933	.4996477
anclassYes	.1500395	.1811464	0.83	0.408	-.2050009	.5050798
anclassMiss	-.2583923	.4703739	-0.55	0.583	-1.180308	.6635236
breastfee~es	.8935332	.1925385	4.64	0.000	.5161647	1.270902
breastfee~ss	-2.386486	3.708591	-0.64	0.520	-9.655191	4.882219
male	-1.358525	.1613159	-8.42	0.000	-1.674698	-1.042352
jan	.2448424	.3607987	0.68	0.497	-.46231	.9519948
feb	.499833	.3827817	1.31	0.192	-.2504054	1.250071
mar	.3215153	.3711064	0.87	0.386	-.4058399	1.048871
apr	1.238469	.379715	3.26	0.001	.4942417	1.982697
may	1.534846	.371403	4.13	0.000	.8069095	2.262782
jun	.971129	.3727944	2.60	0.009	.2404655	1.701793
jul	.9373801	.3782173	2.48	0.013	.1960878	1.678672
aug	1.076166	.3774338	2.85	0.004	.3364095	1.815923
sep	.1869253	.3649736	0.51	0.609	-.5284097	.9022603
oct	.0491259	.3679908	0.13	0.894	-.6721229	.7703746
nov	.7311923	.3637719	2.01	0.044	.0182125	1.444172
black	-3.082562	.5389256	-5.72	0.000	-4.138837	-2.026288
asian	-1.909709	.3567897	-5.35	0.000	-2.609004	-1.210414
otheth	.2539528	.4576674	0.55	0.579	-.6430587	1.150964
_cons	33.55727	2.563539	13.09	0.000	28.53283	38.58172
/sigma_u	7.021163	.0776306			6.870646	7.174976
/sigma_e	6.915974	.05241			6.814012	7.019463
rho	.5075469	.0078951			.492071	.5230114

Likelihood-ratio test of sigma_u=0: chibar2(01)= 2495.72 Prob>=chibar2 = 0.000

```
. xtreg pattcon `panelcontrols3', fe
note: mn_lninc omitted because of collinearity
note: monthsofschoolmiss omitted because of collinearity
note: mn_schoolfees omitted because of collinearity
note: mn_schoolfeesmiss omitted because of collinearity
note: mn_mixedschool omitted because of collinearity
note: mn_mixedschoolmiss omitted because of collinearity
note: mn_nvqNoneM omitted because of collinearity
note: mn_nvq1M omitted because of collinearity
note: mn_nvq2M omitted because of collinearity
note: mn_nvq4M omitted because of collinearity
note: mn_nvq5M omitted because of collinearity
note: mn_nvqosM omitted because of collinearity
note: mn_nvqNoneP omitted because of collinearity
note: mn_nvq1P omitted because of collinearity
note: mn_nvq2P omitted because of collinearity
note: mn_nvq4P omitted because of collinearity
note: mn_nvq5P omitted because of collinearity
note: mn_nvqosP omitted because of collinearity
note: mn_nvqNAP omitted because of collinearity
note: mn_chlsillness omitted because of collinearity
note: mn_chlsillnessmiss omitted because of collinearity
note: telloffmiss omitted because of collinearity
note: mn_regbedN omitted because of collinearity
note: mn_regbedS omitted because of collinearity
note: mn_regbedA omitted because of collinearity
note: mn_regbedM omitted because of collinearity
note: dev_regbedM omitted because of collinearity
note: movedmiss omitted because of collinearity
note: mn_urban omitted because of collinearity
note: mn_urbanmiss omitted because of collinearity
note: mn_imdlow omitted because of collinearity
note: mn_imdhigh omitted because of collinearity
