ESSAYS ON THE ROLE OF COGNITIVE ABILITY IN MIDLIFE RETURNS TO EDUCATION

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Abstract

This thesis comprises three papers exploring the role of cognitive ability in returns to education.

Chapter 2 investigates the selection effect of childhood cognitive ability on three sequential educational decisions after compulsory education, comparing the effects of pre-school cognitive ability (at age 5) and post-compulsory school cognitive ability (at age 16). We construct a measurement model of latent abilities. A structural equation modelling approach is used together with maximum likelihood estimation. Findings show that both early cognitive abilities have positive selection effects on encouraging people to continue education, while post-compulsory school cognitive ability has a longer-lasting influence than pre-school cognitive ability.

Chapter 3 analyses the treatment effect of sequential educational decisions after compulsory education on midlife cognitive ability (at age 46), controlling for early cognitive abilities and socioeconomic factors. All latent abilities are estimated through a measurement model. The model specification is an extension of the framework presented in chapter 2 and is adopted a structural equation modelling approach. We find that completing postgraduate education has positive treatment effects on midlife cognitive ability. However, completing post-compulsory education and undergraduate education has a limited impact.

Chapter 4 explores the mediation effect of midlife cognitive ability on midlife returns to educational decisions, considering midlife earnings, physical health and mental health as outcomes. We use the structural equation modelling approach and extend the model in chapter 3 to rule out selection bias caused by early cognition. Results indicate that midlife cognitive ability mediates the effects of education on midlife physical and mental health. The impact of education on earnings is dominated by the direct impact, while the mediation impact is minimal.

I would like to dedicate this thesis to my loving parents …

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Declaration

I declare that this thesis is a presentation of original work and I am the sole author. This work has not previously been presented for an award at this, or any other, University. All sources are acknowledged as References. This work was not sponsored by any institution or university.

I am the sole author of all chapters. I have presented an earlier version of Chapter 2 at a Seminar of the Health, Econometrics and Data Group (HEDG), University of York. I have presented an earlier version of Chapter 4 as a poster at the International Health Economics Association (IHEA) 2023 Congress, University of Cape Town, and the 10th European Health Economics Association (EuHEA) PhD Conference, University of Bologna.

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Chapter 1

Introduction

This thesis consists of three papers on the determinants and influence of human capital by exploring a potential path mechanism among cognitive ability, educational decisions and midlife outcomes. Human capital often refers to the knowledge, productive skills, health and professional skills of the labour force, which can be increased by investments in people (e.g. education, training, health) (Goldin, 2016). The earliest concept of human capital dates back to Smith (1776), while Fisher (1897) first formally used the term 'human capital' in economics. It was not until the late 1950s, following the works by Mincer (1958) and Becker (1962), that research on human capital became popular. Human capital is generated through investment decisions, the cost of which is primarily the opportunity cost of an individual's time. Education is one of the most typical means of investment. Later, the endogenous growth model of Galor and Weil (2000) enhanced the importance of human capital in economics. The aggregation of people generates knowledge. Knowledge innovation creates technological change and promotes economic growth. Meanwhile, new technologies raise the demand for skilled labour and the return on investment in education. Accordingly, education, in turn, increases an individual's productivity and leads to more technological change. Moreover, education has a positive externality, such as better health and lower crime rates. Thus, investment in human capital not only promotes economic growth but also contributes to poverty eradication, the creation of more inclusive societies and the reduction of income inequality. Given these benefits, understanding the determinants and influence of human capital is important.

Studying the returns to education has always been a popular topic in labour economics. In recent years, with the introduction of cognitive ability into economics as a human cognitive capital, many studies have discussed its relationship with education (e.g. Marjoribanks, 1976; Rohde and Thompson, 2007; Spinath et al., 2006) and its potential as an economic predictor (e.g. Glewwe, 1996; Hanushek and Woessmann, 2008; Heckman and Vytlacil, 2001; Ozawa et al., 2022). However, health economics has focused more on the effect of cognitive function on later health outcomes and its determinants (e.g. Auld and Sidhu, 2005; Black et al., 2015; Bonsang et al., 2012). These studies assign different roles to cognitive ability at different times, with early cognitive abilities considered to be a major cause of selection bias in predicting returns to education, while adult cognitive abilities are often considered to be one of the determinants of relevant health outcomes later in life. We are therefore motivated to build on the existing literature and piece together relevant empirical hypotheses to explore the different roles of cognitive ability over time on returns to education from a broader timeline. We categorise cognitive ability into early (childhood) cognitive ability and adult (midlife) cognitive ability. Controlling for socioeconomic status (SES), early cognitive ability may affect sequential educational decisions after compulsory education, ultimately leading to differences in educational attainment across individuals. Differences in education might then influence adult cognitive ability and adult outcomes. In the meantime, returns to educational decisions may be mediated by adult cognitive ability.

Our study requires longitudinal follow-up interview data over a long period on a fixed population and their cognitive abilities. We make use of the 1970 British Cohort Study (BCS70), a longitudinal survey of people born in one week of April 1970 in the UK (excluding Northern Ireland). The survey includes measures of the cognitive abilities of the target population across various years, which is still being collected and updated. Individuals born in 1970 grew up during a relatively stable economic period in the UK, benefiting from improved healthcare services through the NHS and enhanced social welfare compared to their parents. As teenagers, most were direct beneficiaries of the comprehensive schooling system, an educational reform aimed at bridging the gap between traditional grammar schools and secondary modern schools. This system provides equal educational opportunities for all students, rather than streaming them based on exam results at age 11. Consequently, they experienced a more inclusive education that provided equitable access and minimised the premature streaming of students, thereby creating greater opportunities for obtaining higher qualifications. Low initial ability pupils who would otherwise have attended secondary modern schooling may have beneficial more from the comprehensive schooling system than high ability pupils. Children from low socioeconomic backgrounds also benefit from non-selective systems, which help narrow the achievement gap with their higher socioeconomic peers. In contrast, selective systems tend to favour children from higher socioeconomic backgrounds, who often receive more family support, giving them an advantage in exams(Burgess et al., 2018; Cribb et al., 2013). Following the 1972 Reform, their minimum school leaving age was 16[1]. During secondary education up to age 16, individuals born in 1970 encountered a streaming education system characterised by the O-Level (Ordinary Level) and CSE (Certificate of Secondary Education) examination frameworks[2]. This streaming education system significantly influenced their academic and career opportunities. In contrast, later cohorts, particularly those born in the 1980s and 1990s, were affected by the 1988 Education Reform Act, which introduced a national curriculum and standardised testing, replacing O-Levels and CSE with the GCSE (General Certificate of Secondary Education). This reform mandated that all students sit the same examinations, allowing those with average or lower abilities to obtain nationally recognised qualifications and reducing inequalities associated with academic streaming. As a result, individuals born in the 1970s experienced a less equitable educational environment compared to those born in the 1980s and 1990s[3]. Later on, they entered higher education at the beginning of a period of expansion of higher education in the UK. They benefited from greater access to university opportunities supported by government funding that alleviated financial burdens. Many entered university due to their academic achievements rather than facing the pressures of tuition fees and debt encountered by later cohorts. Upon graduation, they entered a labour market transformed by the deindustrialization associated with Thatcherism, shifting from a manufacturing-dominated economy to one reliant on services and finance. With a lower rate of higher education attainment at the time, university graduates enjoyed a competitive edge in the job market. Despite economic fluctuations, their higher educational qualifications generally enabled them to secure relatively stable and well-paying jobs. Additionally, the 1970 Equal Pay Act and the 1975 Sex Discrimination Act established a legal foundation for women's equal treatment in education and employment, while increasing awareness of gender equality created greater job opportunities for women born in 1970. In contrast, those born in the 1980s and 1990s faced a more saturated higher education environment and structural changes in the job market, leading to a gradual decline in the premium associated with educational qualifications. As a result, the 1970 cohort benefited from a more equitable education system, faced fewer financial barriers to attending university, and had better job prospects compared to later cohorts. This suggests that their educational decisions were more likely driven by their initial abilities than by economic conditions or job market expectations.

[1]Although the raising of the school leaving age to 16 was implemented in 1972, the first cohorts to directly benefit from this policy were those born in 1958.

[2]Those who took the O-Level exams were typically viewed as academically capable, while those opting for the CSE were perceived as having lower abilities.

[3]Individuals born in the 1980s and 1990s experienced a more equitable educational environment as they participated in the General Certificate of Secondary Education (GCSE) exams. However, this fairness came with a highly competitive atmosphere.

The main contribution of this paper is to integrate the recent literature on cognition and education and to propose and validate a path mechanistic framework for how cognitive abilities can play a role in the returns to educational decisions. Our path framework will be visualised and estimated via a structural equation modelling (SEM) approach. Our work contributes to a further understanding of the determinants and mechanisms that influence human capital. Additionally, our research focuses on the cohort born in the UK in 1970. By studying their educational decisions and cognitive development, we contribute to the literature on educational and cognitive differences across generational groups. As the world transitions into an aging society, individuals born in the 1970s are approaching old age. Our study offers valuable insights into addressing cognitive decline, health issues, and social welfare challenges faced by the elderly. These insights can assist policymakers in formulating cost-effective health intervention strategies, optimising the allocation of public resources and reducing inequality. Moreover, many countries are progressively raising the statutory retirement age to mitigate the economic pressures associated with an aging population. Adult education provides opportunities for lifelong learning, allowing older workers to adapt to rapidly changing work environments and technologies. However, there is currently limited research on the long-term impacts of education on later-life outcomes. Our study on the effects of education completed between the ages of 16 and 46 on midlife earnings and health contributes to addressing this gap, providing valuable insights and support for policies aimed at managing the aging workforce and extending the retirement age. For instance, we find that midlife health, an important component to remaining productivity into older age, is determined largely through midlife cognitive ability as a mediator, rather than through the direct effect of educational decisions. In addition to early cognition and education, working in a skilled occupation also shows a positive association with midlife cognitive ability. This suggests that, beyond education, policies could encourage older individuals to leverage their work experience by transitioning into more skilled roles, which would not only help them exercise their cognitive abilities but also support their health and maintain their earnings.

As a measure of human capital, cognitive ability cannot be directly observed by the researcher (Cunha and Heckman, 2008). As such, researchers commonly use principal component analysis (PCA) and factor analysis to reduce a set of observed cognitive measurement variables into latent constructs that reveal latent cognitive abilities. PCA is a descriptive method, which can transform a set of variables into a smaller number of uncorrelated components that do not guarantee factor interpretability (Chumney, 2012). Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) are both based on common factor theory and are applicable when measurement error is expected. EFA can generate correlated or uncorrelated factors from a set of variables, a process that is an interpretation of the raw data. It can help distil data from several variables into a smaller number of representative variables (Brown, 2015). In addition, CFA assumes that associations between multiple variables are determined by the effects of an underlying structure and allows the researcher to specify the relationship between factor and observed variables as well as the relationship between factors. These hypothesised underlying relationships can be tested (Brown, 2015). EFA requires that measurement error be uncorrelated, whereas CFA does not have such a requirement (Hoyle, 2012). We refer to Heckman et al. (2018)'s measurement model of latent abilities and apply CFA to make the factors interpretable. This is one of the main reasons for using the SEM approach, which allows the combination of CFA and multiple regression analysis.

SEM, also known as covariance structure modelling, aims to minimise the discrepancy between the estimated covariance matrix and observed covariance matrix given the data[4]. One of its notable advantages is the capacity to integrate and simultaneously estimate factor analyses and regression analyses, as well as to estimate the relationship between latent variables. It can be realised through measurement models and structural models, where the structural model may contain multiple equations[5]. The advantage of estimating multiple equations simultaneously, rather than separately, is that the overall model fit can be statistically tested, while the advantage of the partial-information approach is that it isolates the effect of errors when there is an incorrectly specified part of the model, rather than allowing them to spread to other parts (Hoyle, 2012). Unlike analysis of variance (ANOVA) and multiple regression (MR), a variable can be both dependent and independent in SEM. In other words, a variable can be the cause of one variable and the outcome of another at the same time, which is another reason why we chose SEM. Furthermore, SEM allows the specification of correlated error terms among equations. The path diagram for SEM also conveniently visualises the relationships between the variables we assume and estimate.

In addition, great care should be taken in constructing structural models. Even if the coefficients of SEM estimation are significant, it does not mean that the effect between variables is causal. Wright (1923) argues that 'prior knowledge of the causal relations is assumed as a prerequisite in the theory of path coefficients', while Pearl (2000) also emphasises that the prerequisite for validating causal conclusions via SEM is the causal assumptions. When the true causal model is unknown, which is the most common scenario

[4]Differ from OLS, the observed and estimated data in SEM are variances and covariances (Hoyle, 2012).

[5]Structural models in SEM typically represent assumptions about hypothesised causal effects between measured variables, while measurement models account for directional effects between observed and latent variables.

in research, even if our hypothesised model matches the data, we can only say that our model is consistent with the data, not that our model has been proven. This is the core difference between SEM and other methods of economics. After all, path analyses were originally intended to estimate the size of effects when the underlying causal paths were already known (Hoyle, 2012). However, Pearl (2012) also notes that, with proper justification, the researcher can interpret the estimated coefficients as tests of causal effects even in the case of cross-sectional designs and correlated data. This means that it is necessary to rely on prior theoretical and empirical knowledge when constructing a pathway model. In other words, we must endeavour to ensure that the model is correctly specified, otherwise, in the case of the full-information approach, a specification error in one part of the model will affect the estimates of the rest of the model, which is the phenomenon of error propagation (Hoyle, 2012). We, therefore, present our framework step-by-step in the following three chapters based on the impacts of interest and explain the causal assumptions underpinning the construction of each pathway by reviewing the literature on the relevant impacts in each chapter, rather than simply presenting our model in one step. We have reviewed as much recent relevant research in the fields of economics, psychology and epidemiology as possible in constructing the empirical framework.

Chapter 2 investigates the impact of early cognition on sequential educational decisions faced after compulsory education. The investment theory (Cattell, 1987; Deary et al., 2010) and dual-process theory (Evans and Stanovich, 2013) explain the internal logic of the impact of early cognition on education. People with greater early cognitive ability have an innate learning advantage and have a selection bias on educational decisions (Heckman et al., 2018). On this basis, we hypothesise that early ability will have a selection effect on educational decisions. We identify two early cognitive abilities: preschool cognitive ability which was measured when children first started primary school at the age of five, and post-secondary cognitive ability measured when children completed their last year of compulsory education at the age of sixteen (within the UK context). Roughly speaking, preschool cognitive ability is expected to depend more on innate factors (and family background to some extent), while post-compulsory school cognitive ability is influenced by compulsory education on this basis. This can give us an idea of whether post-compulsory school cognitive ability still impacts on educational decisions after controlling for preschool cognitive ability. Additionally, our educational decision variables are derived from data on the highest level of educational attainment achieved by age 46. The reason for relaxing the time constraints on educational decisions is to minimise the constraints imposed by early backgrounds (e.g. family income) on educational decisions and to capture the impact of early cognition on lifelong educational decisions, in continuity with the estimation in subsequent chapters. We find that holding other SESs constant, people with higher early cognitive abilities are more inclined to respond positively to educational decisions at all stages, which we refer to as the positive selection effect of early cognitive ability, with the exception of no significant effect of preschool cognitive ability on postgraduate education decision. After controlling for preschool cognitive ability, post-compulsory school cognitive ability still has a sizable selection effect on all educational decisions, which presents the side effect of compulsory education. This chapter contributes to the empirical evidence on the impact of early cognition by exploring two specific periods of early cognitive abilities on educational decisions, emphasises the importance of early cognitive development and sets the tone for subsequent chapters.

Building on the structural model in Chapter 2, Chapter 3 explores the impact of educational decisions on midlife cognitive ability (at age 46)[6]. The study of adult cognitive ability is an emerging area of increasing interest because it has been correlated not only to later life quality but also to many cognitive and mental diseases (e.g. Alzheimer's disease) (Anstey, 2016). Understanding the determinants of adult cognition can help inform policy interventions to maintain a relatively high cognitive stability in the population, thereby reducing healthcare burden and health inequalities. Recent theories (investment theory (Kievit et al., 2017; Schweizer and Koch, 2002), transactional process theory (Dickens and Flynn, 2001; Tucker-Drob et al., 2013) and schooling mechanism theory (Ceci and Williams, 1997; Jacob and Parkinson, 2015; Ritchie and Tucker-Drob, 2018)) suggest that cognition and education have a bidirectional correlation that persists throughout a person's life. Different educational decisions reflect different human capital investment decisions, which can ultimately lead to different levels of midlife cognitive ability. Our study finds that those who completed postgraduate education have higher midlife cognitive ability than those without the corresponding education degree, a difference we refer to as the treatment effect of educational decisions. This positive marginal treatment effect suggests that the overall education effect increases with the level of education, which is generally consistent with the literature (Carlsson et al., 2015; Falch and Sandgren Massih, 2011; Hatch et al., 2007a; Richards and Sacker, 2003). Furthermore, we find limited effects of post-compulsory and undergraduate education on midlife cognitive ability. This contradicts the results of articles that use schooling years as a main independent variable, emphasising the importance of compulsory education and

[6]Our educational decisions are generated based on people's highest educational achievement completed by age 46. This means that all educational choices are made before the age of 46 and before adult cognitive ability is measured. Thus there is no reverse causality.

calling for its extension (Falch and Sandgren Massih, 2011; Meghir et al., 2013). Our study highlights the importance of higher education for adult cognitive development.

Chapter 4 extends the framework of the previous chapter by exploring the mediation effect of midlife cognitive ability in the midlife returns to educational decisions. There is much empirical evidence that suggests that cognitive ability influences on both income (Glewwe, 1996; Murnane and Willett, 1995) and health (Conti et al., 2010; Hatch et al., 2007b; Wrulich et al., 2014). Individuals with high cognitive ability tend to perform better at work and make more rational financial investment decisions, which helps them earn higher incomes. Meanwhile, when it comes to health, those with higher cognitive ability are more likely to adopt healthy behaviours, make more timely use of health services and are better at processing medical information, which helps them maintain better overall health. The logic behind the effects of cognition partially overlaps with the effects of education (Leigh, 1983; Lleras-Muney and Lichtenberg, 2005). On the proposition that educational decisions impact midlife cognition, examining the extent to which returns to educational decisions are influenced by midlife cognition helps us to better understand the mechanisms of returns to education. We consider both monetary returns (earnings) and non-monetary returns to education (health). We find that the impact of educational decisions on midlife earnings is mainly direct, with only a minor mediation effect from midlife cognitive ability (less than 3%). In contrast, educational decisions have a significant and positive mediation effect on midlife physical and mental health through midlife cognitive ability, while the direct effect is nearly negligible. This suggests that the influence of education on later-life health primarily operates through indirect channels, with midlife cognitive ability serving as a key pathway.

Chapter 5 focuses on comparing the findings of each chapter and briefly discusses future areas for research.

Chapter 2

The selection effect of early cognitive abilities on educational decisions

ZUOQI ZHANG

Abstract

Do people with higher early cognitive abilities have a higher probability of moving to the next level of education and which period of early cognitive ability is more important? To analyse these questions, this paper carries out an empirical study to explore the influence of preschool cognitive ability (at age 5) and post-compulsory school cognitive ability (at age 16) on three educational decisions made after compulsory education in Britain, using data from 1970 British Cohort Study. We specify a structural model with a combination of a sequential decision model and a cognitive development model, using confirmatory factor analysis as a measurement model for latent cognitive abilities. A SEM approach is applied for estimation. We find that both early cognitive abilities have positive selection effects on encouraging people to progress to the next stage of their education after compulsory study, although the impact of preschool cognitive ability reduces as the level of education increases. Our findings suggest that post-compulsory school cognitive ability holds a more stable and long-lasting impact on educational decisions relative to preschool cognitive ability.

Keywords: Early cognitive ability, Educational decisions, British Cohort Study, Structural equation modelling

2.1 Introduction

Do you feel that people with high levels of education are smarter? Is this because only people who are smart enough obtain an advanced degree, or is this because smart people are more inclined to continue their education? Intelligence, also called cognitive ability or cognitive skill, is a brain-based ability that is needed in the acquisition of knowledge, manipulation of information, and reasoning. It shapes individual memory, learning, decision-making and language abilities (Michalos, 2014). Evidence shows that cognitive ability is a substantial predictor of academic performance (Glewwe et al., 2017; Glick and Sahn, 2010; Haile et al., 2016; Harris, 1940; Petrides et al., 2005). Therefore, a consensus is that good academic performance is proof of high cognitive ability. Many schools and universities will use academic performance as one of the indicators for admitting students. So the fact that a person has a certain educational degree means that the person's cognitive ability is up to the relevant standard. This 'selection by ability' approach to admission may give a psychological implication that only the cognitively competent can continue their education, which could influence people's educational decisions to some extent. For instance, some people who are not confident in their cognitive abilities are less likely to consider a postgraduate education. Even if their abilities are up to standard, they are not confident that they can graduate.

Most of the literature analyses the correlation between childhood cognitive ability and educational achievement, but little attention has been paid to the influence of early cognitive ability on educational choice preferences. Weisbrod (1962) demonstrates the effect of cognitive ability on education not only on the final education achievement but also on education choice. He reveals that receiving an extra year of schooling opens up options for additional schooling and provides opportunities for learning about personal abilities. On that basis, Heckman et al. (2018) find strong evidence that both cognitive and non-cognitive endowments influence educational choices and outcomes, when estimating causal effects of education on market and non-market outcomes in early adulthood using data from the US. They determine that the outcome difference between education groups consists of the causal effect of education, selection bias, and sorting on gains[1], where the causal effect of education is made up of the anticipated direct effect of education and the perceived continuation value of schooling[2]. They find that high school graduation benefits everyone, especially low-ability

[1] Selection bias refers to the correlation between education and unobservables (cognitive and non-cognitive skills in Heckman et al. (2018)'s context), whereas sorting on gains refers to the correlation between education and educational effects which are assumed to be heterogeneity in Heckman et al. (2018).

[2] Heckman et al. (2018) argue that continuation values come from the dynamic sequential nature of the schooling choice where information is updated and schooling at one stage opens up options for schooling at later stages.

groups. In addition, most individuals in high-ability groups gain substantial benefits from college graduation, which indicates they have positive and substantial post-high school continuation values, making them more inclined to continue their education, whereas the majority of those low-ability individuals stop their studies in high school. This gives a new interpretive perspective of the selection effect of cognitive ability on educational decisions.

Based on the framework of Heckman et al. (2018), this paper investigates the selection effect of early cognitive ability on sequential educational decisions in a British context, holding childhood SES constant. Different from them, with data from the BCS70, two early cognitive abilities are considered: preschool cognitive ability measured at age five and post-compulsory school cognitive ability measured at age 16, since children usually start to enrol into primary school at about age five and are in their final year of compulsory education at age 16 in Britain[3]. This enables us to compare the relative importance of childhood cognitive abilities in educational decisions since preschool cognitive ability is mainly determined by initial conditions and family backgrounds, while post-compulsory school cognitive ability is additionally affected by compulsory education. This study focuses on three sequential educational decisions that people face after completing compulsory education: whether to complete post-compulsory schooling (A-levels); whether to complete undergraduate education after post-compulsory schooling; and whether to complete postgraduate education or above following undergraduate education. These educational decisions are recorded up to midlife (age 46), giving individuals more time to consider and complete these. For example, an individual may want to continue to university after completing compulsory education at the age of 18 but may not end up doing so due to insufficient financial support. He/she may go to work first and then complete their undergraduate education in the future. A longer option period, therefore, allows for greater expression of individual educational preferences while helping to mitigate the effects of early financial constraints.

We modify the dynamic sequential decision model from Heckman et al. (2018) to estimate the selection effect of early cognitive abilities while involving a measurement model to estimate latent cognitive abilities and avoid bias caused by measurement error. To simulate the developmental effect between early cognitive abilities, we use a linear value-added plus lagged inputs model of ability formation which is originally constructed by Todd and

[3]In 1972, the UK government raised the school leaving age to 16. Now under the *Education and Skills Act 2008*, children in England can leave school on the last Friday in June if they turn 16 at the end of the summer holidays. But before they turn 18, they must choose between three options: continuing in full-time education, starting an apprenticeship or traineeship, or spending 20 hours or more a week working or volunteering, while in part-time education or training. In the rest of the UK, the school-leaving age remains at 16. During our target study period, the minimum school leaving age for the sample group was 16.

Wolpin (2007) and developed by Dickerson and Popli (2016). This entire empirical model is estimated by a SEM approach.

We find that early cognitive abilities positively impact educational decisions, while the influence of preschool cognitive ability fades as the educational stage moves up. Even conditional on preschool cognitive ability, post-compulsory school cognitive ability still positively impacts educational decisions, revealing the non-negligible importance of compulsory education. The magnitude of the impact of post-compulsory cognitive ability is significantly greater for post-compulsory and postgraduate education than for undergraduate education. This is not surprising, given the reality that most students who enter post-compulsory schools do so with plans to enter undergraduate education. We also find that children with more educated parents are always more willing to continue their education, compared with children with less educated parents. We further confirm that non-cognitive ability plays a significant role in educational decisions, compared with cognitive ability, which is consistent with Glewwe et al. (2017). Preschool cognition largely influences the development of post-compulsory school cognition, while some early socioeconomic circumstances (e.g. number of siblings and parental education) are closely associated with children's cognitive development.

This paper contributes to the literature on the selection effect of early cognitive ability and to that on the determinants of educational decisions. First, it offers empirical evidence that early cognitive abilities have a positive selection effect on educational decisions after compulsory education, controlling childhood socioeconomic backgrounds, and it confirms that the post-compulsory school cognitive ability plays an important role which suggests that the compulsory education policy can impact decision making about attaining additional education. Second, it develops Heckman et al. (2018)'s multistage sequential decision model using the British educational context. Third, it combines the sequential decision model and cognitive development model and converts them to a SEM framework to inform follow-up research in related fields. At the same time, this paper lays the groundwork for the subsequent chapters of this thesis.

The remainder of this paper is organised as follows. Section 2.2 briefly reviews relevant literature related to the selection effect of cognitive abilities. Section 2.4 introduces the data and variables, while Section 2.3 discusses the model identification strategy. Section 2.5 reports estimation results, and Section 2.6 draws some conclusions.

2.2 Background

2.2.1 Cognitive ability and its measurement

Cognitive abilities, also called cognitive skills or intelligence in some literature, are brain-based abilities that are needed in the acquisition of knowledge, manipulation of information, and reasoning. They dominate individual memory, learning, decision making and language abilities (Michalos, 2014). Cognitive ability mainly consists of four areas (Ozawa et al., 2022) - general intelligence, working memory, executive function and self-regulation skills. General intelligence includes fluid intelligence and crystallised intelligence (Cattell, 1971, 1987). Fluid intelligence is determined by the innate ability to think, reason and solve problems, while crystallised intelligence is a list of abilities that are mastered from education and experience, for instance, vocabulary, literacy, numeracy and mathematical skills (Molfese et al., 2010; Schubert et al., 2019). Working memory (short-term memory) indicates the capability of the brain to reserve and administer information in a short period, even when distracted (Alloway and Packiam Alloway, 2014). Executive function and self-regulation skills contain planning ability, concentration, filtering of distractions, memorising of instructions, multitasking and impulse control (Blair and Razza, 2007; Molfese et al., 2010). Dohmen et al. (2018) argue that these different aspects of cognitive ability can be regarded as lying along a continuum, ranging from conceptual differences in cognitive functioning to practical domains of action and modes of knowledge acquisition.

Most literature on cognitive ability is concentrated in the fields of psychology and epidemiology. Researchers focus on exploring the development mechanism of cognition, to treat mental illness, brain injury and Alzheimer's disease (Campbell et al., 2008). In economics, the study of cognition is still a new and growing research topic. The initial research dates back to when Mincer (1974) introduced the seminal earnings function, which posits that higher educational attainment boosts economic outcomes, increasing earnings, employment opportunities and gross domestic product (GDP). Cognitive ability is one of the factors in the earnings function. In the recent literature, some economists have suggested that educational indicators such as education attainment and school enrolment may not be the most accurate predictors of future economic outcomes and potential human capital returns, and that, cognitive ability may be a better predictor (e.g. Glewwe, 1996; Hanushek and Woessmann, 2008; Heckman and Vytlacil, 2001; Ozawa et al., 2022). In addition, some economists are keen to study the educational, financial and health returns to cognitive ability (e.g. Bijwaard et al., 2015; Boissiere et al., 1985; Heineck and Anger, 2010), while some are interested in the relationship between cognitive ability, risk preference and decision-making (e.g. Agarwal and Mazumder, 2013; Dohmen et al., 2010, 2018).

Cognitive ability is a latent and multidimensional trait; researchers apply different types of achievement or performance tests to measure cognitive ability[4]. The initial interest in measuring cognitive ability was to predict children's academic achievement. It then was gradually applied to hiring and managing human resources (Marks, 2013). The main reason why the study of cognition has developed so late compared with other disciplines is the data limitations. In most previous surveys, information on cognitive ability is often absent (Harrati and Glymour, 2020). The lack of data on cognition makes it difficult to conduct related research and estimation. Some studies even use academic-related skills (literacy and numeracy test scores) and academic performance as indicators of cognitive abilities to estimate returns of cognition on human capital (e.g. Hanushek et al., 2015; Hanushek and Woessmann, 2008; Jacob and Parkinson, 2015). The direct use of educational variables to refer to cognitive ability remains imprecise, although cognitive ability measurements always involve aspects of academic skills and academic achievement tests often relate to domains of cognition (Peng and Kievit, 2020).

Since the late twentieth century, many data designs have begun to collect cognitive-related information. However, due to the limited knowledge of cognitive ability, many studies tend to use cognitive indicators as a proxy for true cognition. IQ score is one of the common indicators and always refers to general intelligence. Ferrer et al. (2007, 2010) find a positive dynamic correlation between IQ and reading from first to 12th grades. Raven (1998) uses Raven's Progressive Matrices to test non-verbal reasoning ability as a measurement of fluid intelligence. Schmitt et al. (2017) discover that executive function (including flexibility, working memory, and inhibition) significantly and positively impacts on reading/mathematical ability among preschool children. Using a large sample of data from the Early Childhood Longitudinal Study, Miller-Cotto and Byrnes (2020) find that working memory and reading/mathematics have bidirectional relations from kindergarten to second grade.

Recently, as the importance of cognition has been recognised, more and more data sets have developed professional and sophisticated mechanisms to capture cognition information. Empirically, what we can observe are multiple cognitive ability test scores. However each of these measures latent cognitive ability with measurement error (Cunha and Heckman, 2008). For example, Jerrim and Vignoles (2013) argue that the same person may have different test

[4]Dohmen et al. (2018) argue that "these tests only capture cognitive ability if other factors that might affect test performance are held constant. For example, distractions on the day of the test, and personality traits that determine task motivation could play a role in test performance."

scores if they complete the test on different days, implying that there will be some noise when using only one test score as an indicator of 'true' cognitive ability. This issue to some extent can be resolved by applying a reasonable cognitive function (measurement model) and involving multiple cognitive ability test scores in estimation. PCA and CFA (usually estimate through SEM approach) are two common methods used to achieve this[5]. For instance, with the data from the BCS70, Feinstein (2003) constructs the cognitive ability index using PCA, and argue that parental SES has a significant and long-term impact on children's cognition development. Dickerson and Popli (2016) apply a SEM approach to test the effect of persistent poverty on early cognitive development, using data from the UK Millennium Cohort Study. McElroy et al. (2021) analyse data from the 1946 National Survey of Health and Development, the 1958 National Child Development Study and the BCS70 to explore the direct and indirect pathways between childhood socioeconomic position and midlife cognitive ability, while latent cognitive abilities are estimated under a SEM framework. In addition, Cunha and Heckman (2008) use a linear factor model to estimate latent cognitive ability and identify the factor loading as the ratio of measurement covariances. On this basis, Cunha (2011) takes the weighted average of the measures to obtain the error-corrected estimate of the latent cognitive ability, which requires that at least one cognitive test is repeated in every measurement period[6]. Many databases struggle to meet this requirement since most cognitive tests are age specific. It is rare for the same test to be performed across periods.

2.2.2 The effect of cognitive ability on education

Since education plays an important role in economic growth, there has been a great interest in trying to understand academic development. The impact of cognitive abilities on education has been a major discussion in cognitive research. Harris (1940) claims that cognitive ability (intelligence) is one of the most crucial determinants of academic success, after reviewing the results of studies on academic performance and intelligence. Subsequently, Marjoribanks (1976) shows that increases in cognitive ability are associated with increments in academic achievement, while Leeson et al. (2008) also argue that cognitive ability plays a unique role in predicting academic performance in youth. Similar conclusions are reached with respect to specific aspects of cognitive ability. Rohde and Thompson (2007) and Spinath et al. (2006)

[5]Explanatory Factor Analysis (EFA) is used less often because the estimation results of EFA are very closed to PCA. However, PCA is much simpler for researchers to use.

[6]More introduction about Cunha and Heckman's factor model identification can be found in Carneiro et al. (2010, 2011); Eisenhauer et al. (2015); Heckman and Vytlacil (2005, 1999, 2007a,b).

report that general cognitive ability predicts academic achievement, while Sun et al. (2018) find that executive function of cognitive ability as well as preschool attendance may mediate early academic achievement gaps in East Asia and the Pacific. Moreover, working memory capacity also affects academic performance (Gathercole et al., 2004; Lu et al., 2011). Peng et al. (2018) note that the working memory function of cognitive ability is implicated in early reading acquisition and is strongly affected in future reading performance as readers gain more reading experience.

Two cognitive theories explain how cognitive ability drives educational outcomes: investment theory and dual-process theory. The investment theory considers that the development of cognitive ability is mainly determined by genetic, biological and health factors, not by education. Therefore, educational outcomes are the results of a combination of environmental stimulation (e.g. educational quality and environment) and investment in cognitive ability (Cattell, 1987; Deary et al., 2010). On the other hand, the dual-process theory posits that individuals need more cognitive resources when processing unfamiliar information autonomously. After a while, sufficient experience is accumulated. Then, individuals can spend less cognitive resources on this process (Evans and Stanovich, 2013). Thus, the extent to which individuals consume cognitive resources in learning tasks depends largely on the efficiency of execution. In the education context, when first exposed to an academic task, individuals are more demanding of cognitive resources and higher cognitive levels. But, as knowledge and experience gradually accumulate, long-term memory about the learning task is developed. Therefore, in the later stage of an academic task, individuals become less dependent on cognitive ability and instead more likely to rely on the direct retrieval of knowledge from long-term memory (Peng and Kievit, 2020).

At the same time, cognitive ability is associated with educational attainment (Wolfle, 1985). Linn (1982) discusses how children with lower cognitive ability have a harder time coping with the requirements of the Western educational systems. Glewwe et al. (2017) report evidence from data on children in rural China that both cognitive and non-cognitive abilities measured in early life are significant predictors of educational attainment after compulsory education. Glick and Sahn (2010) demonstrate that academic performance in early primary school, which reflects children's cognitive ability, has a strong positive association with later school progression. They believe the reason behind this is that a good early academic performance leads parents to expect positive returns on a child's education and be more willing to invest in education. Likewise, Heckman et al. (2018) find strong evidence of ability bias that is caused by cognitive and non-cognitive abilities at each level of education (after compulsory education), and point out that selection bias is a major component of observed educational differentials for some. Based on the view of Weisbrod (1962) that receiving an extra year of schooling opens up options for additional schooling and provides opportunities for learning about personal abilities, Heckman et al. (2018) break down the causal effects of schooling at a specific level into the direct benefits of receiving that education and the possible discounted benefits of receiving subsequent education (continuation value). They find substantial continuation value components of graduating from high school for individuals with high ability, while for low-ability individuals, they gain substantial direct effects of graduating from high school but little continuation value. They suggest that this may account for the willingness of individuals with high cognitive ability to continue their education beyond high school.

From another perspective, the effect of cognitive ability on educational attainments can also be regarded as the effect of cognitive ability on different educational decisions. Frederick (2005) demonstrates that the decision-making of an individual is causally determined by general intelligence or various specific cognitive abilities, while Dohmen et al. (2018) note that decisions made about any given task under risk and uncertainty will, at least in part, be the result of a conscious process of mental deliberation, which consequently requires cognitive abilities such as processing information related to probabilities and stakes, calculating expected values, and evaluating various alternative choices.

In summary, many researchers have explored the relationship between early cognitive ability and educational achievement, but attention to the relationship between early cognitive ability and educational choices remains very limited. Nonetheless, we still find enough prior knowledge from the existing literature to make the necessary assumptions for building a structural model to investigate the selection effects of early cognitive ability on educational decisions. On this basis, unlike most studies that use cognitive abilities in only one period, we select two types of early cognitive abilities (preschool cognitive ability and post-compulsory school cognitive ability) so as to further explore whether cognitive abilities in different periods of childhood may have different impacts on educational choices. This also helps us to improve our understanding of the relationship between early cognition and educational decisions.

2.3 Methods

Our estimation framework is made up of a measurement model and a structural model. The structural model consists of a dynamic sequential educational decision model to investigate the effect of early cognitive abilities on sequential educational decisions, and a value-added plus lagged inputs model to catch the early cognitive development in childhood. The former is extended from Heckman et al. (2018) to fit the educational system in Britain, while the latter references the model of (Dickerson and Popli, 2016; Todd and Wolpin, 2007). Following the findings of Heckman et al. (2018), we hypothesise that selection bias in the decision equation is the result of a combination of cognitive and non-cognitive abilities, both of which are latent variables. The purpose of the measurement model is to estimate these latent abilities based on a set of relevant measurements.

2.3.1 Measurement model

Following Cunha and Heckman (2008), the set of cognitive and non-cognitive abilities $\theta \in \left\{\theta^C, \theta^{NC}\right\}$ are assumed to be latent, which means they cannot be observed and measured directly by researchers. Accordingly, we have several relevant test scores, each of which contains partial information about the relevant latent ability. We can think of each measure as measuring the relevant ability with "measurement error". The purpose of the measurement model is to extract information about these latent abilities from each test score and to predict their "true" values.

For each θ_t, we have m related measures available. Let $\mathrm{M}_{m,t}$ denotes the m^{th} measurement result (e.g. cognitive test score) for θ_t at time t. Since each measure contains partial information about θ_t, $M_t = (\mathrm{M}_{1,t}, ..., \mathrm{M}_{m,t})$ is systematically defined by:

$$M_t = \phi\left(\theta_t, e_t\right)$$

where $e_t = (\mathrm{e}_{1,t}, ..., \mathrm{e}_{m,t})$ is a vector of measurement errors[7]. We assume a linear format for the measurement equations:

$$\mathrm{M}_{m,t} = \alpha_{m,t}\theta_t + \mathrm{e}_{m,t} \tag{2.1}$$

where α is a vector of factor loading that captures the association between the observed measure and the unobserved ability, which presents the part of the information about the latent variables contained in the measurements. To deal with the scaling, we standardise all

[7]We assume that θ is the only factor that affects all related measurements. This assumption differs from Heckman et al. (2018). For example, Heckman et al. (2018)'s cognitive measurement model assumes that non-cognitive abilities affect cognitive variables in addition to including some control variables in the function. The main reason they do this is that one of their cognitive indicators is 9th grade GPA. They argue that academic success, while largely determined by cognitive ability, also depends on socio-emotional characteristics. However, our cognitive indicators are scores on professional cognitive tests, which are less likely to be influenced by other factors.

measurement results and normalise the factor loading of the one measure for each factor in each period to unity[8]. We assume the measurement errors to be normally distributed with mean zero, be independent across measurement equations and over time ($e^{z}_{l,t} \perp e^{z'}_{l',t}$, for $l \neq l'$, $t \in \{1,...,T\}$, $l,l' \in \{1,...,m\}$ and $z,z' \in \left\{\theta^{C}_{t}, \theta^{NC}_{t}\right\}$), and be independent with θ.

After estimating the measurement models, we can obtain the estimated cognitive abilities ($\widehat{C} = \widehat{\theta}^{C}$) and estimated non-cognitive ability ($\widehat{NC} = \widehat{\theta}^{NC}$). We then substitute these estimates into the subsequent structural model.

2.3.2 Early cognitive development model

The early cognitive development model aims to capture the changes in cognition across periods in childhood. Let us assume that the stock of cognitive ability at time t (C_t) is a function of the past cognitive ability stock (C_{t-1}), some exogenous factors (X^{C}_{t}) and an error term ε_t:

$$C_t = f\left(C_{t-1}, X^{C}_{t}, \varepsilon_t\right)$$

where $t \in \{1,...,T\}$ represents the different time periods of life, with $t = 0$ indicates the time of birth. We assume the development of cognitive ability over time has a linear formation[9]:

$$C_t = \gamma_t C_{t-1} + \lambda_t X^{C}_{t} + \varepsilon_t$$

where γ_t is a vector of time-varying parameters to be estimated which denotes the time effect of cognitive development, and ε_t is the error term that is normally distributed with zero mean and is assumed to be independent across individuals and over time. Conditional on X^{C}, ε_t is assumed to be independent of the lagged cognitive ability C_{t-1}[10] and measurement errors e.

For period $t = 0$, as we do not have specific measures to identify the initial cognitive ability C_0, we assume that this initial cognitive ability is proxy by a linear combination of initial circumstance at birth, X^{C}_{0}. Hence, we assume:

$$C_0 = \gamma_0 X^{C}_{0} + \varepsilon_0$$

[8]Switching the normalisation to the loading on other measures has no substantive effect on the results.

[9]This linear formation is known as the value-added specification of cognitive production function. More details of this specification are introduced in Appendix A.1.

[10]We identify the cognitive model and assumptions following Dickerson and Popli (2016), except for excluding the latent parental investment variable from the equations, as this is not relevant to our research interests.

In the empirical model, we consider two periods for cognitive abilities: preschool cognitive ability measured at age 5 (C_5) and post-compulsory school cognitive ability measured at age 16 (C_{16}). Thus, we estimate the following equations:

$$\begin{aligned} C_5 &= \gamma_5 C_0 + \lambda_5 X_5^C + \varepsilon_5 \\ &= \gamma_5 \left(\gamma_0 X_0^C + \varepsilon_0 \right) + \lambda_5 X_5^C + \varepsilon_5 \\ &= \gamma_5 \gamma_0 X_0^C + \lambda_5 X_5^C + (\gamma_5 \varepsilon_0 + \varepsilon_5) \qquad (2.2) \\ C_{16} &= \gamma_{16} C_5 + \lambda_{16} X_{16}^C + \varepsilon_{16} \qquad (2.3) \end{aligned}$$

where $\gamma_5 \gamma_0$ represents the effect of birth conditions on preschool cognitive ability and γ_{16} represents the time effect of preschool cognitive ability on post-compulsory school cognitive ability.

2.3.3 Sequential educational decision model

Heckman et al. (2018) present a multistage sequential model of educational choices with transitions and decision nodes for the US setting[11]. We adjust it to fit the British context and investigate the selection effects of early cognitive abilities on sequential educational decisions over time, which is shown in Figure 2.1. In Britain, children are required to attend compulsory education between the ages of 5 and 16. The minimum school leaving age was 16 for our target population, which indicates that children are allowed to make their educational decisions freely at age 16, which is the starting point of our dynamic sequential decision model. Our dynamic decision model starts with whether to go on to post-compulsory secondary schooling (A Level or equivalent qualifications) after completing compulsory and ends up with choosing whether to attend postgraduate education.

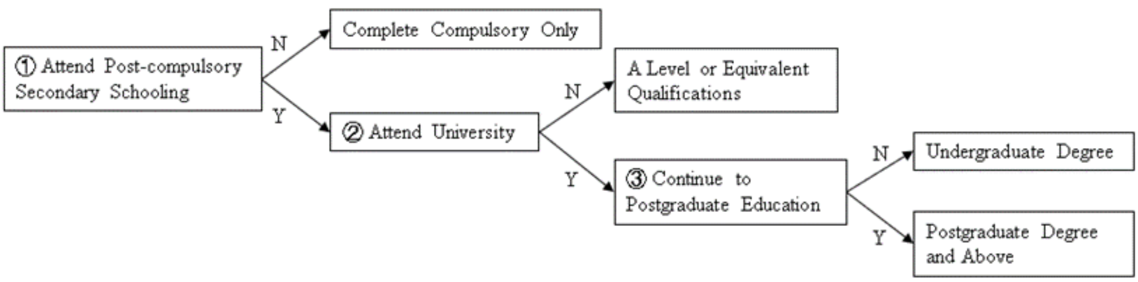

Fig. 2.1 A multistage sequential decision model modified from Heckman et al. (2018)

[11]This sequential decision model also analysed in Cunha and Heckman (2007); Heckman and Navarro (2007).