note: teachtenure omitted because of collinearity
note: teachtenuremiss omitted because of collinearity
note: classcount omitted because of collinearity
note: classcountmiss omitted because of collinearity
note: birthwgtk omitted because of collinearity
note: birthwgtmiss omitted because of collinearity
note: gestation omitted because of collinearity
note: gestationmiss omitted because of collinearity
note: specialcare omitted because of collinearity
note: anclassYes omitted because of collinearity
note: anclassMiss omitted because of collinearity
note: breastfeedYes omitted because of collinearity
note: breastfeedMiss omitted because of collinearity
note: male omitted because of collinearity
note: jan omitted because of collinearity
note: feb omitted because of collinearity
note: mar omitted because of collinearity
note: apr omitted because of collinearity
note: may omitted because of collinearity
note: jun omitted because of collinearity
note: jul omitted because of collinearity
note: aug omitted because of collinearity
note: sep omitted because of collinearity
note: oct omitted because of collinearity
note: nov omitted because of collinearity
note: black omitted because of collinearity
note: asian omitted because of collinearity
note: otheth omitted because of collinearity

Fixed-effects (within) regression               Number of obs      =     21490
Group variable: newid                           Number of groups   =     12845

R-sq:  within  = 0.0795                         Obs per group: min =         1
       between = 0.0137                                        avg =       1.7
       overall = 0.0222                                        max =         2

                                                F(79,8566)         =      9.37
corr(u_i, Xb)  = -0.0384                        Prob > F           =    0.0000

------------------------------------------------------------------------------
     pattcon |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    mn_lninc |  (omitted)
   dev_lninc |  -.2251065   .2372642    -0.95   0.343    -.6902016    .2399886
monthsofsc~l |   .1102202   .0061076    18.05   0.000     .0982479    .1221925
monthsofsc~s |  (omitted)
mn_school~es |  (omitted)
mn_school~ss |  (omitted)
dev_schoo~es |   .6712596   1.010745     0.66   0.507    -1.310044    2.652564
dev_schoo~ss |  -5.116114   2.804408    -1.82   0.068    -10.61343    .3812021
mn_mixedsc~l |  (omitted)
dev_mixeds~l |  -.1096223   2.295487    -0.05   0.962     -4.60933    4.390085
mn_mixedsc~s |  (omitted)
dev_mixeds~s |   2.155871   2.674354     0.81   0.420    -3.086508    7.398251
 mn_nvqNoneM |  (omitted)
    mn_nvq1M |  (omitted)
    mn_nvq2M |  (omitted)
    mn_nvq4M |  (omitted)
    mn_nvq5M |  (omitted)
   mn_nvqosM |  (omitted)
 mn_nvqNoneP |  (omitted)
```

mn_nvq1P	(omitted)					
mn_nvq2P	(omitted)					
mn_nvq4P	(omitted)					
mn_nvq5P	(omitted)					
mn_nvqosP	(omitted)					
mn_nvqNAP	(omitted)					