Assuming that the sequence of decisions is irreversible, we use the nodes $j \in \{1, ..., \overline{p}-1\}$ to describe different educational stages. At the same time, $P = \{1, ..., \overline{p}\}$ is the set of stopping states and $\overline{p}$ is the highest educational attainment. For each node, the agent has two possible options: remain in the node j or progress to the next node $j+1$. An indicator D_j is used to denote the agent's educational choice at node j: $\mathrm{D}_j = 0$ means the agent stops at the node j; $\mathrm{D}_j = 1$ indicates that the agent does not stop and goes on to the next node $j+1$ (continues to the next level of education)[12]. Thus, $\mathrm{D}_p = 0$ indicates that agents stop their education at the state $p \in P$.

We assume this decision process depends on the agent's potential net utility I_j at node j of going on to the next node. People always want to continue education when its related net utility is not less than zero:

$$\mathrm{D}_j = \begin{cases} 1, & \mathrm{I}_j \geq 0 \\ 0, & \mathrm{I}_j < 0 \end{cases} \qquad for \quad \mathrm{Q}_j = 1, j \in J, J = \{1, ..., \overline{p}-1\}$$

where Q_j indicates whether an agent reaches decision node j. $\mathrm{Q}_j = 0$ if the agent never progresses to node j, while $\mathrm{Q}_j = 1$ indicates the person gets to the node j and makes a related educational decision Q_j. $\mathrm{Q}_j = 1$ also implies that agents provide a positive response to all the decision nodes before j. By conditioning on $\mathrm{Q}_j = 1$, we make sure that we pay attention to agents who are eligible to make the transition.

Individuals make their educational decisions depending on the perceived gains (utility). We assume that selection into schooling can be fully accounted for by using observed characteristics and unobserved abilities. Conditional on $\mathrm{Q}_j = 1$, the unobserved and continuous utility I_j is approximated by a model:

$$\mathrm{I}_j = \phi_j \left(\mathrm{X}^D, \theta, \eta\right), j \in \{1, ..., \overline{p}-1\} \tag{2.4}$$

where X^D is a vector of observed exogenous variables that determine the transition decisions of the agent at different nodes, and θ is a vector of unobserved abilities which are latent

[12]Heckman et al. (2018) use the opposite notation that $\mathrm{D}_j = 0$ if a person at node j transit to next node $j+1$;$\mathrm{D}_j = 1$ if a person stops at node j.

cognitive and non-cognitive abilities[13]. η is an idiosyncratic error term and assumed to be normally distributed with mean zero.

Empirically, we cannot verify the agent's utility of every option but only observe their educational choice at each stage. And in line with our research interests, we list early cognitive abilities separately and group non-cognitive ability into control variables (X^D). So, for the specific binary educational decision at node j, D_j, the relevant utility I_j is assumed to be linearly identified by the estimated cognitive abilities ($\widehat{C}$) and a vector of exogenous controls (X_j^D)[14]. Thus, we have:

$$I_j = \beta_j^5 C_5 + \beta_j^{16} C_{16} + \pi_j X_j^D + \eta_j \tag{2.5}$$

where β_j indicates the selection effect of early cognitive abilities on the educational decision D_j. The error term η is assumed to be independent of factors C and X^D, as well as e and ε, which implies that the error terms of the different equations are uncorrelated. Conditional on X^D, η is assumed to be independent across individuals and transitions ($\eta_k \perp \eta_{k'}, k \neq k',\ and\ k, k' \in \{1, ..., \overline{p} - 1\}$). This sequential educational decision model is estimated by probit regression.

2.3.4 SEM framework

Figure 2.2 is a simplified diagram, presenting the structural and measurement model estimated by the SEM approach[15]. The unobserved variables (e.g. latent abilities and error terms) are drawn in ellipses and the observable variables are in rectangles. The single-headed arrows give us the unidirectional causal connections between two variables.

The dashed rectangle shows the measurement models of preschool cognition C_5 and post-compulsory school cognition C_{16} (given by Equation (2.1)). For the measurement model

[13] Heckman et al. (2018) defined that utility is determined by the observed and unobserved endowments. The unobserved endowment is then decomposed into two parts: interpretable sources of omitted variable bias and the idiosyncratic error term, while this part of interpretable sources of omitted variable bias determine how the unobservables mediate the causal effect of education on adult outcomes. According to the latest literature that both cognitive and non-cognitive skills play an important role in shaping educational choices and mediating the causal effect of education, they categorise the unobservables into cognitive and non-cognitive abilities.

[14] Linearity is assumed for ease of interpretation, but it is not necessary. For example, using data from National Longitudinal Survey of Youth in America, Ganzach (2000) estimates the influence of cognitive ability in a non-linear formulation and finds that cognitive ability and mother's education has an offsetting relationship on educational expectation and educational attainment, while cognitive ability has a synergistic relationship with educational expectation in determining educational attainment.

[15] Since there are binary variables in the model, the traditional SEM approach does not work. Instead, we apply the generalised SEM to fit this generalised linear model. Estimation is performed by using the GSEM command in Stata version MP18.

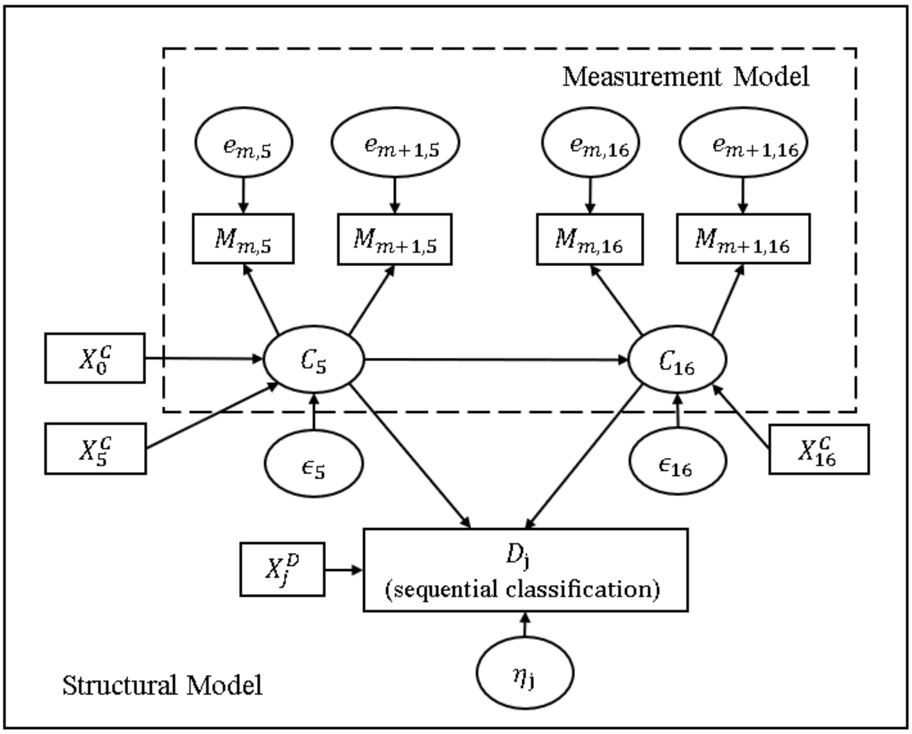

Fig. 2.2 Structural equation modelling framework

of latent cognitive ability at age t, to simplify, we list only two cognitive measures $M_{s,t}$ and $M_{s+1,t}$[16]. Our measurement model has a reflective format which presumes that latent factors affect observed indicators, and not vice versa (Hoyle, 2012), which is estimated via the Confirmatory Factor Analysis (CFA) in SEM.

The structural model (given by Equation (2.2), (2.3), and (2.5)) is illustrated in the large rectangle. For the structural model, the latent preschool cognition (C_5) is influenced by birth conditions (X_0^C) and exogenous covariates (X_5^C), when the post-compulsory school cognition (C_{16}) is affected by past cognitive ability (C_5) and other exogenous covariates (X_{16}^C). Besides, each educational decision (D_j) is determined by both early cognitive abilities (C_5, C_{16}) and exogenous covariates (X^D). These equations are estimated by maximum likelihood. In the empirical application, we adopt a one-step estimation approach - the measurement and structural models are estimated simultaneously.

[16]To simplify the graph, we neglect the measurement model of latent non-cognitive ability as well.

2.4 Data

Our individual-level data comes from the BCS70, which is a longitudinal and multipurpose study, following the lives of around 17,000 people who were born in one week of 1970 in Scotland, England and Wales. There are currently 11 waves in the BCS70, covering interviews with respondents from birth to age 51[17]. Each wave collected detailed information on health, educational and social development, and economic circumstances among other factors. Most importantly, the BCS70 tracks and measures individual cognitive ability from early childhood to later adulthood, which allows researchers to discover the development pattern of human cognition and study the effect of cognitive ability on other aspects of life. This fits well with our research question.

The sample for this paper is drawn from the nine main waves of BCS70, as detailed in Table 2.1. Due to the extended time span, natural attrition occurs in the data (e.g., loss of contact due to relocation and changes in contact information during certain periods). Given the research questions, our study requires participants to have taken at least one cognitive test at ages 5 and 16. Our explanatory variables are derived from four waves corresponding to the ages of birth, 5, 10, and 16. This yields a 'core sample' size of 4096. The substantial reduction in the 'core sample' size is attributed to the fact that significantly fewer individuals took the cognitive test at age 16 compared to age 5. Our explanatory variables include educational decisions made after compulsory education. To minimise information loss, we incorporated education data from the waves corresponding to ages 30 through 46, including intermediate years. For participants who did not report education information at age 46, we used their earlier (post-30) education data. We excluded the 26-year-old wave because most individuals who pursued postgraduate education had not yet completed their degree at that point. We believe that educational changes are relatively minimal after age 30.

After merging, we obtain two samples. The 'baseline sample', which includes only the main variables of interest—namely, all cognitive test scores related to early cognition and education in adulthood—has a sample size of 4,552. In contrast, the 'full sample', which includes additional control variables, has a sample size of 2,363. As shown in Table 2.1, despite our efforts to streamline the control variables, the sample size is significantly reduced after excluding observations with missing values. To assess whether this sample attrition could introduce potential bias, we compare the distributions of the control variables in our sample with those in the original data, as presented in Table A.1. The distribution of the control variables differed significantly between the two samples, except for mother's age at

[17]People were interviewed at the ages of birth, 5, 10, 16, 26, 30, 34, 38, 42, 46, and 51. The latest wave for the 51-year-old interview has not yet been compiled and is not available at the time of our study.

birth. In Section 2.5.1, we further compare the distributions of cognitive abilities estimated from the measurement model in the sample with those from the original data. The results indicate minimal differences between the two distributions. Therefore, we conclude that the loss of sample due to attrition may lead to bias in our model estimates. To explore the bias, we apply inverse probability weighting to adjust for attrition and compare these results to our main estimation results. In Section 2.5.3, we will further compare and discuss the estimation results for the 'baseline sample' and the 'full sample'.

Table 2.1 Number of observations changed when merging data

Data	Achieved sample	number of non-missing observations
Birth Sweep	17196	17058
Age 5 Sweep	13135	12794
Age 10 Sweep	14875	18584
Age 16 Sweep	11622	3694
Age 30 Sweep	11261	11226
Age 34 Sweep	9665	9665
Age 38 Sweep	8874	8874
Age 42 Sweep	9841	9841
Age 46 Sweep	8581	8581
No. obs in baseline sample		4552
No. obs in selected sample		2363

The baseline sample includes non-missing observations in cognitive ability tests and educational decisions. The selected sample includes non-missing observations in baseline sample and covariates. The education decision variables are generated from the last five sweeps. Source: the BCS70 wave 1, 2, 3, 4, 6, 7, 8, 9 and 10.

2.4.1 Sequential educational decisions

We consider three sequential educational decisions that people face after compulsory secondary education, which are listed in Table 2.2. Only after completing the previous education may a person decide whether to move on to the next educational decision. Therefore, the number of observations decreases as the educational level increases. Each educational decision is a dummy indicator, with 1 representing a positive answer. We extrapolate people's educational decisions based on the highest educational qualification they have obtained up to midlife (30-46 years old), which contains four groups: compulsory schooling, post-compulsory education, undergraduate education, and postgraduate education[18]. This categorical variable

[18]Our measure of educational decision is obtained by extrapolating back from the individual's highest educational achievement. A positive answer to an educational decision implies that the person has chosen to

Table 2.2 Descriptive statistics of sequential educational decisions

	N	Min	Max
D1: Whether to complete post-compulsory schooling	2363	0	1
No	874		
Yes	1489		
D2: Whether to finish undergraduate education, after post-compulsory schooling	1489	0	1
No	363		
Yes	1126		
D3: Whether to complete postgraduate education, after undergraduate education	1126	0	1
No	875		
Yes	251		

Source: the BCS70 wave 10.

is gained by combining two variables from the BCS70 — the individual's highest National Vocational Qualification (NVQ) level from an academic qualification and the highest NVQ level from a vocational qualification - and transforming five NVQ levels into educational levels[19]. The first and second NVQ levels are classed as compulsory secondary education. The third level of the NVQ is equivalent to post-compulsory education. Additionally, the fourth level of the NVQ equals undergraduate education, while the fifth level of the NVQ is analogous to postgraduate education.

Table 2.2 shows that in the sample, around 63% of people chose to continue their education after completing compulsory secondary schooling. This is 8 percent points higher than the general population in wave 10. Afterwards, 76% of these individuals chose to finish their undergraduate degrees (compared to 75% of the Wave 10 population), while only about 22% continued to complete the postgraduate education after finishing their undergraduate education (compared with 20% of the Wave 10 population). It can be seen that the proportions of educational decisions in the sample are close to the population, except for the proportion of those who completed post-compulsory schooling, which is higher in the sample than in the whole.

pursue a certain level of education and has obtained the appropriate degree certificate. For example, if a person chooses to go to university but for some reason drops out and does not receive a diploma, in our case, the answer to this educational decision is by default negative. In addition, we missed those who are undertaking some stage of education at the time of the interview but have not yet obtained a certificate, as we did not have the relevant information.

[19]The transformation is following the guidance from https://cls.ucl.ac.uk/wp-content/uploads/2018/06/Deriving-highest-qualification-in-NCDS-and-BCS70.pdf

2.4.2 Early cognitive abilities

Preschool cognitive ability and post-compulsory school cognitive ability are the two early cognitive abilities that we focus on in this paper. Both are latent variables and cannot be observed directly by researchers. Instead, multiple age-specific cognitive ability tests designed by psychologists are conducted in each testing period of the BCS70. We construct a measurement model to measure early cognitive abilities separately using these cognitive test scores. Table 2.3 presents descriptive statistics for all related cognitive test scores. We compute the total score for each cognitive ability test and use the standardised score in the measurement model (Moulton et al., 2020).

Preschool cognitive ability is assessed at age five via five tests. First, the copying design test requires the child to make two copies of eight shapes to show their visuospatial abilities. Next is the English picture vocabulary test which asks the child to pick one from four photos that match a particular word (a total of 56 sets). This test aims to examine the child's verbal ability. The human figure drawing test measures the general perceptual ability, in which a child is asked to draw a picture of a man or a woman. To examine children's spatial development, the complete profile test requires children to fill in the features of a profiled human face, such as a nose, eyes, and so on. Last, the Schonell reading test is used to evaluate children's "reading age" by asking them to read 50 words.

Post-compulsory school cognitive ability is also examined at age 16 by five cognitive tests. In the spelling test, the cohort member must distinguish whether 100 words are spelled correctly. Next, from a multiple-word choice list (75 items in total), in the vocabulary test, the teenager needs to find the one word that shares the same meaning as the term that is presented. The five-subscales of the condensed Edinburgh Reading Test measure a teenager's verbal (reading) skills from vocabulary, grammar, sequencing, comprehension, and retention. Then, an arithmetic test includes 60 multiple-choice questions on topics such as probability, arithmetic, and other subjects. The final test poses 11 out of the 28 matrix questions from the matrices section of the British Ability Scales (BAS) test, which assesses the non-verbal reasoning ability of teenagers.

2.4.3 Socioeconomic background

We control an individual's initial birth conditions and family circumstances. Table 2.4 shows the selection of control variables used in each estimated equation, while Table 2.5 displays the descriptive statistics of these control variables.

Table 2.3 Descriptive statistics of cognitive test scores

	N	Mean	s.d.	Min	Max
Cognitive ability tests at age 5					
Copying designs test	2362	5.07	1.93	0	8
Complete a profile test	2292	7.16	3.93	0	16
English picture vocabulary test	1796	34.76	8.72	6	51
Human figure drawing test	2341	10.77	3.03	1	21
Shortened Edinburgh reading test	1175	4.08	6.21	0	49
Cognitive ability tests at age 16					
Shortened Edinburgh reading test	1097	56.58	12.37	14	75
BAS matrices test	1130	9.00	1.62	1	11
Arithmetic test	1361	38.18	11.37	0	60
Spelling test	2230	164.81	26.42	0	198
Vocabulary test	2212	43.92	12.43	0	75

Source: the BCS70 wave 2 and 4.

Table 2.4 Selection of control variables in each structural equation

	Eqn (2.2)	Eqn (2.3)	Eqn (2.5)
Mother's age at birth	$\surd$		
Birth weight	$\surd$		
Gender	$\surd$	$\surd$	$\surd$
Parental education (age 5)	$\surd$	$\surd$	$\surd$
Number of siblings (age 5)	$\surd$	$\surd$	$\surd$
Non-cognitive ability (age 10)			$\surd$
Family income (age 16)		$\surd$	$\surd$

Note: Preschool cognitive ability for Eqn (2.2); Post-compulsory school cognitive ability for Eqn (2.3); Educational decisions for Eqn (2.5).

Case and Paxson (2010) emphasise the importance of birth weight in cognitive functions. Birth weight is measured in kilograms, and together with mother's age at delivery, accounts for initial endowment and early disadvantage that the child might face, since a child with low birth weight or younger mother more often comes from a disadvantaged background (Hawkes and Joshi, 2012; Nakamuro et al., 2013). Gender is a dummy indicator where 1 equals male.

We select four factors to proxy early family circumstances. The number of children in the household is likely to influence the allocation of parental resources, affecting cognitive development (Azmitia and Hesser, 1993; Dai and Heckman, 2013; Downey, 2001) and educational decisions (Jensen and McHale, 2015; Karwath et al., 2014). We count the number of siblings of cohort members and divide them into three categories: none, one sibling, and two or more siblings. Parental education and family income are indicators of socioeconomic gradient that is closely associated with early cognitive development (González et al., 2020; Khanam and Nghiem, 2016; Schady, 2011) and educational decisions (Hegna and Smette, 2017; Taubman, 1989). Respondents report the types of educational qualifications that their father and mother hold. Due to a large number of missing values, we construct a new derived variable, the highest parental qualification, which refers to the mother's or father's highest qualification, if one is missing. This variable contains three categories: no qualification, lower than A level, A level and above. As for family income, the BCS70 offers a derived variable which groups the weekly household income of cohort members into 11 categories, ranging from less than £50 to more than £500. We recode them into three groups: low-income group, medium-income group and high-income group, according to classification guidance from the government[20]. The guidance suggests that the low-income group includes those incomes less than 60% of the national median, and the high-income group contains those incomes in the top 10% of the national distribution. We find that the 60% of the sample median is located in the '£100–149 per week' range, and then arrange that family income less than £150 as the low-income group, while those families with incomes more than £350 per week comprise the high-income group. The rest of the sample belong the medium-income group. When estimating, each type of categorical covariate is transformed into a dummy indicator.

Furthermore, we include the non-cognitive ability to control the additional ability bias[21]. The BCS70 measures children's non-cognitive ability at age 10. Table 2.6 presents six selected measurements following Conti et al. (2010): the locus of control (caraloc) scale, the perseverance scale, the cooperativeness scale, the persistence scale, the attentiveness scale and the completeness scale. The locus of control scale, which has 20 questions, measures children's perceived achievement control. Five distractor questions are deleted so we obtain a raw score range from 0 to 15 where high scores show more self-esteem and internalisation[22]. The perseverance scale is based on the question 'How much perseverance does the child

[20]The classification of the low-income group is follows a government website: $https://commonslibrary.parliament.uk/research-briefings/sn07096/$.

[21]Strictly speaking, there may be other unobservable factors that lead to omission bias. Here, we hypothesise, based on Heckman et al. (2018)'s findings, that selection bias in the educational decision-making equation arises from both cognitive and non-cognitive abilities.

[22]Questions 4, 7, 11, 15, and 19 are deleted. Each "No" response counts as one point, except for question 10 where the "Yes" response earns one point. Conti et al. (2010) only deleted 4 questions and received raw scores ranging from 0 to 16. This transformation follows the guidance of the UCL website: $https://cls.ucl.ac.uk/wp-content/uploads/2017/07/CARALOC_LAWSEQ.pdf$.

Table 2.5 Sample sizes of control variables

Variable	N	Min	Max
Initial birth conditions			
Mother's age at birth	2363	15	46
Birth weight in kilograms	2363	1.16	6.46
Gender	2363	0	1
female	1384		
male	979		
Early family circumstances			
Number of siblings at age 5	2363	1	3
none	258		
one sibling	1275		
two or more siblings	830		
Parental education at age 5	2363	1	3
no qualification	1080		
lower than A level	898		
A level and above	385		
Family income at age 16	2363	1	3
low-income group	692		
medium-income group	1289		
high-income group	382		

Source: the BCS70 wave 1, 2, and 4.

show in the face of difficult tasks?', while the cooperativeness scale comes from the question 'How cooperative is the child with his peers?'. Next, the persistence scale originates from the question 'Does the child show perseverance and persist with difficult or routine work?'. The attentiveness scale derives from the question 'Does the child pay attention to what is being explained in class?'. Last, the completeness scale is measured by the question 'Does the child complete tasks which are started?'. The raw scores of the latter five scales range from 1 to 47.

2.5 Results

2.5.1 Descriptive analysis of cognitive abilities

There are three latent variables that need to be estimated in this paper: preschool cognitive ability at age five, post-compulsory school cognitive ability at age 16, and non-cognitive ability measured at age 10. The BCS70 offers multiple measurements for each latent variable,

Table 2.6 Descriptive statistics of non-cognitive test scores

	N	Mean	s.d.	Min	Max
Locus of control scale	2363	7.62	2.92	0	15
Perseverance scale	2307	30.93	10.78	1	47
Cooperativeness scale	2331	32.73	8.68	1	47
Completeness scale	2331	35.40	12.58	1	47
Attentiveness scale	2332	34.43	12.17	1	47
Persistence scale	2340	30.87	13.03	1	47

Source: the BCS70 wave 3.

Table 2.7 The correlation between cognitive test scores at age five

	cd5	cp5	epvt5	hfd5	srt5
Copying designs test (cd5)	1				
Complete a profile test (cp5)	0.153	1			
English picture vocabulary test (epvt5)	0.201	0.112	1		
Human figure drawing test (hfd5)	0.270	0.224	0.110	1	
Shortened Edinburgh reading test (srt5)	0.213	0.050	0.085	0.123	1

Source: the BCS70 wave 2.

which we have introduced in Tables 2.3 and 2.6, respectively. Tables 2.7 and 2.8 shows the pairwise correlations between cognitive test scores, and Table A.2 displays the correlation between non-cognitive measurements[23]. We find a positive correlation between all the measures. The average correlation between measures for post-compulsory school cognitive ability is larger than the others. The correlation between the shortened Edinburgh Reading Test and the vocabulary test especially is 0.757. This reveals that the measurements at age 16 have some overlap, but they still contain some idiosyncratic parts of cognitive ability.

Then we estimate these latent variables using the measurement model[24]. Table 2.9 presents the estimated factor loading of measurement models which indicates the impact of the latent variable on the related measure. It reveals that all measures are loaded positively and significantly at the 1% significance level. The factor loading of the copying designs test, shortened Edinburgh Reading Test and locus of control scale is constrained to equal one

[23] A preliminary factor analysis has been performed on these measurements, while the Velicer (1976) minimum average partial correlation criterion is suggested to retain one component.

[24] In our sample, we only require participants to complete at least one cognitive ability test. Hence, some observations may contain missing values in some cognitive tests. The SEM approach by default applies an equation-wise deletion approach for models with continuous latent variables, that allows estimating all observations even with missing values, while the traditional SEM approach requires no missing values in the sample.

Table 2.8 The correlation between cognitive test scores at age sixteen

	srt16	m16	vt16	at16	st16
Shortened Edinburgh reading test (srt16)	1				
BAS - matrices test (m 16)	0.504	1			
Vocabulary test (vt16)	0.757	0.387	1		
Arithmetic test (at16)	0.679	0.503	0.635	1	
Spelling test (st16)	0.559	0.369	0.567	0.543	1

Source: the BCS70 wave 4.

(anchoring). The magnitudes of the standardised loading of remaining measures are above 0.50, which indicates that each measure is a significant indicator of its underlying variable. With these loadings, we can predict the latent variables.

Figure 2.3 presents distribution graphs for two estimated cognitive abilities. The right column displays the distribution of preschool cognitive ability (at the top) and post-compulsory school cognitive ability (at the bottom) within the sample, while the left column shows the corresponding distributions for the tested waves. As illustrated, the shape of the distribution curve for the sample closely resembles the overall distribution shape. In the right column, the predicted preschool cognitive ability follows a normal distribution, which remains robust under skewness and kurtosis tests. Conversely, the distribution of the predicted post-compulsory school cognitive ability is negatively skewed (skewness = -0.97).

To assess how much discontinuity exists in cognitive performance between ages five and 16, we group cognitive ability in each period by quartile, so that individuals are each classified into one of the four quartile groups. By cross-tabulating the quartile groups in the two periods, we obtain the quartile transition matrices and reassign names to each group based on cognitive ranking changes (See Table 2.10) (Feinstein and Bynner, 2004). Table 2.11 displays summary statistics (proportions) for the five groups. We find that the low-low group is at the bottom of the five groups in terms of average early parental education and family income, while the high-high group is well ahead in all aspects. It seems that early family background has an association with cognitive development. Comparing Groups 1 (low-low) and 2 (escapers), we find that it is children with higher educated parents and higher family income who are able to overcome their early cognitive developmental disadvantages and catch up in adolescence. By comparing Group 4 (fallers) with the other groups (Groups 3 and 5), we find that children with less educated parents and slightly lower family incomes seem to be more likely to fall behind in adolescent cognitive development, even if they gain an advantage in early cognitive development. Since the number of escapers (Group 2) is close to twice the number of fallers (Group 4), the distribution of cognitive ability changes from normal to skewed in Figure 2.3.

Figures 2.4 and A.1 show the density curve and the mean of early cognitive abilities by the response to the three educational decisions in order from left to right. The top row shows the relationship between preschool cognition and educational decisions, while the bottom row shows the relationship between post-compulsory school cognition and educational decisions. We find that the cognitive density curves of the positive respondents are all shifted to the right compared with the cognitive density curves of the negative respondents, except for the graph in the upper right corner. Within cognitive ability, there is a significant gap between the different response groups for each decision. From Figure A.1, we can visualise that the overall level of early cognitive abilities rises with the level of education and that groups with higher cognitive ability are more likely to respond positively to each educational decision. This trend is more evident in post-compulsory school cognitive ability. In addition, Figure A.2 presents the probability of continuing education in each of the three educational decisions for each of the five groups. Children in the high-high group had the highest probability of giving a positive response to each of the educational decisions, while those in the low-low group had the lowest. These descriptive analyses all suggest a correlation between early cognition and educational decisions.

Table 2.9 Predicted latent abilities: Loading of measurement models

	Cognitive ability at age 5		Cognitive ability at age 16		Non-cognitive ability	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Copying designs test	1	constrained				
Complete a profile test	0.396***	(0.043)				
English picture vocabulary test	0.769***	(0.059)				
Human figure drawing test	0.734***	(0.046)				
Shortened Edinburgh reading test	0.632***	(0.068)				
Shortened Edinburgh reading test			1	constrained		
BAS - matrices test			0.601***	(0.032)		
Arithmetic test			0.835***	(0.027)		
Spelling test			0.596***	(0.024)		
Vocabulary test			0.839***	(0.023)		
Locus of control scale					1	constrained
Perseverance scale					3.107***	(0.244)
Cooperativeness scale					1.595***	(0.143)
Completeness scale					2.571***	(0.208)
Attentiveness scale					2.791***	(0.223)
Persistence scale					2.979***	(0.236)

Note: $^{***}p \leq 0.01$.

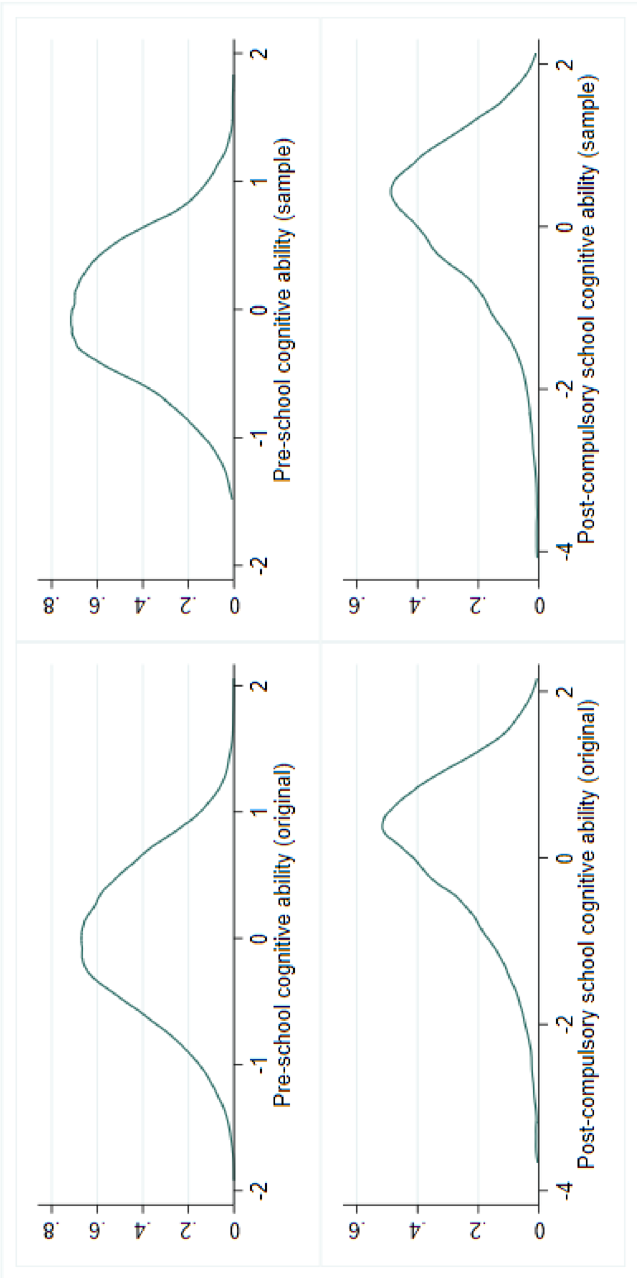

Fig. 2.3 Kernel density estimates for two early cognitive abilities predicted from measurement model, for the survey data (the left) and the selected sample (the right). There were 13,049 individuals attended at least one cognitive test at the age 5 wave, while there were 6,044 individuals at the age 16 wave. There were 2,363 individuals in the sample.

Table 2.10 Definition of groups indicating change or persistence in childhood

<table>
<tr><td></td><td colspan="4">Quartile at age 16</td></tr>
<tr><td>Quartile at age 5</td><td>1 (Low)</td><td>2</td><td>3</td><td>4 (High)</td></tr>
<tr><td>1 (Low)</td><td>Group 1 (Low-Low)</td><td colspan="3">Group 2 (Escapers)</td></tr>
<tr><td>2</td><td colspan="4">Group 3 (Median)</td></tr>
<tr><td>3</td><td colspan="4">Group 3 (Median)</td></tr>
<tr><td>4 (High)</td><td colspan="2">Group 4 (Fallers)</td><td colspan="2">Group 5 (High-High)</td></tr>
</table>

Note: This table references the design of Feinstein and Bynner (2004).

Table 2.11 The number of observations in each group (5 and 16)

	Gender	Parental education (5)	Number of siblings (5)	Family income (16)	N	%
Group 1 (Low-Low)	0.46	1.30	2.41	1.51	259	10.96%
Group 2 (Escapers)	0.42	1.59	2.33	1.80	332	14.05%
Group 3 (Median)	0.40	1.71	2.22	1.88	1182	50.02%
Group 4 (Fallers)	0.43	1.65	2.26	1.85	169	7.15%
Group 5 (High-High)	0.40	2.05	2.14	2.11	421	17.82%

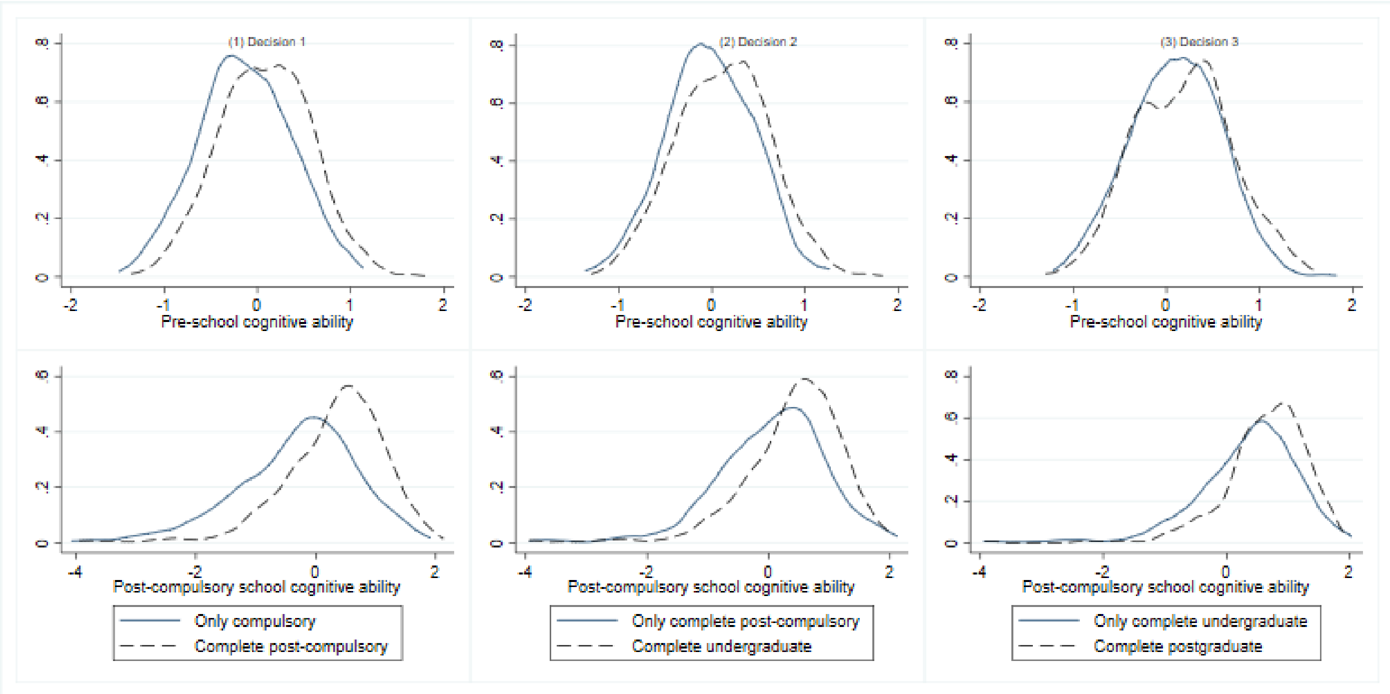

Fig. 2.4 Kernel density estimates for predicted early cognitive abilities, for the first educational decision (the left), the second educational decision (the middle) and the third educational decision (the right). The dashed line illustrates density for having a positive response for a given decision ($D_j = 1$), while the solid line presents density for having a negative response ($D_j = 0$).

2.5.2 Effect of cognitive development

Table 2.12 shows the effect of cognitive development. The first column displays regression results of preschool cognitive ability (Equation (2.2)), while the second column presents regression results of post-compulsory school cognitive ability (Equation (2.3))[25]. We find that preschool cognitive ability is positively associated with two birth conditions (birth weight and mother's age at delivery). A child birth weight of one kilogram is more likely to result in higher preschool cognitive ability by 0.186 standard deviations, controlling early family backgrounds. In contrast, for families with two or more siblings, children's average preschool cognitive ability is lower than the others. This can be explained by resource dilution (Azmitia and Hesser, 1993). Having more siblings during childhood will lead to a reduction in parental attention and investment allocation, affecting early cognitive development.

Next, the time effect of preschool cognitive ability on post-compulsory school cognitive ability is 0.763 at the 1% significance level, indicating that a one standard deviation increase in preschool cognitive ability will lead to 0.763 standard deviations of extra improvement in post-compulsory school cognitive ability holding other factors constant. It appears that preschool cognitive ability dominates the development of post-school cognitive ability. We also find that children from middle- and high-income groups have an advantage in early cognitive development over children from low-income groups.

Parental education has a sustained positive influence on both early cognitive abilities. The higher the level of parental education, the greater the improvement in the child's cognitive development. For instance, the average post-compulsory school cognitive ability of children whose parents have an A-level or above qualification is 0.266 standard deviations higher than that of children whose parents have no educational qualifications, while children whose parents have primary school qualifications have only 0.128 standard deviations higher of post-compulsory school cognitive ability. In addition, girls are likely to have a higher level of preschool cognitive ability than boys on average, and this gap tends to widen over time.

[25]Equations are estimated by maximum likelihood (ML) by default.

Table 2.12 Results of cognitive development models

	Cognitive ability at age 5		Cognitive ability at age 16	
	Coef.	Std. Err.	Coef.	Std. Err.
Preschool cognitive ability (age 5)			0.763***	(0.063)
Mother's age at delivery	0.023***	(0.003)		
Birth weight	0.186***	(0.030)		
Gender (baseline = female)	-0.050	(0.034)	-0.149***	(0.043)
Number of siblings at age 5 (baseline = no sibling)				
one sibling	-0.007	(0.054)	-0.040	(0.070)
two or more siblings	-0.298***	(0.058)	-0.134*	(0.075)
Parental education at age 5 (baseline = no qualification)				
lower than A level	0.268***	(0.037)	0.128**	(0.050)
A level and above	0.464***	(0.049)	0.266***	(0.071)
Family income at age 16 (baseline = low-income)				
middle-income			0.211***	(0.050)
high-income			0.403***	(0.070)

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$.

2.5.3 Selection effect of early cognitive abilities

Table 2.13 displays probit regression results of the sequential educational decision model. The first row lists the selection effects of preschool cognitive ability on three sequential educational decisions, while the second row presents the selection effects of post-compulsory school cognitive ability. Preschool cognitive ability has the greatest impact on the likelihood of completing undergraduate education after post-compulsory schooling, followed by its impact on completing post-compulsory education. In contrast, it has no significant effect on the probability of completing postgraduate education. Specifically, a one standard deviation increase in preschool cognitive ability is associated with a 16.2 percentage point higher probability of completing post-compulsory education and a 22.4 percentage point higher probability of completing undergraduate education. Post-compulsory school cognitive ability exhibits the strongest influence on the completion of post-compulsory education, followed by its impact on postgraduate education, and lastly, on undergraduate education. For instance, a one standard deviation increase in post-compulsory school cognitive ability results in a 32.7 percentage point increase in the probability of completing post-compulsory education, while the probability of completing postgraduate education increases by 20.3 percentage points. Both early cognitive abilities have positive selection effects on encouraging people to move on to the next stage of education. Relatively speaking, preschool cognitive ability reflects more of an individual's innate cognition, whereas post-compulsory school cognitive ability is influenced by compulsory education, building upon preschool cognition. The impact of preschool cognition on educational decisions is partly direct and selective, but also occurs indirectly by affecting post-compulsory school cognitive ability, which in turn influences educational decisions. In other words, post-compulsory school cognitive ability partially mediates the effect of preschool cognitive ability on educational outcomes. This relationship is captured in our structural model. Regarding the magnitude and significance of estimated coefficients, the influence of post-compulsory school cognitive ability on educational decisions appears to be more consistent and stable compared to preschool cognitive ability. This suggests that post-compulsory school cognitive ability may be a more effective predictor of educational outcomes than preschool cognitive ability. Our findings are consistent with Heckman et al. (2018), that is, people with high cognitive ability are more willing to pursue higher education beyond compulsory education than those with relatively low cognitive ability. They argue that the high-ability group has a higher probability to continue higher education not only because they can do it but also because of other potential benefits – sorting on gains.

It comes as no surprise that we see the positive impact of parental education on the educational decisions of children. If one of the parents has received a certain level of education, their child will have a greater probability of completing further education after compulsory education. Particularly, children of parents with an A-level qualification or higher are about 45 percentage points more likely to choose to complete a postgraduate education after being an undergraduate than children of less educated parents. We find that individuals with more than two siblings have a 21.3 percent points lower probability of completing post-compulsory education and, as a result, lose the opportunity to continue subsequent education. This may be attributed to the fact that parents in larger families face greater financial burdens and may encourage their children to enter the workforce earlier to ease the family's financial strain. Given this, it is unsurprising that families with higher incomes are more willing to allow their children to continue with post-compulsory education. For those who have completed post-compulsory education, we find that family income has no direct impact on whether they complete tertiary education. One possible explanation is that, at the time, students are largely exempt from university tuition fees[26], and the cost of living for university students was typically covered by a combination of family support, grants[27] and student loans. Therefore, it is unlikely that family finances played a significant role in influencing educational decisions. Meanwhile, gender differences in educational preference are mainly observed in post-compulsory education. The proportion of men completing post-compulsory education is 12.5 percentage points higher than that of women. One possible explanation is that the UK government's higher education reforms in the 1990s, along with the growing demand for high-skilled jobs, significantly increased female participation in higher education, gradually equalising it with that of men. Thus, while there was a gender gap in post-compulsory education decisions made before 1990, this gap became less pronounced in decisions related to subsequent education.

We do consider the potential endogeneity of early cognitive abilities. Apart from early family circumstances, ignoring unobserved non-cognitive ability is very likely to cause omitted bias. For instance, children who have more patience and self-control are more likely to gain more knowledge and get more practice in thinking in their early home and kindergarten education - and thus score better on cognitive tests. They are also more likely to achieve

[26] British university students typically complete their undergraduate education between the ages of 21 and 23. For the individuals in our sample, this would generally have occurred between 1991 and 1993, assuming they pursued undergraduate studies. Notably, university tuition fees were low and paid by the local government in the UK until 1998.

[27] The amount of the living grant is related to family income. Students from high-income families may receive a smaller grant, or even none at all, while students from low-income families may receive a larger grant to cover living expenses.

better educational performance and have more opportunities in later education. Therefore, we use the measurement model to estimate the latent non-cognitive ability and include it as a control in the outcome regression. From the third row of Table 2.13, we find a strong positive association of non-cognitive ability with all educational decisions. For an undergraduate, a one standard deviation increase in non-cognitive ability at age 10 raises the probability of completing a postgraduate education by 80.4 percentage points, compared with 20.3 percentage points for post-compulsory school cognitive ability. Although a direct comparison of the coefficients between the two is not meaningful due to differences in measurement, the results still highlight the significance of non-cognitive abilities in education.