dev_nvqNoneM	.1284479	1.173092	0.11	0.913	-2.171095	2.427991
dev_nvq1M	3.406338	1.336662	2.55	0.011	.7861574	6.026518
dev_nvq2M	.258292	.809266	0.32	0.750	-1.328064	1.844648
dev_nvq4M	-.1501306	.8242551	-0.18	0.855	-1.765869	1.465608
dev_nvq5M	-.7356703	.9478136	-0.78	0.438	-2.593613	1.122273
dev_nvqosM	1.317335	1.487398	0.89	0.376	-1.598323	4.232994
dev_nvqNoneP	1.486175	.9325725	1.59	0.111	-.3418914	3.314242
dev_nvq1P	2.200552	1.132905	1.94	0.052	-.0202145	4.421319
dev_nvq2P	1.041826	.7387116	1.41	0.158	-.4062272	2.489878
dev_nvq4P	.1849578	.7741386	0.24	0.811	-1.332541	1.702456
dev_nvq5P	.0963287	.8544468	0.11	0.910	-1.578593	1.77125
dev_nvqosP	-1.695185	1.25053	-1.36	0.175	-4.146525	.7561544
dev_nvqNAP	.9549041	.7668938	1.25	0.213	-.5483926	2.458201
married1	-.6570213	1.597408	-0.41	0.681	-3.788327	2.474284
marriedmiss	1.847201	2.616428	0.71	0.480	-3.281629	6.976031
respart1	2.13747	1.571336	1.36	0.174	-.9427284	5.217668
respartmiss	-3.94264	5.638196	-0.70	0.484	-14.99486	7.109584
natfath1	.9731207	1.254577	0.78	0.438	-1.486152	3.432393
siblings	-.184784	.2476928	-0.75	0.456	-.6703216	.3007535
mn_chlsi~ess	(omitted)					
mn_chlsi~iss	(omitted)					
mgenhealthex	.1649134	.2358245	0.70	0.484	-.2973595	.6271862
mgenhealthfp	.3291828	.3130956	1.05	0.293	-.2845601	.9429257
mgenhealth~s	-3.826851	9.780838	-0.39	0.696	-22.99965	15.34595
dev_chls~ess	.0083017	.2730309	0.03	0.976	-.5269047	.543508
dev_chls~iss	-.9204799	4.899365	-0.19	0.851	-10.52442	8.683455
mlsillness	-.1426682	.2966549	-0.48	0.631	-.7241833	.4388469
mlsillness~s	.0580112	.283974	0.20	0.838	-.4986464	.6146687
depression	-.3887575	.5521818	-0.70	0.481	-1.471167	.693652
depression~s	-4.503005	6.938089	-0.65	0.516	-18.10333	9.097321
pgenhealthex	.1224413	.2461587	0.50	0.619	-.360089	.6049715
pgenhealthfp	-.0815212	.3277019	-0.25	0.804	-.7238958	.5608534
pgenhealthNA	-6.950148	7.356572	-0.94	0.345	-21.3708	7.470506
plsillness	-.1171467	.2705084	-0.43	0.665	-.6474083	.4131149
plsillNA	7.508854	3.689755	2.04	0.042	.2760454	14.74166
parttime	-.2684873	.2748266	-0.98	0.329	-.8072136	.2702391
fulltime	.0663106	.3573612	0.19	0.853	-.6342035	.7668248
tenureMO	.6460028	.5646624	1.14	0.253	-.4608715	1.752877
tenureCR	-.4916906	.8335043	-0.59	0.555	-2.12556	1.142179
tenuremiss	1.742263	5.695386	0.31	0.760	-9.422065	12.90659
car1	.4038526	.4520853	0.89	0.372	-.4823436	1.290049
carmiss	2.425423	1.454112	1.67	0.095	-.4249877	5.275833
holiday1	.2076372	.2399853	0.87	0.387	-.2627918	.6780662
holidaymiss	25.24043	9.985549	2.53	0.011	5.666346	44.81451
homeatmosp~e	.0129946	.0390827	0.33	0.740	-.0636169	.0896061
readdayM	-.1816985	.235327	-0.77	0.440	-.6429961	.2795992
readweekM	-.601405	.2285776	-2.63	0.009	-1.049472	-.1533379
readneverM	-.7817703	.6159542	-1.27	0.204	-1.989189	.4256484
readmissM	-2.104698	6.933043	-0.30	0.761	-15.69513	11.48574
readdayP	-.2224335	.2945577	-0.76	0.450	-.7998375	.3549706
readweekP	-.1364965	.2224105	-0.61	0.539	-.5724746	.2994816
readneverP	-.0917209	.4468737	-0.21	0.837	-.9677011	.7842592