To assess the robustness of our results, we conducted a series of robustness tests and summarised the results in Table 2.14. Results of Model (1) represent our main findings discussed above, while Model (2) applies inverse probability weight to address the potential sample attrition bias[28]. The two sets of results are essentially identical, with the only notable difference being that the coefficients for preschool cognitive ability becomes smaller and insignificant. This suggests that post-compulsory school cognition may fully mediate the effect of preschool cognition on educational decisions. However, this does not alter our conclusion that post-compulsory school cognition may be a better predictor of educational decisions than preschool cognition. Model (3) examines the case of excluding post-compulsory school cognition. We find that even without considering post-compulsory school cognition, preschool cognition still has no significant direct effect on the likelihood of completing postgraduate education. Model (4) is the scenario where no control variables are included. We observe that the coefficients of preschool cognitive ability become larger. Additionally, by excluding control variables, we can use a larger sample, referred to as the 'baseline sample' in Section 2.4. Model (6) is estimated using this 'baseline sample'. The results are very similar to those of model (4). This suggests that sample size does not substantially affect the estimated results. Model (5) excludes the cognitive development model, reducing our structural model to a probit regression of the three education equations. Although the results do not differ significantly from our main model, the latter provides a more detailed examination of the potential transmission pathways through which preschool cognitive abilities influence education.

[28]Following the approach outlined by Jones et al. (2006); Robins et al. (1995); Wooldridge (2002), we estimated the inverse probability weight based on the probability of sample loss, using non-missing variables from the birth wave. In the birth wave, there were only about 10 variables without missing values, none of which were related to social status or family background. Some variables also had a potential multicollinearity risk, particularly in relation to previous pregnancy or abortion experiences. After careful consideration, three independent variables were selected for the probability regression: the number of previous pregnancies, the mother's participation in completing the family background questionnaire, and region.

Table 2.13 Results of sequential educational decision models

	post-compulsory schooling		undergraduate education		postgraduate education	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Preschool cognitive ability (age 5)	0.162**	(0.082)	0.224**	(0.110)	-0.024	(0.124)
Post-compulsory school cognitive ability (age 16)	0.327***	(0.046)	0.164***	(0.062)	0.203**	(0.083)
Non-cognitive ability (age 10)	0.507***	(0.128)	0.479***	(0.168)	0.804***	(0.227)
Gender (baseline = female)	0.125**	(0.058)	-0.052	(0.076)	-0.007	(0.089)
Number of siblings (baseline = no sibling)						
one sibling	-0.058	(0.095)	0.122	(0.116)	0.023	(0.141)
two or more siblings	-0.213**	(0.099)	0.110	(0.125)	-0.064	(0.154)
Parental education (baseline = no qualification)						
lower than A level	0.276***	(0.065)	0.151*	(0.085)	0.101	(0.108)
A level and above	0.455***	(0.096)	0.315***	(0.117)	0.446***	(0.130)
Family income (baseline = low-income)						
middle-income	0.033	(0.067)	-0.031	(0.091)	-0.105	(0.117)
high-income	0.197**	(0.101)	0.100	(0.126)	0.009	(0.142)

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$.

Table 2.14 Robustness checks

	(1) main			(2) IPW			(3) C5		
	D1	D2	D3	D1	D2	D3	D1	D2	D3
C5	0.162**	0.224**	-0.024	0.120	0.170	-0.062	0.316***	0.263***	0.062
	(0.082)	(0.110)	(0.124)	(0.083)	(0.110)	(0.129)	(0.066)	(0.087)	(0.097)
C16	0.327***	0.164***	0.203**	0.322***	0.167***	0.201**			
	(0.046)	(0.062)	(0.083)	(0.049)	(0.063)	(0.081)			
NC10	0.507***	0.479***	0.804***	0.518***	0.494***	0.894***	0.843***	0.649***	0.961***
	(0.128)	(0.168)	(0.227)	(0.137)	(0.180)	(0.234)	(0.130)	(0.164)	(0.223)
Covariates		√			√			√	
Cog-model		√			√			√	
N		2363			2363			2363	
AIC		87512.84			479839.1			67918.26	
BIC		88066.53			480392.8			68322	
	(4) no control			(5)no cog model			(6) large sample		
	D1	D2	D3	D1	D2	D3	D1	D2	D3
C5	0.303***	0.244**	0.044	0.149*	0.151	-0.069	0.360***	0.297***	0.128
	(0.080)	(0.104)	(0.116)	(0.079)	(0.104)	(0.118)	(0.058)	(0.078)	(0.089)
C16	0.403***	0.248***	0.325***	0.336***	0.179***	0.207**	0.403***	0.202***	0.342***
	(0.045)	(0.059)	(0.079)	(0.048)	(0.064)	(0.087)	(0.034)	(0.045)	(0.060)
NC10				0.335***	0.375**	0.724***			
				(0.130)	(0.172)	(0.233)			
Covariates					√				
Cog-model		√						√	
N		2363			2363			4552	
AIC		53167.92			87403.41			102099.1	
BIC		53398.63			87887.9			102356.1	

Note: $*p \le 0.1$, $**p \le 0.05$, $***p \le 0.01$. All models were estimated by one-step GSEM approach. Model (1) shows the unweighted results, while model (2) presents the IPW results.

2.6 Conclusions

The purpose of this paper is to investigate the selection effect of two early cognitive abilities on three sequential educational decisions made after compulsory education in Britain, using data from the BCS70. This selection effect refers to the fact that people with different cognitive abilities may have different preferences for educational decisions. We adopt a SEM approach, with a measurement model for latent abilities and a structural model which combines a dynamic sequential decision model and a cognitive development model.

Our findings show a positive selection effect of early cognitive ability on individual educational decisions. This finding is consistent within the existing literature (see e.g. Frederick, 2005; Heckman et al., 2018). The direct influence of post-compulsory school cognitive ability persists in all three educational decisions, while the effect of preschool cognitive ability disappears as the level of educational attainment increases. We find a large discontinuity in cognitive performance between ages five and 16, which is strongly associated with family background. This is consistent with Feinstein and Bynner (2004), who also report that changes in mid-childhood also strongly impact early adult outcomes, even more so than the impact of cognitive development before age five. Given the finding from the early cognitive development model that preschool cognition governs the development of post-compulsory school cognition, post-compulsory school cognitive ability may mediate the influence of preschool school cognitive ability on educational decisions. The importance of early cognition is widely recognised, but which period of cognitive ability plays a greater role has not been compared yet. Our findings help to fill this research gap by confirming that after controlling for preschool cognitive ability, the selection effect of post-compulsory school cognitive ability on educational decisions remains significant.

The range of educational decisions people make after compulsory education is linked to subsequent educational attainment and later adult outcomes. Exploring the determinants of the individual educational decision-making process can support policymakers in better designing related policy. Our findings also confirm the need for active intervention in early cognitive development and the significance of compulsory education policy. Many researchers have emphasised the importance of early investments, especially for infancy and early childhood (see e.g. Cunha and Heckman, 2008; Ozawa et al., 2022). Our findings suggest that children's cognitive development in the middle and later childhood also deserves attention.

In addition to cognition (intelligence), parental education and family income are often recognised as significant predictors of children's educational outcomes. We find that children with educated parents tend to have a higher probability of continuing their education, a phenomenon referred to as the intergenerational transmission of educational attainment. Ganzach (2000) suggests that more educated parents are better equipped to facilitate children's learning by creating a better social and physical environment. The importance of family background on education is well established in the literature (see e.g. De Graaf and Huinink, 1992; White, 1982; Wilson, 2001).

There are two primary reasons why family income has an impact on educational decisions. The first is the willingness to pursue education. Higher-income parents are generally better educated and demonstrate a stronger preference for higher education for their children. They also have greater access to educational resources that enhance their children's academic performance and college readiness (Looker, 1997; Pfeffer, 2018), thereby shaping their children's attitudes towards education and expectations of future attainment. Considine and Zappalà (2002) argued that social and economic disadvantage can significantly affect academic achievement and thus educational decisions. The second factor is the cost of education. The high cost of tuition and living expenses can deter students from pursuing higher education. The ability to receive direct financial support from family while at university is crucial for students, particularly those facing academic challenges (Pfeffer, 2018). Using longitudinal data from Canada, Looker (1997) found that financial constraints can limit students' access to preferred educational pathways, such as universities, pushing students to community colleges as a fallback option. Lunn and Kornrich (2018) found that even in times of economic uncertainty, families with higher incomes continued to prioritise investment in education. Our findings demonstrate a positive association between family income and the probability of completing post-compulsory education. Using the same dataset, Bratti (2007) employed an instrumental variable approach to control for the potential endogeneity of family income and found that parental income has a strong effect on the likelihood of a child dropping out of school at age 16. This suggests that lower family income may lead to earlier exits from the education system, thereby reducing access to higher education. However, we did not find a significant correlation between family income and the decision to enter higher education. This may be attributable to the specific context of the time, when British universities were tuition-free (covered by the government) and offered a variety of government grants and student loans, which greatly reduced the negative impact of financial constraints on higher education. Additionally Leeson et al. (2008) found that both cognitive ability and gender play a unique role in predicting academic performance in youth. However, we do not observe significant gender differences in long-term educational decision-making preferences. As we discussed earlier, it may be that the educational reforms of the UK government and the transformation of social productivity in the 1990s led to this outcome.

Non-cognitive ability is known as personal traits or personality. The Literature has shown that non-cognitive ability strongly influences academic achievement (see e.g. Gottfried, 1990; Greven et al., 2009; Spinath et al., 2006) and economic success (Almlund et al., 2011; Borghans et al., 2008). This is largely because positive self-concept and non-cognitive skills are strong predictors of student persistence, particularly in challenging environments (Ryberg, 2018). Coneus and Laucht (2014) argued that these traits can significantly influence a student's decision to continue their education. Heckman et al. (2006) found that improvements in non-cognitive abilities such as self-control and self-esteem, significantly increase the likelihood of completing a four-year college degree, even when controlling for cognitive abilities. Moreover, Zimmermann and Kao (2019) argued that non-cognitive abilities can influence teachers' perceptions and expectations, which in turn affects the academic trajectories of students from various racial and ethnic backgrounds. From a labour market perspective, employers are increasingly valuing non-cognitive and cognitive abilities, suggesting that these traits are essential for success in both educational and career (Hora and Blackburn Cohen, 2018). Heckman et al. (2006) emphasised that non-cognitive skills, such as perseverance and social skills, are crucial to success in the labour market and are comparable to cognitive abilities in predicting educational attainment and employment outcomes. Furthermore, Kautz et al. (2014) state that non-cognitive skills tend to be malleable during adolescence, indicating that they can be enhanced through targeted interventions. Our findings reaffirm the importance of non-cognitive abilities.

Chapter 3

The treatment effect of educational decisions on midlife cognitive ability

Abstract

Do educational decisions after compulsory education affect midlife cognitive ability? In this paper, we investigate the effect of three educational decisions on midlife cognitive ability (at age 46), after controlling for early cognitive abilities and socioeconomic factors, with data from the 1970 British Cohort Study. We use a structural equation modelling approach which includes a measurement model for latent abilities and a structural model to address the research question. We find that postgraduate education has a positive treatment effect on midlife cognitive ability. Since education levels are sequential, the total educational effect on midlife cognitive ability is cumulative, which indicates that higher the levels of education lead to higher midlife cognitive ability.

Keywords: Midlife cognitive ability, Sequential educational decisions, British Cohort Study, Structural equation modelling

3.1 Introduction

People's cognitive ability generally develops during childhood and then gradually declines from early adulthood (Salthouse, 2009). Abundant research focuses on early cognitive ability and its effect on long-term human capital (Carneiro et al., 2007), but little attention has been paid to adult cognitive ability (Moulton et al., 2020). In epidemiology, adult cognitive ability is referred to as cognitive reserve, which refers to differences among individuals in performing tasks (Stern, 2012). Evidence shows that poor cognition in adulthood is strongly associated with the risk of major depression, alcohol abuse or dependence, post-traumatic stress disorder and Alzheimer's disease (Gale et al., 2008; Stern, 2012). Understanding the determinants of adult cognitive ability can help people maintain healthy adult cognition and prevent or postpone the diseases of ageing.

Socioeconomic factors and early cognitive abilities are widely recognised as determinants of adult cognitive ability (Foverskov et al., 2019; Kaplan et al., 2001; McElroy et al., 2021). Of these, education is considered to be one of the most effective means to improve cognitive ability and reduce the risk of developing diseases associated with cognitive decline such as Alzheimer's and brain injury (Stern, 2012). Using data from the 1946 National Birth Cohort, Richards and Sacker (2003) and Hatch et al. (2007a) both find that education completed in early adulthood positively correlates to all measures of midlife cognitive ability. In 2022, with the adoption of the Marrakech Framework for Action, more than 140 countries agreed to take action to advocate and assist lifelong learning. In 2023, British Parliament considered passing the Lifelong Learning (Higher Education Fee Limits) Bill that allows the government to provide individuals with a Lifelong Loan Entitlement to the equivalent of four years of post-18 education (approximately £37,500). This paper is timely in investigating the effect of educational decisions on midlife cognitive ability (at age 46). With data from the BCS70, in terms of educational variables, we no longer need to use early adulthood as a cut-off point, but can extend analysis to mid-adulthood, making it possible to encompass the impact of lifelong learning. To understand whether different levels of education have different marginal effects on midlife cognition, rather than using a traditional educational setting (e.g. years of schooling), we adopt three educational decisions that individuals face after compulsory education: whether to finish post-compulsory schooling (leading to A levels or equivalent qualifications), whether to obtain an undergraduate degree and whether to complete postgraduate education. We refer to the effect of each educational decision as the 'treatment effect'. Adding up these relevant effects gives us an idea of the cumulative impact of receiving a particular level of education on midlife cognitive ability. In addition, we extend our analysis of the effects of education completed in early adulthood on adult cognition over time, and these results are valuable both for comparison with findings from other studies and for observational comparisons of whether education received at different stages has varying effects on cognition across the lifespan.

Given that cognitive ability is latent, to avoid measurement error, we estimate it based on related cognitive test scores. We apply the SEM approach that consists of a measurement model to estimate latent cognitive abilities and a structural model, which includes a multistage sequential decision model modified from Heckman et al. (2018) and a cognitive development model adapted from Dickerson and Popli (2016); Todd and Wolpin (2007). By adding midlife cognitive ability to the existing structural model, the research framework of this paper is an extension of the previous chapter. Within the structural model, we attempt to decompose the bidirectional relationship between education and cognition found in cross-sectional analyses into an 'early cognition to education to midlife cognition' relationship.

We find a positive effect of postgraduate education on midlife cognitive ability. People who completed postgraduate education, their midlife cognitive ability is, on average, 0.132 standard deviations higher than that of those without a postgraduate degree. However, we do not observe a significant treatment effect of post-compulsory schooling and undergraduate education on midlife cognition. We find that people with high early cognitive ability have an advantage in cognitive development. Consistent with the previous chapter, we demonstrate that both early cognitive abilities positively influence sequential educational decisions. In extended analyses, we affirmed the effect of post-compulsory education completed in early adulthood on early adulthood cognition, while undergraduate education completed early had no significant effect. A potential reason is that the effect of undergraduate education on adult cognition emerges in midlife. In contrast, the effect of postgraduate education on adult cognition has remained stable and significant. Our findings are broadly consistent with the existing literature and emphasise the importance of higher education on midlife cognitive development. This suggests that policymakers should be more proactive in encouraging people to pursue higher education.

This paper contributes to the literature on the determinants of adult cognition by providing empirical evidence that education positively impacts on midlife cognitive ability. We indicate that only education at the undergraduate level or above has a positive treatment effect on midlife cognitive ability, while this positive impact is cumulative with education level. Next, by categorising cognitive abilities into pre-adulthood and post-adulthood abilities, we illustrate the channels through which early cognition can influence midlife cognition by influencing educational decision-making, thus providing evidence for the study of the bidirectional relationship between education and cognition. Finally, by extending the analysis of the previous chapter, our new structural model informs research into the relationship between education and adult cognition. In addition, this paper lays the groundwork for the final chapter which examines the mediation effect of midlife cognitive ability in returns to education.

The rest of this paper is structured as follows. Section 3.2 provides a concise literature review of cognitive development and the bidirectional relationship between education and cognition. The model identification strategy is covered in Section 3.3, while the data and variables are introduced in Section 3.4. The results are reported in Section 3.5, and conclusions are discussed in Section 3.6.

3.2 Literature review

3.2.1 Cognitive development

Cognitive ability, which is often generally referred to as components of human intelligence, comprises a series of brain-based capacities, such as memory, thinking, reasoning and problem-solving. It was once thought to be ‘innate’ because early psychologists believed it was based on genetics and relatively fixed over life. However, it is now recognised that cognitive development is strongly influenced by environmental and experiential factors as well as genetics. At the individual level, cognitive ability is a ‘cognitive endowment’ which contributes to many aspects of daily life, such as managing finances and managing medical conditions, and determines relative life quality (Anstey et al., 2013b; Starr et al., 2003). As for the societal level, cognitive ability is considered ‘cognitive capital’. It enriches the innovative and productive capacity of a nation and increases the productivity of both the paid and unpaid workforce (Beddington et al., 2008). Hence, increasing overall cognitive capital will improve employment and economic benefits and reduce the financial burden of healthcare (Anstey, 2016).

Cognitive development is fluid and dynamic, usually increasing in childhood, peaking in early adulthood, stabilising in midlife and declining in later life (see Figure 3.1). When cognitive decline reaches a certain level, it leads to cognitive impairment. Mild cognitive impairment can affect quality of life and the ability to live independently (Anstey et al., 2013b). Even if the cognitive impairment is not severe enough for dementia, it influences about 10% of adults in their 60s (Anstey et al., 2013a) and 20% of adults over 70 (Plassman et al., 2008), which is roughly three to four times as many as older adults with dementia.

Moreover, a large proportion of these patients will eventually develop dementia (Farias et al., 2009). The accumulation of cognitive growth in both childhood and early adulthood shapes cognitive ability in later life. Richards et al. (2004) find that after controlling for educational attainment and SES, childhood cognitive ability is significantly and negatively associated with midlife cognitive decline, especially in memory and search speed. They conclude that cognitive ability in childhood has an important protective effect in cognitive decline in midlife and beyond, and this protective effect may also be acquired in adulthood. To achieve optimal cognitive ageing, Anstey et al. (2014) argue that increasing the peak of cognitive function in early adulthood by actively investing in early cognitive development, and maintaining cognitive ability in midlife will help older people to live comfortably and minimise the risk of cognitive impairment. Of course, this requires policymakers to understand the potential elements of the cognitive trajectories and to adopt appropriate interventions for the different stages.

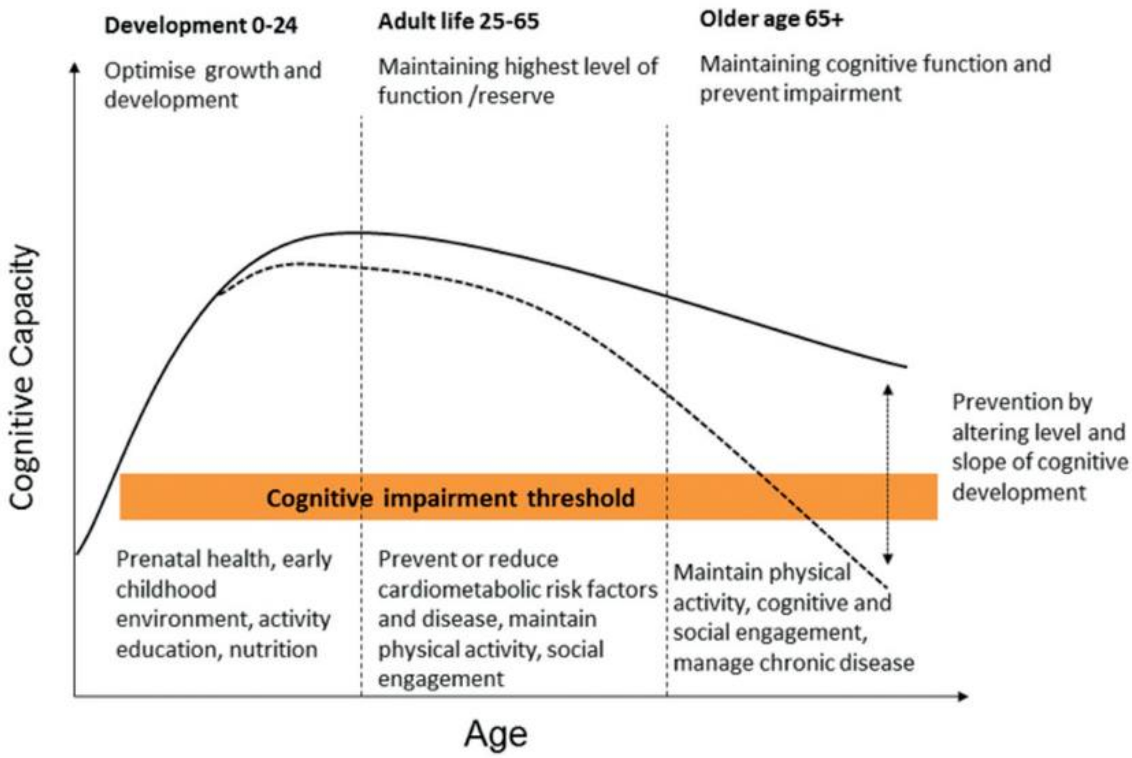

Fig. 3.1 The general trajectory for cognitive development throughout life (Anstey, 2016)

A huge amount of research has explored the influence of parental characteristics, early family environment, school quality, genetics, and SES in developing cognitive ability (Fotuhi et al., 2012). However, this literature has not yet reached a consensus on the mechanisms of cognitive development and the relative contribution of these discussed inputs (Todd and Wolpin, 2007)[1]. Boardman and Murnane (1979) were the first to establish a cumulative model of the cognitive achievement production function with a value-added specification. Todd and Wolpin (2003) review the literature on cognitive production function and propose the identification assumptions of alternative estimators. Subsequently, Todd and Wolpin (2007) develop the cumulative production function by assuming that the children's cognitive achievement is dependent on prior family background, mother's ability, school inputs and heritable endowments. Furthermore, Cunha and Heckman (2008) extend the cognitive production function by incorporating the non-cognitive skills to affect cognitive development, addressing the problem of endogenous parental inputs. They find non-cognitive skills can promote cognitive skills but not vice versa. This formation of cognitive function is also used by several subsequent studies (see e.g. Conti et al., 2010; Heckman et al., 2018). These papers focus on childhood cognitive development and their findings support the view that 'skill acquisition is a cumulative process'.

Most of the existing literature has focused on early cognitive ability. The main motivation behind this is the impact of early cognitive ability on adult pecuniary and non-pecuniary outcomes. For instance, Whalley et al. (2004) find evidence that better early cognitive ability is associated with longer life expectancy and lower risk of dementia and developing cognitive impairment in later life. Given the importance of early cognitive ability, some studies have been interested in the SES that influences early cognitive development. Using data from the BCS70, Feinstein (2003) states that parental SES will lastingly affect children's cognitive development. The advantage of good initial cognitive development for a child coming from a family with low SES quickly erodes. Conversely, a child with poor initial cognitive development, who comes from a family with medium or high SES, still has the opportunity to catch up later in life. With data from the Millennium Cohort Study, Goodman and Gregg (2010) explain the influence of parental behaviour on the rich-poor gap in children's cognitive ability, while Blanden and Machin (2010) test the relation between parental income and a child's vocabulary ability and behaviours and find that higher family income leads to better child outcomes.

Relatively, there is less attention paid to adult cognitive ability (Moulton et al., 2020). One potential reason is that cognitive change in healthy adults is very slow compared with early cognitive development, which makes it difficult to detect the effects of external interventions (Anstey, 2016). However, adult cognitive ability is receiving more awareness as society ages

[1] Todd and Wolpin (2003) argue that, due to the implementation of different empirical identification strategies, even when the same data set is used, the empirical findings vary widely.

and with the high prevalence of diseases associated with cognitive impairment. Kaplan et al. (2001) show that childhood SES (educational attainment, parental occupation and parental education) is robustly correlated with adult cognition, while McElroy et al. (2021) estimate the latent cognitive ability using the SEM approach and reveals that this relation is fully mediated by childhood cognitive ability, educational attainment and occupational status. In searching for the association between SES and adult cognitive ability, controlling for early cognitive ability causes bias. With data from the 1946 National Birth Cohort, Richards and Sacker (2003) use path analysis to model lifetime antecedents of midlife cognitive ability which is proxyed by the National Adult Reading Test score, verbal memory, and timed visual search at age 53. They find positive (independent) paths from childhood cognition, educational attainment in early adulthood and adult occupation to midlife cognitive ability. These path effects show that the path effect of childhood cognitive ability is the strongest, while that from adult occupation is the weakest. Moreover, Power and Elliott (2006) report that after controlling for cognitive ability (at age 12), the correlation between early childhood SES and adult cognitive function decreases. Foverskov et al. (2019) also argue that without adjusting for childhood cognitive ability, the association between childhood SES and adolescent/adult cognitive ability is likely to be overestimated.

3.2.2 The bidirectional relationship between cognition and education

The traditional view of the relation between cognitive ability and education assumes that cognitive ability is the fundamental factor which drives educational outcomes (Cattell, 1987; Sternberg et al., 2008). This view is supported by two cognitive theories we introduced in section 2.2.2: investment theory and dual-process theory. However, this unidirectional opinion is challenged by the bidirectional theory, as there exists some evidence suggesting that education also critically impacts cognitive performance[2]. Using data from the 1946 National Birth Cohort, Hatch et al. (2007a) find that educational attainment completed by early adulthood correlates to all measures of late-midlife cognitive ability, and the continued effect of education only appears in verbal ability (including verbal memory and verbal fluency). They claim that education has wider health benefits and can help delay cognitive decline in later life, given the positive association between education and midlife cognitive ability. Behrman et al. (2014) use longitudinal data to estimate production functions for adult cognitive abilities (verbal and non-verbal) and find that school educational attainment substantially impacts adult verbal cognitive ability but not adult non-verbal cognitive ability.

[2](See e.g. Alwin and McCammon, 2001; Kaplan et al., 2001; McElroy et al., 2021; Rutter, 1985).

Conditional on early cognitive ability, one year of schooling can raise early adulthood IQ by 2.9-3.5 points (about 0.2 standard deviations) (Falch and Sandgren Massih, 2011). With Swedish data, Carlsson et al. (2015) show that an extra 10 days of schooling increases crystallised intelligence scores by around 1% of a standard deviation, while fluid intelligence scores only increase modestly with age. Furthermore, Sandry and Sumowski (2014) and Sumowski et al. (2014) find that the degree of activation of specific brain regions during working memory tasks is associated with higher levels of education. This evidence explains why people with higher education and higher cognitive ability seem to have a lower risk of developing dementia from the perspective of neurology. If education has a lasting effect on adult cognition, then it is important to encourage and promote not only early education but also lifelong education.

It seems that education and cognitive ability have a symbiotic relationship that lasts for the whole of an individual's life (Peng and Kievit, 2020), and they both have an important role in determining midlife outcomes. This new perspective of the relation between cognitive ability and education claims that higher cognitive ability can improve educational outcomes and that education supports the development of cognitive ability - these are mutually beneficial interactions (Van Der Maas et al., 2006). It means that cognitive ability and education outcomes may affect each other throughout the whole development of human capital. There are three mechanism theories supporting this cognitive-educational bidirectional relation perspective: investment theory, transactional process theory and schooling mechanism theory. First, investment theory considers that reasoning - one of the cognitive abilities - is the primary ability domain of academic achievement, since higher reasoning ability is very helpful in dealing with analogies and abstract problems which leads to better organisation of academic knowledge (Schweizer and Koch, 2002), while on the other hand, solid knowledge can train and upgrade reasoning efficiency by using advanced verbal/vocabulary skills to decompose abstract problems (Kievit et al., 2017). Next, transactional process theory argues that genetic factor have a lifelong effect on cognitive ability, then simultaneously affects academic achievement through the cognitive-academic bidirectional relation, though these impacts are more outstanding in those with advantaged SES (Dickens and Flynn, 2001; Tucker-Drob et al., 2013). In their paper, Armor et al. (2018) reveal that schooling and learning experiences associated with family SES are common environment elements. Finally, schooling mechanism theory explains that children use cognitive abilities to learn a variety of academic skills from different tasks during schooling, and these academic skills such as reading/mathematics to some extent systematically train cognitive abilities (e.g. reasoning and execution function) (Ceci and Williams, 1997; Jacob and Parkinson, 2015;

Ritchie and Tucker-Drob, 2018). Peng and Kievit (2020) conduct a systematic literature review on related bidirectional studies. They summarise that the associations between reading/mathematics and working memory/reasoning increase with age, reading/mathematics and cognitive ability can predict each other; the effect of intensive short-term cognitive ability training on academic achievement remains unclear, while direct academic instruction positively impacts cognitive ability development; the cognitive-educational bidirectional relation is weaker among disadvantaged children.

Empirically, studies pay more attention to determining potential moderators of bidirectional cognitive-educational relations. Ferrer et al. (2010) find that IQ is associated with reading during development and concurrently manages bidirectionality. Findings from several papers suggest that the magnitude of cognitive-educational bidirectionality can be moderated by individuals' development stages, types of academic skills and cognitive abilities, and relevant social-emotional factors (Peng and Kievit, 2020; Schmitt et al., 2017). Hofman et al. (2018) claim that, even though the bidirectional relation between cognitive ability and education varies with age, the effects of age remain inconclusive. Additionally, the learning experiences or opportunities correlated with SES may also drive the bidirectional relation. Consistent with the transactional process theory, children in high-SES environments tend to have more opportunities for productive learning experiences than children from low-SES backgrounds (Duncan and Murnane, 2011). This finding is also coherent with Heckman et al. (2018)'s discussion of ability bias - advantaged individuals (high-SES and/or relatively high cognitive ability) are more likely to activate and benefit from cognitive-educational relations, especially in childhood. Subsequently, Jenkins et al. (2018) report that high-quality schooling may cancel out the negative influence of a low-SES context on academic achievement, while Peng et al. (2018) argue that high-quality schooling can balance the suppressive effects of low SES on the bidirectionality of the cognitive-educational relation.

In summary, there is much theoretical and empirical evidence to suggest that cognition and education have a reciprocal relationship and that this influence continues throughout life. However, attention to education and adult cognition remains very limited. Based on this existing knowledge, two structural models were constructed. The first model assumes that only early cognition and educational decisions influence adult cognition, while the second model builds on this by assuming that early cognitive ability affects educational decisions, and these educational decisions and early cognition jointly influence adult cognitive ability. Given the strong relationship between cognitive performance in mid- and late-life and the risk of developing multiple diseases during these stages, we will focus on midlife cognition and analyse the treatment effect of educational decisions on midlife cognitive ability. This will enhance our understanding of the relationship between cognition and educational decisions, and provide insights and rationale for policy development.

3.3 Methods

As in the previous chapter, our empirical model consists of two parts. One is a measurement model to measure latent cognitive abilities (also noncognitive ability) and the other is a structural model to estimate the treatment effect of educational decisions. The measurement model remains the same as that outlined in the Section 2.3.1 and is therefore not repeated here.

In the previous chapter, we acknowledged that one of the costs of structural model complexity is a reduction in sample size. Therefore, to maximise the use of available data, we considered two structural models of varying complexity. The first focuses on the cognitive development equation, which examines the effects of early cognition and educational decisions on midlife cognition, the latter being the primary focus of this chapter. We refer to this as the 'baseline' setting. The second model, which we refer to as the 'full' setting, extends the baseline model by incorporating the education equations from the previous chapter. Although this model may not seem directly related to our primary research question, we include it based on the assumption that the effects of education and cognitive ability are mutually reinforcing. To further clarify this mechanism and address the issue of reverse causality, we hypothesise that early cognitive ability influences a range of educational decisions made by individuals, which in turn determines the level of education they attain. These educational choices subsequently affect the stock of cognitive ability in midlife. By adding the sequential educational decision model to the structural model, we are able to account for the selection effect of early cognitive ability.

3.3.1 The 'baseline' structural model

Consistent with the previous chapter, a value-added specification of cognitive production function[3] is used to simulate childhood cognitive development (Dickerson and Popli, 2016; Todd and Wolpin, 2007), with minor modifications.

According to the previous identification of cognitive development model, the midlife cognitive equation would be linearly determined by the previous stock of cognitive ability

[3] See Section 2.3.2 for more details.

and a vector of exogenous covariates.

$$C_{46} = \gamma_{46} C_{16} + \lambda_{46} X_{46}^{C} + \varepsilon_{46} \tag{3.1}$$

where the error term ε_{46} is normally distributed and assumed to be independent over periods and individuals, and the parameter γ_{46} captures the time effect of cognitive development. Conditional on X_{46}^{C}, the shock ε_{46} is independent of the lagged cognitive ability C_{16}.

Since our structural model does not include the two early cognitive development equations [4], we add the preschool cognition on the right-hand side of the equation to control for the potential effects of innate endowment. Based on this, we additionally identify the effect of educational decisions in the equation:

$$C_{46} = \sum_{j=1}^{3} \delta_j D_j + \gamma_{46}^{5} C_5 + \gamma_{46}^{16} C_{16} + \lambda_{46} X_{46}^{C} + \varepsilon_{46} \tag{3.2}$$

where γ_{46} represents the time effect of early cognitive abilities on midlife cognitive ability. Conditional on C_5, C_{16} and X_{46}^{C}, δ_j captures the marginal treatment effect of giving a positive response to educational decision D_j at stage j on midlife cognitive ability. Accordingly, $\sum_1^j \delta_j D_j$ indicates the cumulative treatment effect of educational decisions up to stage j on midlife cognitive ability.

3.3.2 The 'full' structural model

The 'full' structural model builds upon the 'baseline' structural model by incorporating the educational decision equations. Figure 3.2 displays the educational process of a person completing post-compulsory education in Britain, where the nodes labelled with numbers are the educational decisions we consider. In Britain, people usually enter compulsory education at the age of five. After completing compulsory education at the age of 16, people must decide whether or not to pursue post-compulsory secondary schooling. This is the first educational decision they make for themselves and is also the starting point for Figure 3.2.

Let $j \in \{1,2,3\}$ denote different educational stages and D_j denotes the general educational decision at stage j. For each stage j, people can choose to complete a certain level of education with $D_j = 1$; conversely, $D_j = 0$. We then let Q_j denote whether an agent reaches decision node j, and define that when individuals reach stage j, the educational decisions $(D_j|Q_j = 1)$ are called sequential educational decisions. In this case, a person must complete

[4]Here refers to Equations (2.2) and (2.3) in Chapter 2

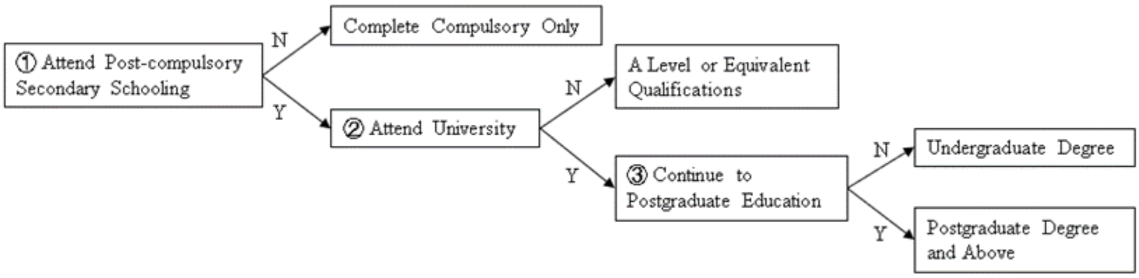

Fig. 3.2 A multistage sequential decision model modified from Heckman et al. (2018)

all the preceding education to reach stage j. For sequential decision decision at stage j, $\mathrm{D}_j = 0|\mathrm{Q}_j = 1$ means people stop at current educational state, while $\mathrm{D}_j = 1|\mathrm{Q}_j = 1$ indicates people continue education and moving to next educational stage $j+1$. Table 3.1 presents the difference between sequential setting and general setting of educational decisions. Within general education decisions, those who give a negative response to a specific educational decision, can still participate in subsequent choices, but all answers will be no by default. Within sequential education decisions, their answers in subsequent choices will be coded as missing values.

Table 3.1 Difference between general educational decisions and sequential educational decisions

	Sequential setting			General setting		
	D_1	D_2	D_3	D_1	D_2	D_3
Compulsory schooling	0	-	-	0	0	0
Post-compulsory schooling	1	0	-	1	0	0
Undergraduate education	1	1	0	1	1	0
Postgraduate education	1	1	1	1	1	1

Note: The first left column shows people's highest educational qualification.

Notably, we use the general educational decisions (D_j) rather than the sequential educational decision ($\mathrm{D}_j|\mathrm{Q}_j = 1$) in the structural model to ensure that the sample size remains constant over three educational decisions so that the education variables are independent at the same time in the equation (3.2). This avoids failure of the model estimates due to multicollinearity.

Correspondingly, for the educational decision equations, unlike in Section 2.3.3, which uses sequential educational decisions as outcomes, we switch to general educational decisions. Similarly, we assume that for each education stage j, people will choose to continue education as far as the internal utility of continuing education is not less than zero, while this utility I_j is determined by their preschool cognitive ability (C_5), post-compulsory school cognitive ability (C_{16}) and a vector of exogenous covariates (X^D)[5].

$$\mathrm{D}_j = \begin{cases} 1, & \mathrm{I}_j \geq 0 \\ 0, & \mathrm{I}_j < 0 \end{cases}, \quad where \quad \mathrm{I}_j = \beta_j^5 \mathrm{C}_5 + \beta_j^{16} \mathrm{C}_{16} + \pi_j \mathrm{X}_j^D + \eta_j \tag{3.3}$$

where η_j is an idiosyncratic error term that has a normal distribution with mean zero, β_j refers to the selection effect of early cognitive abilities on the educational decision. This was the main research interest in the previous chapter. Equations 3.2 and 3.3 together form the 'full' structural model, drawing on the analytical framework presented in Heckman et al. (2018). In a similar vein, we assume that the selection on unobservables stems entirely from unobserved early cognitive abilities[6], after accounting for exogenous covariates. Conditional on the measurement models, there is assumed to be conditional independence and any remaining unobservables can be treated as uncorrelated. Therefore, we assume that the error term η is independent of early cognitive abilities, C, exogenous covariates, X^D and ε. Conditional on X^D, it is independent across individuals and educational stages ($\eta_k \perp \eta_{k'}, k \neq k',\ and\ k, k' \in \{1,2,3\}$). Empirically, Equation (3.3) is estimated by probit regression.

3.3.3 SEM framework

Figures 3.3 and 3.4 show what our models look like in the SEM framework respectively. The unobservable factors are drawn in ellipses, including latent cognitive abilities ($\mathrm{C}_5, \mathrm{C}_{16}, \mathrm{C}_{46}$) and error terms, while other observable variables are drawn in rectangles. Each single-headed arrow refers to an unidirectional causal connection between two variables. The dashed

[5]The identification of the sequential educational decision model presented in Section 2.3.3 was conditional on $\mathrm{Q}_j = 1$. Here we have removed this assumption and the remaining assumptions are consistent with the original model. To avoid repetition, we omit some details and only briefly describe the educational decision equation.

[6]In Heckman et al. (2018), they examine the adult returns to education and hypothesize that selection bias arises from unobserved early cognitive and non-cognitive abilities. The existing literature generally indicates that early noncognitive abilities can impact early cognitive development (Cunha and Heckman, 2007; Heckman et al., 2006); however, there is a lack of evidence regarding their influence on adult cognition. It is commonly assumed that early non-cognitive influences on adult cognition operate primarily through indirect pathways, such as education and health behaviours (Moffitt et al., 2011). Therefore, in our model, we only assume that the selection on unobservables only from unobserved cognitive abilities.

rectangle marks the measurement models for latent cognitive abilities[7]. The large rectangle presents the full structural model. Ideally, we employ the one-step estimation approach, which simultaneously estimates both the measurement model and the structural model. When the model is complex and the sample size limited, one-step estimation may not be feasible due to problems with model convergences. In such instances, we turn to a two-step estimation approach, in which we first estimate the measurement model separately to obtain predicted abilities. In a second step, we estimate the structural model by substituting the predicted ability from the first stage. At this stage, as we rely on predicted ability, the standard errors of the structural model will be incorrect and biased. Instead, we estimate these by bootstrap.

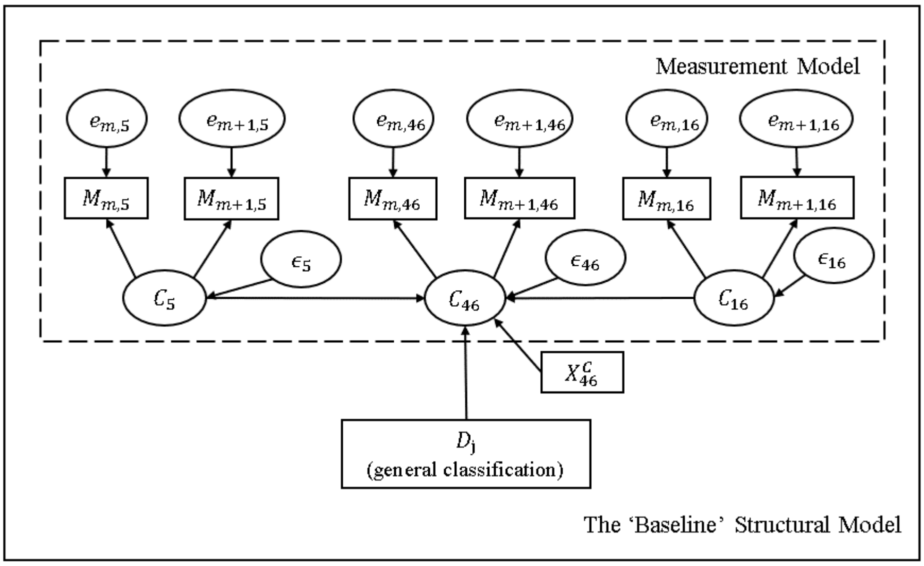

Fig. 3.3 Structural equation modelling framework for the 'baseline' model

[7]To simplify the graph, not all measures are shown. For the measurement model of latent cognitive ability at age t, we list only two cognitive measures $M_{s,t}$ and $M_{s+1,t}$. We neglect the measurement model of latent non-cognitive ability as well.

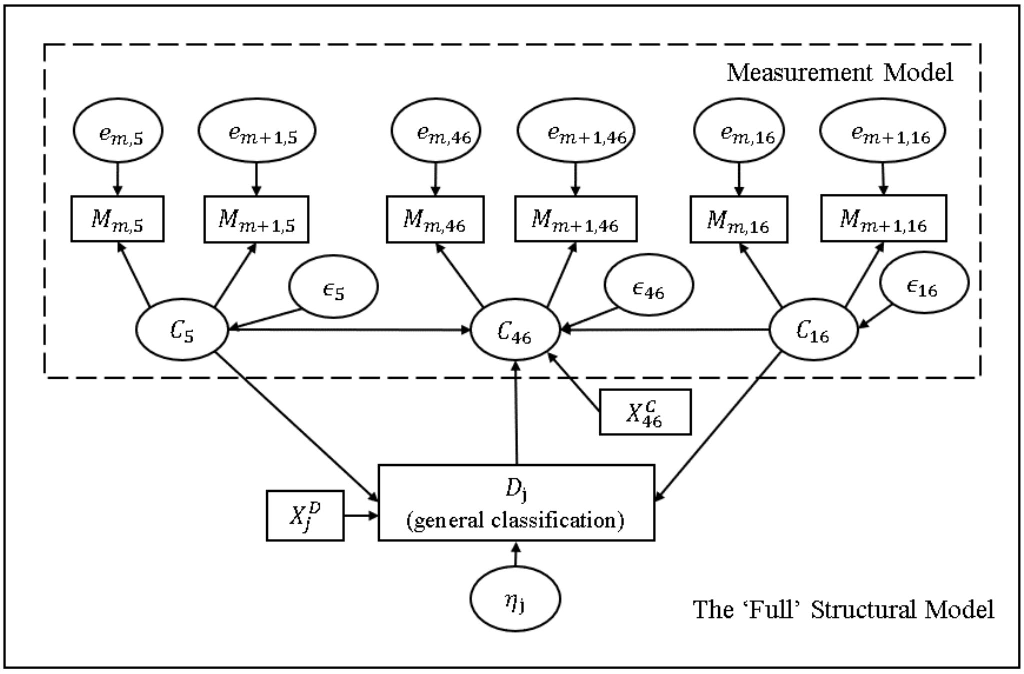

Fig. 3.4 Structural equation modelling framework for the 'full' model

3.4 Data

We use individual-level data from the BCS70, a longitudinal and multipurpose study that follows the lives of around 17,000 people who were born in England, Scotland and Wales during a single week in 1970. BCS70 gathers information on economic circumstances, educational achievement, health status, and social development. In addition, the BCS70 assesses and follows each person's cognitive ability from early childhood through midlife adulthood, which is appropriate given our research question.