readnaP	7.807895	7.349284	1.06	0.288	-6.598472	22.21426
libraryN	-.0335173	.2151149	-0.16	0.876	-.4551943	.3881597
libraryW	-.3726696	.3119123	-1.19	0.232	-.9840928	.2387537
timeplenty	.2357334	1.140257	0.21	0.836	-1.999446	2.470912
timenote	.3560871	.3112557	1.14	0.253	-.2540491	.9662233
timena	-7.764274	5.968722	-1.30	0.193	-19.46441	3.93586
playday	.2752775	.2848849	0.97	0.334	-.2831656	.8337205
playless	.3691333	.2067318	1.79	0.074	-.0361108	.7743774
playNA	.4056521	6.247702	0.06	0.948	-11.84135	12.65265
smack	.1323056	.2232264	0.59	0.553	-.3052719	.5698831
smackmiss	-.336538	.5825311	-0.58	0.563	-1.478439	.8053633
telloff	-.0838148	.289617	-0.29	0.772	-.6515338	.4839043
telloffmiss	(omitted)					
mn_regbedN	(omitted)					
mn_regbedS	(omitted)					
mn_regbedA	(omitted)					
mn_regbedM	(omitted)					
dev_regbedN	.56742	.4957298	1.14	0.252	-.4043298	1.53917
dev_regbedS	.3140418	.3804058	0.83	0.409	-.4316451	1.059729
dev_regbedA	.0672269	.1942221	0.35	0.729	-.3134952	.447949
dev_regbedM	(omitted)					
tvnone	.1396188	.6244513	0.22	0.823	-1.084456	1.363694
tvless1hr	.1684337	.2242015	0.75	0.453	-.2710552	.6079226
tv3plushrs	.0414661	.2433957	0.17	0.865	-.435648	.5185803
moved1	-.1629745	.2643925	-0.62	0.538	-.6812474	.3552985
movedmiss	(omitted)					
mn_urban	(omitted)					
mn_urbanmiss	(omitted)					
mn_imdlow	(omitted)					
mn_imdhigh	(omitted)					

dev_urban	-.8559975	.8236143	-1.04	0.299	-2.47048	.758485
dev_urbanm~s	-.7105835	2.457236	-0.29	0.772	-5.527359	4.106192
dev_imdlow	.4992956	.7594303	0.66	0.511	-.9893708	1.987962
dev_imdhigh	.1603273	.7111121	0.23	0.822	-1.233624	1.554278
teachtenure	(omitted)					
teachtenur~s	(omitted)					
classcount	(omitted)					
classcount~s	(omitted)					
birthwgtk	(omitted)					
birthwgtmiss	(omitted)					
gestation	(omitted)					
gestationm~s	(omitted)					
specialcare	(omitted)					
anclassYes	(omitted)					
anclassMiss	(omitted)					
breastfee~es	(omitted)					
breastfee~ss	(omitted)					
male	(omitted)					
jan	(omitted)					
feb	(omitted)					
mar	(omitted)					
apr	(omitted)					
may	(omitted)					
jun	(omitted)					
jul	(omitted)					
aug	(omitted)					
sep	(omitted)					
oct	(omitted)					
nov	(omitted)					
black	(omitted)					
asian	(omitted)					
otheth	(omitted)					
_cons	48.34745	1.344863	35.95	0.000	45.71119	50.9837
sigma_u	9.6760888					
sigma_e	6.9080457					
rho	.66238528	(fraction of variance due to u_i)				

F test that all u_i=0: F(12844, 8566) = 2.73 Prob > F = 0.0000

Raw Output for Table 4.6 – Hausman Test (Model C, Raw PC Scores)

```
. hausman F5 R5, equations(1:1) sigmamore
```

Note: the rank of the differenced variance matrix (78) does not equal the number of coefficients being tested (79); be sure this is what you expect, or there may be problems computing the test. Examine the output of your estimators for anything unexpected and possibly consider scaling your variables so that the coefficients are on a similar scale.