In this study, we focus on eight waves of the BCS70, and construct two samples to serve different structural models. We construct two samples based on the need to satisfy different structural models. For the 'baseline' model, we have an estimation sample of 2,830 observations, while for the 'full' model, we obtain with an estimation sample of 1,537 observations.

3.4.1 Variables

Cognitive ability tests: We mainly consider three kinds of cognitive abilities in this paper: preschool cognitive ability measured at age five, post-compulsory school cognitive ability measured at age 16, and midlife cognitive ability measured at age 46. The BCS70 conducted multiple age-specific cognitive tests designed by psychologists in each testing wave, as the dimensions of cognitive ability measured at each test age may vary according to cognitive development. We use these cognitive tests to predict latent cognitive abilities. When estimating latent ability, we use the standardised test score for each cognitive ability test (Moulton et al., 2020). Tables B.1 and B.2 show descriptive statistics for all cognitive ability test scores.

We have already described the cognitive tests at ages 5 and 16 in Section 2.4.2, and here we will only briefly describe the cognitive tests administered at age 46. There are also five cognitive ability tests at age 46: the animal naming task, the letter cancellation task (speed), the letter cancellation task (accuracy), the immediate word-list recall test, and the delayed word-list recall test. In order to evaluate verbal fluency, participants must name as many animals as they can in a minute for the animal naming task. For the letter cancellation tests, participants are given a page of randomly selected letters and are required to read each row from left to right, cross out as many 'Ps' and 'Ws' as they can in the allotted one minute and then underline the final letter that they read when the time is over. The overall number of letters searched is the speed score of the letter cancellation task, and the total number of target letters cancelled is the accuracy score of the letter cancellation task. In the word-list recall test, the interviewer chooses one of four lists of 10 common terms and then presents the related recorded voice to participants at a rate of one word every two seconds. Participants must recall as many words as they can in two minutes (in any sequence), and the number of words is recorded as the immediate word-list recall test score, testing their immediate verbal memory ability. After completing other cognitive tests, participants must recall these words again, and the total number of recalled words is the score of the delayed word-list recall test, which measures their delayed verbal memory ability[8].

General educational decisions: This paper looks at three educational decisions which people had to make following compulsory schooling. As in the previous chapter, to minimise information loss due to sample attrition, we combined education data from the waves aged 30 to 46 (including intermediate years). For participants who did not report educational information at age 46, we interpolated using their earlier (after age 30) educational data. The educational variables were constructed in the same way as in the previous chapter, while the only difference is using the general classification rather than the sequential classification. For sequential classification, only those who have completed their current education are able to

[8]All cognitive measures at this wave are the same as those used in the 2002 English Longitudinal Study of Ageing (Moulton et al., 2020).

move to the next pool of educational decisions. Accordingly, the number of observations decreases as the educational level rises, since a negligible proportion of individuals will cease to choose continued education at each decision node. However, for general classification, all those who respond negatively to a specific educational decision are by default refused access to all subsequent education. Thus, the number of observations is constant for all decisions. Table 3.2 lists three educational decisions on which we focus. Each educational decision is represented by a dummy variable, with a value of 1 denoting a positive response. We can see that the distribution of each educational decision is very close in both samples.

Controls for midlife cognition equation: Apart from educational decisions, preschool cognitive ability and post-compulsory school cognitive ability, we control for gender, occupation (Feinkohl et al., 2021; Jorm et al., 1998) and marital status (Håkansson et al., 2009; Liu et al., 2019), the latter two serving as proxy variables for adult SES associated with adult cognitive development. The dummy variable gender has a value of zero for females. People reported their legal marital status at age 46, and this is recoded into three categories: never married or in a civil partnership, married but separated for some reason (divorced/legally separated/widowed), and married. The occupation status in the BCS70 is classified into eight categories based on the National Statistics Socio-economic classification. We simply transform them into three groups according to the National Readership Survey social grade system[9]: professional (higher managerial, administrative and professional occupations), intermediate (intermediate occupations), and manual (routine and manual occupations).

Controls for educational decision equations: We control for early SES conditions including gender, noncognitive ability, number of siblings, parental education, family income and . We introduced these variables in Section 2.4.3 and will not repeat them here. The descriptive statistics of above covariates are summarised in Table 3.2, while the descriptive statistics of noncognitive tests are displayed in Table B.3.

Exclusive restriction and sample attrition: We have various exclusion restrictions that affect educational decisions but not the midlife cognition. The three early SES variables listed in Table 3.2 will serve as exclusion restrictions for the model. The effect of early SES on midlife cognition is primarily achieved by influencing early cognitive development and the adult environment. Conditional on post-compulsory school cognitive ability and educational decisions, early SES is unlikely to directly influence midlife cognition. In Table B.4, we display the distributions of variables in the selected sample and in the original dataset to provide a brief overview of sample attrition. For some variables, there are differences in

[9]The transform of occupation follows the guidance of government website (see section 7): *https : //www.ons.gov.uk/methodology/classificationsandstandards/otherclassifications/thenationalstatisticss ocioeconomicclassificationnssecrebasedonsoc*2010.

distribution; for instance, the probability of individuals completing undergraduate education is lower in the original dataset than in the selected sample, which may introduce bias. To address this, we will further present the estimation results using inverse probability weighting (IPW).

3.4.2 Descriptive analysis of cognitive abilities

We show the correlations of cognitive measures in the two samples in Tables B.5 and B.6, respectively. All the measures have a positive association, except the speed score and accuracy score of the letter cancellation task at age 46, which are negatively correlated. We find the associations between some measures are higher than 0.50, which indicates there is considerable overlap between these measures, but each measure still includes some distinctive aspects of cognitive ability.

Then, we use these measures to estimate latent variables via the measurement model[10]. We treat the copying designs test, shortened Edinburgh Reading Test and immediate word-list recall test as anchors. The estimation results of measurement models are summarised in Tables B.7 and B.8. The coefficients estimated from the measurement models reflect the influence of latent variables on the related measures. The magnitudes of the standardised loading of the remaining measures are mostly above 0.50 and significant at the 1 percentage significance level, which shows that these measures are significant indicators on their underlying latent scale. These loadings allow us to post-estimate latent cognitive abilities.

Figure 3.5 displays distributions of the three cognitive abilities estimated from the measurement model. The left column presents the distributions of estimated cognitive abilities in the original tested waves, and the right column shows the distributions of estimated cognitive abilities in the baseline sample. The shape of the distribution on both sides is relatively close. The shapes of the distributions of preschool cognitive ability and midlife cognitive ability are very close to a normal distribution, while post-compulsory school cognitive ability has a negatively skewed distribution. This ‘normal-skewed-normal’ variation in cognitive distributions reveals the discontinuity of cognitive development[11]. In the previous chapter, we

[10]In our sample, we only require participants to attend at least one cognitive ability test. Hence, some observations may contain missing values in some cognitive tests. The SEM approach by default applies an equation-wise deletion approach for models with continuous latent variables) so that allows us to estimate all observations even with missing values, while the traditional SEM approach requires no missing values in the sample.

[11]We also present the distribution of cognitive abilities predicted from the original BCS70 data at ages 5, 16, 34, 42, and 46 in Figure B.2. The distribution of cognitive abilities shows a negative skew as individuals age, with the most pronounced skewness observed at age 34. By age 46, however, there is a trend suggesting a return toward a normal distribution.

Table 3.2 Descriptive statistics of selected variables

Variable	Baseline Sample	Full Sample
Educational decisions by the age of 46		
D1: Whether to complete post-compulsory schooling	2830	1537
No	993 (35%)	501(33%)
Yes	1837(65%)	1036(67%)
D2: Whether to finish undergraduate education	2830	1537
No	1392(49%)	732(48%)
Yes	1438 (51%)	805 (52%)
D3: Whether to complete postgraduate education	2830	1537
No	2519 (89%)	1360 (88%)
Yes	311 (11%)	177 (12%)
Covariates		
Gender	2830	1537
female	1602 (57%)	898 (58%)
male	1228 (43%)	639 (42%)
Number of siblings at age 5		1537
none		173 (11%)
one sibling		850 (55%)
two or more siblings		514 (33%)
Parental education at age 5		1537
no qualification		660 (43%)
lower than A level		606 (39%)
A level and above		271 (18%)
Family income at age 16		1537
low-income group		385 (25%)
medium-income group		878 (57%)
high-income group		274 (18%)
Marital status at age 46	2830	1537
never married/ in a civil partnership	527 (19%)	278 (18%)
divorced/legally separated/widowed	431 (15%)	223 (15%)
married	1872 (66%)	1036 (67%)
Occupation at age 46	2830	1537
manual	647 (23%)	317 (21%)
intermediate	615 (22%)	332 (22%)
professional	1568 (55%)	888 (58%)

Source: the BCS70 wave 2, 4, 6-10. The distribution of the variables in the two samples is fairly balanced.

found that the advantages of early family background can compensate to some extent for the disadvantages of early cognitive development, which in turn skews the distribution to the left. It is also possible that compulsory education may contribute to the generally higher scores of most people on cognitive tests in adolescence. After the age of 16, education becomes non-compulsory and can be freely chosen. By middle age, the differences at adolescence have moderated, but the midlife cognitive distribution is still more flattened than the preschool cognitive distribution.

Similar to the previous chapter, we categorised people into five groups based on cognitive ranking changes between the ages of 16 and 46 to assess the degree of discontinuity in cognitive performance (see Table B.10). We present some descriptive statistics (proportions) for the five groups in Table B.11. We find that in terms of socioeconomic characteristics and proportion of education, the high-high group leads on all counts, while the low-low group lags behind the other four groups. The change in the distribution of cognitive abilities from skewed to normal in Figure 3.5 should be attributed to the presence of escapers (Group 2) and fallers (Group 4). Unexpectedly, we find that fallers (Group 4) have a higher proportion of education than escapers (Group 2), which seems to suggest that those who are at a relative advantage in terms of education are not necessarily at an advantage in terms of their adult cognitive level. At the same time, by comparing Group 1 (low-low) with Group 2 (escapers), we find that those with a better socioeconomic background who were educated are better able to overcome the disadvantages of cognitive development in adolescence and catch up in midlife. We also note that the proportion of highly educated individuals (completing undergraduate and/or postgraduate) in Group 5 is significantly higher than in Group 4 (fallers), which may imply that access to higher education is positively associated with maintaining an advantage in adolescent cognitive development.

In Figure 3.6, we present the density curve of three cognitive abilities by the response to each educational decision[12]. In the bottom row of the table, we find that the average midlife cognitive ability of those who have earned a degree is higher than the average cognitive ability of those who have not earned a degree at every stage of educational decision. The former has a left-skewed midlife cognitive distribution (the solid line), whereas the latter has a normal midlife cognitive distribution (the dashed line).

[12]Figures B.1 displays several box plots showing the correlation between the mean of cognitive abilities by the response to each educational decision.

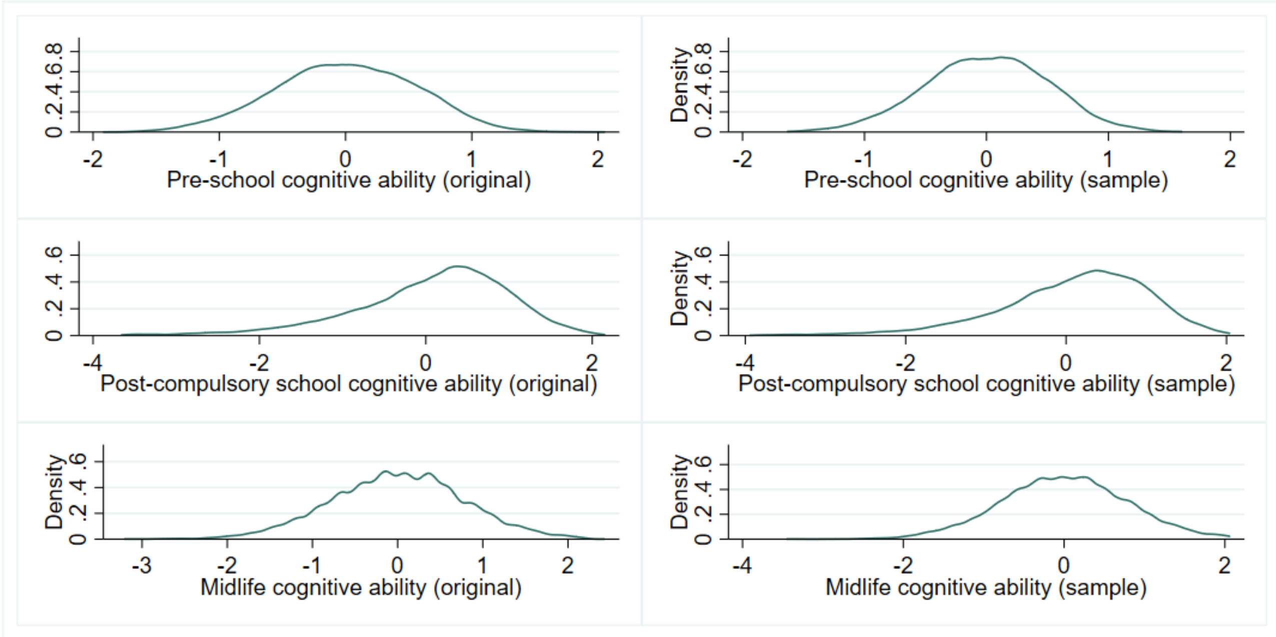

Fig. 3.5 Kernel density estimates for three cognitive abilities predicted from measurement model, for the survey data (the left) and the selected sample (the right). There were 13049 individuals at the age 5 wave, 6044 individuals at the age 16 wave, and 8509 individuals at the age 46 wave, who attended at least one cognitive test. There were 2830 individuals in the baseline sample.

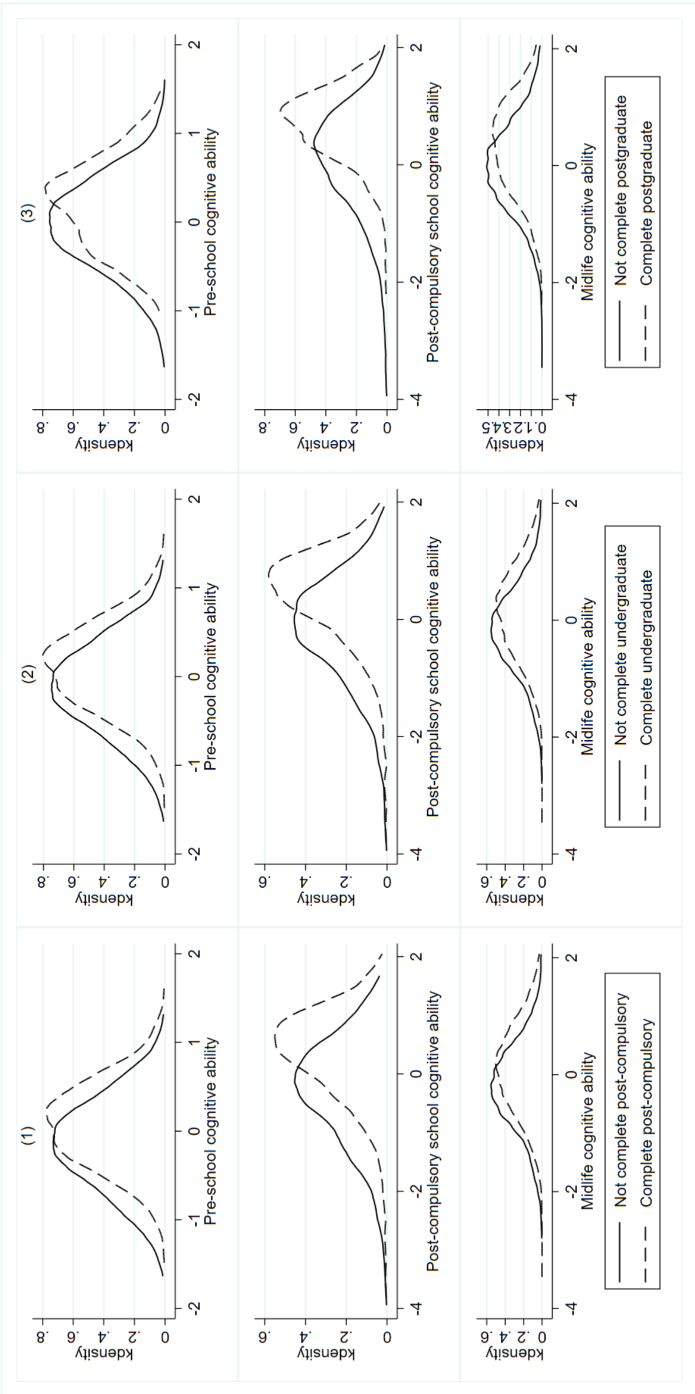

Fig. 3.6 Kernel density estimates for predicted cognitive abilities, for the first educational decision (the left), the second educational decision (the middle) and the third educational decision (the right). These educational decisions are measured by general identification. The dashed line illustrates density for having a positive response for a given decision ($D_j = 1$), while the solid line presents density for having a negative response ($D_j = 0$).

3.5 Results

3.5.1 Treatment effect of educational decisions

Table 3.3 shows the main estimation results of our structural model. We have two different structural models. The coefficients in the first three rows refer to the treatment effects of educational decisions on midlife cognitive ability, which directly responds to our main research question. Column (1) shows the results of the 'baseline' structural model. We only find significant treatment effects on the latter two educational decisions, conditional on early cognitive abilities and SES. People with an undergraduate degree have, on average, 0.110 standard deviations higher midlife cognitive ability than those who have only completed post-compulsory schooling. In addition, the average midlife cognitive ability of those who finished postgraduate education is 0.155 standard deviations higher than those who had no postgraduate education. This suggests that the marginal treatment effect of education on midlife cognitive ability is incremental. Since higher levels of education usually require that people have completed prerequisite education, by summarising the treatment effects, we demonstrate that completing undergraduate education improves midlife cognitive ability by 0.167 standard deviations, while completing postgraduate education increases midlife cognitive ability by 0.322 standard deviations.

In addition, we find a positive effect of both preschool cognitive ability and post-compulsory school cognitive ability on midlife cognitive ability. A one standard deviation increase in post-compulsory school cognitive ability enhances midlife cognitive ability by 0.166 standard deviations at the 1% significant level, while each standard deviation increase in preschool cognitive ability is associated with 0.270 standard deviations increase in midlife cognitive ability. Moreover, we notice that an individual's marital status is closely associated with their midlife cognitive ability. Compared with people who have never been married, those who have had a partner (divorced/legally separated/widowed) have an average increase in cognition of 0.201 standard deviations at midlife. This contrasts with 0.206 standard deviations for those who are married. Meanwhile, there is a significant correlation between occupation and midlife cognitive ability as well. Compared to manual workers, those in intermediate occupations have 0.101 standard deviations higher midlife cognitive ability, while those professionals have 0.142 standard deviations higher midlife cognitive ability.

Column (2) displays the results of the 'full' structural model. As in the previous chapter, we found a positive selection effect of early cognitive abilities on educational decisions, with the exception of preschool cognition, which has no significant selection effect on postgraduate education. Compared to the 'baseline' structural model, the treatment effect of completing an undergraduate degree on midlife cognition decreased by 0.026 standard deviations, while the treatment effect of completing a postgraduate degree declined by 0.023 standard deviations, when the educational decisions equations were taken into account. The 'full' structural model reveals only a significant treatment effect of completing postgraduate education on midlife cognition, while controlling for other factors.The main difference between the base structure model and the full structure model is that the former takes into account only the direct effects of early cognition on midlife cognition, whereas the latter additionally accounts for the indirect effects of early cognition on midlife cognition through educational decisions[13]. On this basis, we found that the effect of post-compulsory school cognition on midlife cognition increased by 0.007 standard deviations. This smaller difference implies that the effect of post-compulsory school cognition on midlife cognition is still mainly direct. In contrast, the effect of preschool cognition on midlife cognition decreased from 0.270 standard deviations to 0.165 standard deviations, with the decrease being mediated by educational decisions. In addition, we found that occupation, especially professional occupation, was significantly less associated with midlife cognition.

We then assessed the robustness of our results by altering estimation methods and applying weights, and summarised results in Table 3.4[14]. Column (1) is the 'baseline' model regression from Table 3.3, while column (2) estimates the same model using a two-step approach, consistent with the approach used for the 'full' model. By comparing the results of columns (1) and (2), we intend to verify whether the different estimation approaches significantly affect the outcomes. The findings indicate that while there are minor differences in coefficient magnitudes, the conclusions remain unchanged. Column (3) employs traditional OLS to estimate the structural model, in contrast to the maximum likelihood method used in GSEM. The point estimates from both methods are identical, with only slight variations in standard errors. To account for the potential issue of sample attrition, which may result in estimates that are not representative of the entire population, we additionally conducted estimation with IPW. We first estimated the probability of sample loss using non-missing variables from the birth wave [15]. During this process, we identified a small subset of individuals who were excluded from the birth wave but appeared in later

[13]Notably, the model fit statistics of the two models are not comparable due to the differences in the samples.

[14]The complete results are in Tables B.12, B.13 and B.14.