	Coefficients (b) F5	Coefficients (B) R5	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
dev_lninc	-.2251065	-.2544973	.0293908	.1282866
monthsofsc~l	.1102202	.1045961	.0056241	.0029556
dev_schoo~es	.6712596	.5037572	.1675024	.3133854
dev_schoo~ss	-5.116114	-2.679924	-2.43619	1.269923
dev_mixeds~l	-.1096223	.1687963	-.2784185	.7559788
dev_mixeds~s	2.155871	.0406144	2.115257	.8398706
dev_nvqNoneM	.1284479	-1.175742	1.30419	.7726287
dev_nvq1M	3.406338	.8939998	2.512338	.8725449
dev_nvq2M	.258292	-.4903335	.7486255	.506285
dev_nvq4M	-.1501306	-.731477	.5813463	.5146976
dev_nvq5M	-.7356703	-.9865692	.250899	.5692939
dev_nvqosM	1.317335	.4747141	.8426214	.9005981
dev_nvqNoneP	1.486175	.8219379	.6642375	.597307
dev_nvq1P	2.200552	.9754372	1.225115	.6993312
dev_nvq2P	1.041826	.4005873	.6412382	.4441597
dev_nvq4P	.1849578	-.3844597	.5694175	.4648453
dev_nvq5P	.0963287	-.5289761	.6253047	.4961697
dev_nvqosP	-1.695185	-1.454177	-.2410082	.7635645
dev_nvqNAP	.9549041	.3624693	.5924348	.4854166
married1	-.6570213	-.0533007	-.6037207	1.5227
marriedmiss	1.847201	-.8243717	2.671573	1.371497
respart1	2.13747	.081061	2.056409	1.506073
respartmiss	-3.94264	.5339711	-4.476611	3.388467
natfath1	.9731207	.9425062	.0306145	1.195583
siblings	-.184784	-.1903241	.00554	.2336904
mgenhealthex	.1649134	-.0107836	.175697	.1685583
mgenhealthfp	.3291828	.0525285	.2766543	.2290631
mgenhealth~s	-3.826851	-2.019419	-1.807432	7.372427
dev_chls~ess	.0083017	-.0845313	.092833	.1359938
dev_chls~iss	-.9204799	-1.495432	.5749518	2.79475
mlsillness	-.1426682	-.0864981	-.0561701	.2209568
mlsillness~s	.0580112	.0449027	.0131084	.1277433
depression	-.3887575	-.0455567	-.3432008	.5253346
depression~s	-4.503005	-3.612489	-.8905154	4.897588
pgenhealthex	.1224413	.0892645	.0331768	.1700181
pgenhealthfp	-.0815212	-.3702503	.2887291	.2166217
pgenhealthNA	-6.950148	-6.554555	-.3955922	5.53645
plsillness	-.1171467	.0659589	-.1831056	.1955376
plsillNA	7.508854	5.136077	2.372777	2.187807
parttime	-.2684873	-.1400845	-.1284028	.2149198
fulltime	.0663106	-.0850345	.1513451	.2882441
tenureMO	.6460028	.5753217	.0706812	.5098488
tenureCR	-.4916906	-.1482419	-.3434487	.7833261
tenuremiss	1.742263	.8321778	.9100854	3.345219
car1	.4038526	.7503573	-.3465046	.3738249
carmiss	2.425423	2.594231	-.1688085	.7139494
holiday1	.2076372	.2885139	-.0808768	.1755403
holidaymiss	25.24043	6.990298	18.25013	7.329086
homeatmosp~e	.0129946	.0755512	-.0625566	.0279395
readdayM	-.1816985	-.2963637	.1146652	.1619814
readweekM	-.601405	-.4643853	-.1370198	.1465859
readneverM	-.7817703	-1.040836	.2590658	.4025125
readmissM	-2.104698	-.174662	-1.930036	3.45101
readdayP	-.2224335	-.1640512	-.0583823	.1985922
readweekP	-.1364965	-.1374941	.0009976	.1438638
readneverP	-.0917209	-.3978662	.3061453	.2848244
readnaP	7.807895	5.845108	1.962787	5.174507
libraryN	-.0335173	-.4225543	.389037	.1570252
libraryW	-.3726696	-.1784667	-.1942029	.2126443
timeplenty	.2357334	-.8511311	1.086865	.7237101
timenote	.3560871	.5310761	-.174989	.1971671
timena	-7.764274	-3.416534	-4.34774	3.032332
playday	.2752775	-.1648493	.4401268	.1752891
playless	.3691333	.1781467	.1909867	.1281012
playNA	.4056521	-.4290128	.8346649	3.162255
smack	.1323056	-.0298893	.1621949	.1727698
smackmiss	-.336538	-1.014645	.6781073	.4313736
telloff	-.0838148	-.3218661	.2380513	.203457
dev_regbedN	.56742	.4770847	.0903353	.2760978
dev_regbedS	.3140418	.4325827	-.1185409	.2058037
dev_regbedA	.0672269	.0290175	.0382094	.0902412
tvnone	.1396188	-.4817971	.6214158	.4123865
tvless1hr	.1684337	-.0021779	.1706116	.1508563
tv3plushrs	.0414661	-.1910136	.2324797	.1626556
moved1	-.1629745	-.4838216	.3208471	.1728444
dev_urban	-.8559975	-.5409976	-.3149999	.4439204
dev_urbanm~s	-.7105835	2.924928	-3.635512	2.142672
dev_imdlow	.4992956	.3408477	.1584479	.446857
dev_imdhigh	.1603273	.3972879	-.2369606	.3697336

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

```
chi2(78) = (b-B)'[(V_b-V_B)^(-1)](b-B)
         =       99.36
Prob>chi2 =      0.0518
```

Raw Output for Table 5.6

```
. do "C:\Users\Olivia\AppData\Local\Temp\STD00000000.tmp"

.         xi: regress zpattcon i.LALYpc*time i.LAAYpc*time i.LAHYpc*time i.AALYpc*time ///
>         i.AAHYpc*time i.HALYpc*time i.HAAYpc*time i.HAHYpc*time, cluster(mcsid)
i.LALYpc          _ILALYpc_0-1        (naturally coded; _ILALYpc_0 omitted)
i.LALYpc*time     _ILALXtime_#        (coded as above)
i.LAAYpc          _ILAAYpc_0-1        (naturally coded; _ILAAYpc_0 omitted)
i.LAAYpc*time     _ILAAXtime_#        (coded as above)
i.LAHYpc          _ILAHYpc_0-1        (naturally coded; _ILAHYpc_0 omitted)
i.LAHYpc*time     _ILAHXtime_#        (coded as above)
i.AALYpc          _IAALYpc_0-1        (naturally coded; _IAALYpc_0 omitted)
i.AALYpc*time     _IAALXtime_#        (coded as above)
i.AAHYpc          _IAAHYpc_0-1        (naturally coded; _IAAHYpc_0 omitted)
i.AAHYpc*time     _IAAHXtime_#        (coded as above)
i.HALYpc          _IHALYpc_0-1        (naturally coded; _IHALYpc_0 omitted)
i.HALYpc*time     _IHALXtime_#        (coded as above)
i.HAAYpc          _IHAAYpc_0-1        (naturally coded; _IHAAYpc_0 omitted)
i.HAAYpc*time     _IHAAXtime_#        (coded as above)
i.HAHYpc          _IHAHYpc_0-1        (naturally coded; _IHAHYpc_0 omitted)
i.HAHYpc*time     _IHAHXtime_#        (coded as above)

Linear regression                                      Number of obs =   14174
                                                       F( 17,  7086) =  774.15
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.4974
                                                       Root MSE      =  .70935

                                 (Std. Err. adjusted for 7087 clusters in mcsid)
```

zpattcon	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
_ILALYpc_1	-1.423765	.0567723	-25.08	0.000	-1.535056	-1.312475
time	.0558742	.0255912	2.18	0.029	.0057078	.1060405
_ILALXtime_1	.2547302	.0406686	6.26	0.000	.1750076	.3344527
_ILAAYpc_1	-1.488067	.0661051	-22.51	0.000	-1.617653	-1.358481
_ILAAXtime_1	.432198	.0468794	9.22	0.000	.3403004	.5240957
_ILAHYpc_1	-1.496155	.0752319	-19.89	0.000	-1.643632	-1.348678
_ILAHXtime_1	.5149608	.0533661	9.65	0.000	.4103473	.6195743
_IAALYpc_1	.0978981	.042151	2.32	0.020	.0152696	.1805266
_IAALXtime_1	-.1346295	.0378497	-3.56	0.000	-.2088263	-.0604327
_IAAHYpc_1	-.0867218	.0411632	-2.11	0.035	-.167414	-.0060297
_IAAHXtime_1	.0855129	.0372433	2.30	0.022	.012505	.1585208
_IHALYpc_1	1.681203	.0588035	28.59	0.000	1.56593	1.796475
_IHALXtime_1	-.675231	.0453859	-14.88	0.000	-.7642008	-.5862612
_IHAAYpc_1	1.491468	.04906	30.40	0.000	1.395296	1.587641
_IHAAXtime_1	-.4723836	.0387927	-12.18	0.000	-.548429	-.3963382
_IHAHYpc_1	1.440932	.04627	31.14	0.000	1.350229	1.531635
_IHAHXtime_1	-.3451631	.0357115	-9.67	0.000	-.4151683	-.2751579
_cons	-.0901893	.0294308	-3.06	0.002	-.1478825	-.032496

```
.         xi: regress zpattcon i.LALYps*time i.LAAYps*time i.LAHYps*time i.AALYps*time ///
>         i.AAHYps*time i.HALYps*time i.HAAYps*time i.HAHYps*time, cluster(mcsid)
i.LALYps          _ILALYps_0-1        (naturally coded; _ILALYps_0 omitted)
i.LALYps*time     _ILALXtime_#        (coded as above)
i.LAAYps          _ILAAYps_0-1        (naturally coded; _ILAAYps_0 omitted)
i.LAAYps*time     _ILAAXtime_#        (coded as above)
i.LAHYps          _ILAHYps_0-1        (naturally coded; _ILAHYps_0 omitted)
i.LAHYps*time     _ILAHXtime_#        (coded as above)
i.AALYps          _IAALYps_0-1        (naturally coded; _IAALYps_0 omitted)
i.AALYps*time     _IAALXtime_#        (coded as above)
i.AAHYps          _IAAHYps_0-1        (naturally coded; _IAAHYps_0 omitted)
i.AAHYps*time     _IAAHXtime_#        (coded as above)
i.HALYps          _IHALYps_0-1        (naturally coded; _IHALYps_0 omitted)
i.HALYps*time     _IHALXtime_#        (coded as above)
i.HAAYps          _IHAAYps_0-1        (naturally coded; _IHAAYps_0 omitted)
i.HAAYps*time     _IHAAXtime_#        (coded as above)
i.HAHYps          _IHAHYps_0-1        (naturally coded; _IHAHYps_0 omitted)
i.HAHYps*time     _IHAHXtime_#        (coded as above)

Linear regression                                      Number of obs =   14174
                                                       F( 17,  7086) =   78.04
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.1272
                                                       Root MSE      =  .93477

                                  (Std. Err. adjusted for 7087 clusters in mcsid)
------------------------------------------------------------------------------
             |               Robust
    zpattcon |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   _ILALYps_1 |  -.6268503   .0791074    -7.92   0.000    -.7819244   -.4717762
        time |   .0414539   .0324514     1.28   0.201    -.0221605    .1050682
 _ILALXtime_1 |  -.0511569    .044758    -1.14   0.253     -.138896    .0365823
   _ILAAYps_1 |  -.3070528   .0825213    -3.72   0.000    -.4688192   -.1452864
 _ILAAXtime_1 |   .0046966   .0475567     0.10   0.921    -.0885288     .097922
   _ILAHYps_1 |  -.1758197   .0901821    -1.95   0.051    -.3526035    .0009642
 _ILAHXtime_1 |  -.0363662    .053111    -0.68   0.494    -.1404797    .0677472
   _IAALYps_1 |  -.1084836   .0793311    -1.37   0.172    -.2639962    .0470291
 _IAALXtime_1 |  -.0813067   .0478641    -1.70   0.089    -.1751347    .0125212
   _IAAHYps_1 |   .1712259   .0778019     2.20   0.028     .0187109    .3237408
 _IAAHXtime_1 |   .0376535   .0447399     0.84   0.400      -.05005     .125357
   _IHALYps_1 |    .266035   .0877385     3.03   0.002     .0940414    .4380287
 _IHALXtime_1 |  -.1568629   .0504449    -3.11   0.002    -.2557499   -.0579758
   _IHAAYps_1 |   .4206826    .076291     5.51   0.000     .2711294    .5702358
 _IHAAXtime_1 |  -.1036341   .0447567    -2.32   0.021    -.1913706   -.0158976
   _IHAHYps_1 |   .4836509   .0735432     6.58   0.000     .3394842    .6278175
 _IHAHXtime_1 |   -.013719   .0428486    -0.32   0.749    -.0977151    .0702771
       _cons |  -.0208811   .0553072    -0.38   0.706    -.1292998    .0875376
------------------------------------------------------------------------------
```