[15]In the birth wave, there were only about 10 variables without missing values, none of which were related to social status or family background. Some variables also had a potential multicollinearity risk, particularly in relation to previous pregnancy or abortion experiences. After careful consideration, three independent variables were selected for the probability regression: the number of previous pregnancies, the mother's participation in completing the family background questionnaire, and region.

waves[16]. These individuals were excluded from the analysis, and IPW was applied to the remaining sample. The weighted and unweighted results are displayed in columns (4) and (5), respectively. The unweighted results are largely consistent with those in column (1). After weighting, we found a relatively significant increase in the treatment effect of completing post-compulsory education (by 0.042 standard deviations), while the treatment effect of completing postgraduate education reduced by 0.034 standard deviations. However, overall, completing post-compulsory education remains the least impactful of the three educational decisions on midlife cognitive ability.

Columns (6) to (9) present the results of the 'full' model, all estimated using the two-step approach. In column (6), GSEM is used to simultaneously estimate multiple equations within the structural model, while column (7) employs OLS to estimate the equations separately. As our model assumes that there is no selection on unobservables once the unobserved cognitive ability is controlled for and predicted through the measurement model, the error terms of education and midlife cognition are therefore independent. It is not surprising to find that point estimates of OLS align with those from GSEM, with only minor differences in standard errors. Similarly, columns (8) and (9) display the IPW weighted and unweighted estimation results, respectively. We find that the weighted treatment effects of educational decisions are close to the effects in column (4). This suggests that, holding other factors constant, the treatment effect of educational decisions on midlife cognition increases with higher levels of education for the overall population.

[16]There are three factors that contribute to this situation(Silverwood et al., 2021). First, some children were born abroad and therefore did not participate in British Births. Second, some may have participated in British Births but were later adopted or had their names changed for other reasons. Third, some were born in the UK but were not identified for British Births.

Table 3.3 Results of two structural models

	(1) 'Baseline' model	(2) 'Full' model			
	C46	D1	D2	D3	C46
Whether finish post-compulsory schooling (D1)	0.057				0.091
	(0.051)				(0.056)
Whether to complete undergraduate education (D2)	0.110**				0.084
	(0.051)				(0.058)
Whether to obtain postgraduate education (D3)	0.155***				0.132**
	(0.055)				(0.065)
Preschool cognitive ability (age 5)	0.270***	0.229***	0.269***	0.083	0.165***
	(0.043)	(0.076)	(0.072)	(0.102)	(0.040)
Post-compulsory school cognitive ability (age 16)	0.166***	0.279***	0.311***	0.323***	0.173***
	(0.026)	(0.046)	(0.049)	(0.074)	(0.023)
Gender (baseline = female)	-0.041	0.083	0.003	-0.080	-0.007
	0.033)	(0.073)	(0.070)	(0.094)	(0.039)
Noncognitive ability (age 10)		0.622***	0.626***	0.708***	
		(0.163)	(0.157)	(0.244)	
Number of siblings at age 5 (baseline = no sibling)					
one sibling		-0.090	0.016	0.115	
		(0.117)	(0.111)	(0.156)	
two or more siblings		-0.295**	-0.140	-0.004	
		(0.123)	(0.118)	(0.165)	
Parental education at age 5 (baseline = no qualification)					

(To be continued on the next page)

(table continued)

lower than A level		0.293***	0.234***	0.138	
		(0.077)	(0.076)	(0.110)	
A level and above		0.513***	0.492***	0.453***	
		(0.114)	(0.104)	(0.127)	
Family income at age 16 (baseline = low-income)					
middle-income		-0.003	-0.014	-0.106	
		(0.090)	(0.089)	(0.122)	
high-income		0.164	0.231**	0.053	
		(0.123)	(0.116)	(0.053)	
Marital status (baseline = never married)					
Divorced/legally separated/widowed	0.201***				0.189***
	(0.056)				(0.069)
Married	0.206***				0.232***
	(0.043)				(0.054)
Occupation (baseline = manual)					
Intermediate	0.101**				0.090
	(0.049)				(0.056)
Professional	0.142***				0.053
	(0.044)				(0.053)
N	2,830		1,537		
AIC	94779.47		8030.394		
BIC	95112.56		8270.585		

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. C46 refers to midlife cognition.

Table 3.4 Robustness checks

	Baseline model				
	(1)	(2)	(3)	(4)	(5)
Whether finish post-compulsory schooling	0.057	0.052	0.052	0.104*	0.062
	(0.051)	(0.042)	(0.043)	(0.059)	(0.052)
Whether to complete undergraduate education	0.110**	0.093**	0.093**	0.126*	0.116**
	(0.051)	(0.044)	(0.044)	(0.066)	(0.052)
Whether to obtain postgraduate education	0.155***	0.129***	0.129***	0.130*	0.164***
	(0.055)	(0.048)	(0.049)	(0.075)	(0.056)
Preschool cognitive ability	0.270***	0.233***	0.233***	0.277***	0.269***
	(0.043)	(0.028)	(0.029)	(0.044)	(0.043)
Post-compulsory school cognitive ability	0.166***	0.164***	0.164***	0.163***	0.164***
	(0.026)	(0.017)	(0.017)	(0.033)	(0.026)
Approach	GSEM (one-step)	GSEM (two-step)	OLS	GSEM (IPW)	GSEM (one-step)
N	2830	2830	2830	2745	2745
AIC	94779.47	6187.896	6185.896	571445.1	91889.58
BIC	95112.56	6259.272	6251.324	571776.5	92220.96
	Full model				
	(6)	(7)	(8)	(9)	
Whether finish post-compulsory schooling	0.091	0.091	0.110*	0.082	
	(0.056)	(0.057)	(0.060)	(0.058)	
Whether to complete undergraduate education	0.084	0.084	0.126*	0.102*	
	(0.058)	(0.060)	(0.075)	(0.060)	

(To be continued on the next page)

(table continued)

Whether to obtain postgraduate education	0.132**	0.132**	0.133	0.146**
	(0.065)	(0.066)	(0.086)	(0.068)
Preschool cognitive ability	0.165***	0.165***	0.154***	0.163***
	(0.040)	(0.040)	(0.039)	(0.039)
Post-compulsory school cognitive ability	0.173***	0.173***	0.191***	0.171***
	(0.023)	(0.025)	(0.029)	(0.025)
Approach	GSEM (two-step)	OLS	GSEM (IPW)	GSEM (two-step)
N	1537	1537	1496	1496
AIC	8030.394	3388.099	90232.45	7815.804
BIC	8270.585	3446.813	90471.43	8054.779

Note: *$p \leq 0.1$, **$p \leq 0.05$, ***$p \leq 0.01$. For those model estimated by two-step approach, standard errors are further estimated by bootstrap (with 2000 repetitions).)

3.5.2 Extended analysis: the impact of education on cognition throughout adulthood

In this section, we further compare the effects of educational decisions on adult cognition over time. We use three waves of the BCS70, which conducted cognitive assessments at ages 34, 42, and 46[17][18]. Similarly, we used age 34 as a cutoff point to construct the education variables[19]. For the adult cognitive equations in the structural model, we considered three sets of scenarios. Group (1) estimated the ‘baseline’ model without accounting for the effect of early cognition. Group (2) estimated the ‘baseline’ model with early cognition included, while Group (3) estimated the ‘full’ structural model. We summarise the estimated treatment effects of educational decisions made before age 34 on different periods of adult cognition for the two scenarios described above in Table 3.5, while all estimation results are displayed in Table B.16.

Our analysis shows that, after controlling for early cognitive abilities, the impact of educational decisions on adult cognition is significantly diminished across all ages. Specifically, the effects of completing undergraduate education became small and statistically insignificant, while the positive effects of post-compulsory and postgraduate education on adult cognition remained. In line with the cognitive development trajectories introduced earlier (see Figure 3.1), one possible explanation is that pre-adult education and early cognitive development largely determine the level of early adult cognition, leaving undergraduate education with a limited effect on already established cognitive abilities. In contrast, the more rigorous learning environment of postgraduate education appears to exert a positive and sustained influence on adult cognition. Another possible explanation is that the impact of undergraduate education may be delayed, with its effects on cognition taking longer to manifest. Supporting this view is the observation that the coefficient for undergraduate education is significantly larger at age 46 (though direct comparisons between coefficients across different ages are not meaningful by variations in cognitive measures). Moreover, when using the education variable measured at age 46, undergraduate education shows a positive and significant effect on adult cognitive ability (see results in Table 3.3).

To make the effects of the education variable at age 34 with those at age 46 on cognitive ability at age 46 directly comparable, we re-estimated the model using a consistent sample,

[17]The introduction of two additional adult cognition measures are included in the appendix B.1.

[18]The BCS70 data also includes cognitive assessments at age 44. However, given the close proximity of this wave to the assessments at ages 42 and 46, significant fluctuations in cognition over such a short period are unlikely. Therefore, we excluded the age 44 data from our analysis.

[19]Related descriptive statistics are summarised in Table B.17

and the relevant results are displayed in Table B.18. For the 'full' model, We find a 0.009 standard deviation increase in the treatment effect of completing post-compulsory education, alongside a 0.016 standard deviation decrease in the treatment effect of completing undergraduate education, and a 0.034 standard deviation decrease in the treatment effect of completing a postgraduate education. These gaps should be attributed to the additional education received during the age range of 34 to 46[20], but may also be influenced by natural cognitive decline. As individuals grow older, natural cognitive decline becomes more likely. The impact of completing post-compulsory and undergraduate education on midlife cognition shows little variation. While the effect of postgraduate education has declined noticeably, possibly due to the ageing process after entering middle age diminishing its influence, it remains the most significant. This suggests that completing postgraduate education may be one of the most effective means of resisting or delaying cognitive decline.

Table 3.5 Extended analysis: the impact of education (completed before age 34) on different periods of adult cognition

(1)	Age 34	Age 42	Age 46
Whether finish post-compulsory schooling	0.388***	0.402***	0.200***
	(0.043)	(0.085)	(0.052)
Whether to complete undergraduate education	0.096**	0.189**	0.151***
	(0.043)	(0.086)	(0.052)
Whether to obtain postgraduate education	0.219***	0.452***	0.283***
	(0.051)	(0.102)	(0.062)
Early cognitive abilities			
Controls	√	√	√
Educational equations			
One-step	√	√	√
N	3104	1088	2703
(2)	Age 34	Age 42	Age 46
Whether finish post-compulsory schooling	0.257***	0.218***	0.110**
	(0.040)	(0.069)	(0.051)
Whether to complete undergraduate education	0.017	-0.034	0.080
	(0.040)	(0.070)	(0.051)
Whether to obtain postgraduate education	0.101**	0.240***	0.199***

(To be continued on the next page)

[20]The proportions of individuals in the sample who had completed their post-compulsory, undergraduate, and postgraduate education by the age of 34 were 65.67 %, 49.49 %, and 9.00 %, respectively. The corresponding proportions at age 46 were 69.33 %, 53.69 %, and 11.78 %, respectively.

(table continued)

	(0.048)	(0.083)	(0.060)
Early cognitive abilities	√	√	√
Controls	√	√	√
Educational equations			
One-step	√	√	√
N	3104	1088	2703
(3)	Age 34	Age 42	Age 46
Whether finish post-compulsory schooling	0.275***	0.154	0.096*
	(0.051)	(0.108)	(0.056)
Whether to complete undergraduate education	0.061	0.056	0.095*
	(0.041)	(0.099)	(0.057)
Whether to obtain postgraduate education	0.121**	0.293***	0.167**
	(0.038)	(0.079)	(0.071)
Early cognitive abilities	√	√	√
Controls	√	√	√
Educational equations	√	√	√
One-step			
N	1687	594	1477

Note: *$p \leq 0.1$, **$p \leq 0.05$, ***$p \leq 0.01$. As the variables included in the model vary, the corresponding sample size also changes. SES is measured in accordance with the update of adult cognition.

3.6 Conclusions

This paper uses the BCS70 data to investigate the association between educational decisions and midlife cognitive ability, controlling for early cognitive ability and SES. We adopt the SEM approach, considering two different structural models depending on whether cognition is allowed to interact with educational choices in development.

We consider three educational decisions that people face after compulsory education: whether to complete post-compulsory schooling; whether to finish undergraduate education; and whether to complete postgraduate education. We find positive and incremental treatment effects of the postgraduate education on midlife cognitive ability, while post-compulsory schooling and undergraduate have a limited contribution to midlife cognition. This also implies that the cumulative effect of access to higher levels of education on cognitive ability in midlife is incremental. Highly educated people tend to have greater cognitive abilities in middle age. Our finding that education positively impacts on cognitive ability, is consistent with several studies (Carlsson et al., 2015; Falch and Sandgren Massih, 2011; Hatch et al., 2007a; Richards and Sacker, 2003).

We further explored the effects of education on different periods of adult cognition (at ages 34, 42, and 46). We found that post-compulsory education completed before the age of 34 contributed to cognition in early adulthood but had a limited effect on midlife cognition. In contrast, completing undergraduate education had no significant effect on early adulthood cognition, with its impact only becoming apparent in midlife. Meanwhile, the effect of postgraduate education remained stable over time. After reviewing the literature on educational effects on cognitive abilities, Ritchie and Tucker-Drob (2018) find consistent evidence that an additional year of education increases cognitive ability by approximately one to five IQ points, and this positive educational effect persists across the lifespan. They argue that education is the most consistent, robust and enduring method of increasing intelligence yet discovered. This implies that the cumulative timing of access to education matters and that longer periods of education can help people maintain higher levels of adult cognition. In the meantime, based on an education policy reform in Sweden, Meghir et al. (2013) find that increasing the number of compulsory years of schooling significantly improves children's cognitive ability, with greater benefits for children with poorer initial cognitive endowments. This seems to imply that the timing of access to education matters such that longer compulsory education can help people reach higher cognitive peaks in early adulthood.

Our findings emphasise the importance of the timing of access to education. While access to post-compulsory education is crucial for cognitive development in early adulthood, its effects are difficult to sustain into midlife. One possible reason is that according to Figure 3.1, cognitive development begins to decline after peaking in early adulthood. We cannot rule out the possibility that the effect of education on midlife cognition influences the rate of cognitive decline[21]. Post-compulsory education may contribute to higher cognitive peaks in early adulthood. However, it may offer limited assistance in delaying or maintaining cognitive levels in mid-adulthood. In contrast, the treatment effect of higher education, especially postgraduate education, on midlife cognitive ability is more pronounced and stable. This suggests that policies should focus on encouraging individuals to pursue post-compulsory education during adolescence and early adulthood, while promoting higher education, particularly postgraduate education, in the later stages of adulthood. Such efforts could enhance overall midlife cognitive abilities in society, helping to mitigate the risk of cognitive decline and related diseases.

[21]Our model makes no assumptions about the rate of cognitive decline or the factors that influence it.

Consistent with the results of the previous chapter, the early cognitive ability strongly impacts the later cognitive ability. There is no denying that the cognitive developmental advantages of those with strong early cognitive ability persist. Kremen et al. (2019) report that additional education accounts for little variance in late midlife cognitive ability in men aged 56-66, after controlling for general cognitive ability at age 20. They argue that, if cognitive development peaks in early adulthood and early cognition has a greater impact on midlife cognition than additional education in adulthood, then policy interventions to improve education should take place during childhood and adolescence. Our findings suggest that active intervention in early cognitive development is as important as encouraging continuing education in adulthood. Anstey (2016) also calls for the need for policy interventions to improve the quality of education, encourage children to stay in school, and promote lifelong learning and vocational training for adults.

Our results remain robust after considering different structural models and applying the IPW approach to mitigate sample attrition bias. In the identification of the structural model, we assumed that selection on unobservables is entirely due to unobserved early cognitive ability. Thus, after controlling for latent early cognition through the measurement model and considering the presence of exclusion restrictions, we are on safe ground regarding endogeneity. Further research could relax this assumption if valid and instrumental variables can be located. In analysing the effects of education on cognition across adulthood, there are two cognitive tests at age 34 and only one at age 42. The limited number of cognitive tests may result in an incomplete measure of cognition, and the smaller sample size at age 42 may introduce some bias in the results. However, this is unlikely to affect our main conclusions. Our study makes no assumptions about the quality of education people receive at each stage since we focus on measuring the average treatment effect of educational decisions. Further study can relax this assumption with suitable data and allow different types of schools to cause heterogeneity in the treatment effect of education on midlife cognitive ability.

Chapter 4

The mediation effect of midlife cognitive ability on the midlife returns to educational decisions

Abstract

Recent literature has shown that early cognitive ability influences the education-health nexus due to the ‘selection effect’. In this paper, we investigate whether midlife cognitive ability has a ‘mediation effect’ in the correlation between educational decisions and midlife outcomes by adopting a structural equation modelling approach. With data from the 1970 British Cohort Study, we consider three outcomes, midlife physical health, mental health and earnings. Our findings suggest that education (via midlife cognition) have a positive and significant mediation effect on midlife physical and mental health, while the direct effect of education on midlife health is not significant. The effect of undergraduate and postgraduate education on midlife weekly earnings is mainly direct, with a negligible mediation effect.

Keywords: British Cohort Study, Cognitive ability, Non-cognitive skills, Returns to educational decisions, Mediation effect, Structural equation modelling

4.1 Introduction

In Chapter 2, we showed that early cognitive ability has a positive selection effect on educational decisions after compulsory schooling, controlling for childhood SES. Then, in Chapter 3, we discussed the treatment effect of educational decisions on midlife cognitive ability, controlling for early cognitive ability and adult SES. In this chapter, building on the modelling in the previous two chapters, we focus on returns to educational decisions and explore the mediation effect of midlife cognitive ability on midlife financial and health returns of educational decisions.

An interest in the study of returns to education is established by Becker (1962, 2009), who emphasises the importance of the rate of return for determining the effectiveness of human capital investment. According to Weisbrod (1962), completing one year of schooling increases a person's chances for further education and other life opportunities. The financial return to education is the first and most frequently discussed. Card (1999) provides major theoretical and empirical evidence on the causal link between education and income. A higher level of education increases overall income not only by increasing labour wages but also by promoting personal engagement in financial markets and enhancing saving and/or investment decisions (Cole et al., 2014). Recently, the non-pecuniary effect of education has received more attention. Health is a typical non-pecuniary return on education. Bijwaard et al. (2015) argue that the correlation between health and education is mostly causal, while Cutler and Lleras-Muney (2006) conclude that the monetary value of the health returns to education is about half of the income returns to education. However, other literature fails to demonstrate a direct causal effect of education on health (Albouy and Lequien, 2009; Arendt, 2005; Braakmann, 2011; Clark and Royer, 2013; Grossman, 2015). When estimating the returns to education, it is worth exploring channels of influence other than its direct impact. For health in particular, the limited evidence of a direct impact of education in the literature may indicate that the impact of education on health may be acting through other factors. One such factor is cognitive ability.

Cognitive ability plays a role in returns to education. Griliches (1977) argues that the cause of ability bias is the correlation between income determinants and education. Someone with more education might have superior intrinsic abilities that allows them to earn more money even in the absence of education. Auld and Sidhu (2005) investigate the role of cognitive ability in the health–education nexus using National Longitudinal Survey of Youth data and finds that the causal effect of schooling on health is large only for respondents with low levels of schooling and low cognitive ability. With the same data, Heckman et al.

(2018) estimate the returns to education by developing a dynamic discrete educational choice model and a reduced-form treatment approach. They decompose ex post treatment effects into the direct benefit of moving from one level of schooling to the next and the continuation values of receiving additional education after the next level of schooling. They find that high-ability individuals are likely to continue their education after high school because they have substantial post-high school continuation values, while low-ability individuals stopped in high school because they gained primarily from post-high school. Auld and Sidhu (2005) argue that the regression results of most of the past literature on health returns to education are not credible if they do not deal with ability bias.

Cognitive ability has been shown to be an important predictor of income (Glewwe, 1996) and health differences (Conti et al., 2010) in adults. Researchers show that education is one of the significant determinants of adult cognitive ability, after adjusting for childhood cognitive ability (Hatch et al., 2007a; McElroy et al., 2021; Richards and Sacker, 2003). Higher levels of education can influence thinking and decision-making patterns (Cutler and Lleras-Muney, 2006). Grossman (1972) suggests that the correlation between education and health may be because education enhances health production efficiency, which means that under the same conditions (including education achievements), individuals with higher cognitive ability are healthier, as they can deal with diverse information on the relationships between health behaviours and treatments and potential health outcomes. For example, educated individuals are more likely to use health services in a more timely and appropriate manner, take up recently developed pharmaceuticals, adopt healthier living habits, and make careful choices of occupation (Leigh, 1983; Lleras-Muney and Lichtenberg, 2005). These findings suggest that cognitive ability can be a channel through which education can influence health. However, existing literature only emphasises the importance of early cognitive ability in returns to education.

This paper investigates the mediation effect of midlife cognitive ability on the correlation between educational decisions and midlife outcomes (financial and health) using a SEM approach. Building on the model of the previous two chapters, we add a midlife outcome equation to the structural model. With data from the BCS70, we find a positive mediation effect of midlife cognitive ability on the association between education decisions and midlife health outcomes. However, the mediation effect of midlife cognitive ability only accounts for less than 3% of the total effect of earning returns to educational decisions, which indicates that the direct effect of education dominates the total effect of educational decisions on midlife earnings.

This paper contributes to the literature on the returns to education by exploring a potential pathway through which educational decisions influence midlife outcomes. Our research suggests that midlife cognitive abilities play an important mediating role in the relationship between education and midlife health. We construct a framework that attempts to explain the relationship between education, cognition, and midlife outcomes to inform subsequent related research. Unlike most of the literature, we incorporate cognitive abilities across time and distinguish between the roles of early and midlife cognitive abilities. Early cognition has a selection effect on educational decisions and dominates adult cognitive development, while midlife cognitive ability influences midlife outcomes directly and acts as a mediator in the returns to educational decisions. In addition, we do not find a significant overall effect of educational decisions on health, but the existence of the mediation effect on health suggests that the influence of education on health may be realised through other unnoticed channels.

The remainder of this paper contains five sections. A brief literature review is provided in Section 4.2, and the data and variables are presented in Section 4.4. Section 4.3 introduces the model and estimation approach, while Section 4.5 reports estimation results. Finally, we discuss the results and draw conclusions in Section 4.6.

4.2 Cognitive ability and returns to education

4.2.1 Cognitive ability and income returns to education

Labour economists are interested in the market returns to education. In the human capital literature, education is treated as an investment input, and individuals are assumed to choose their level of education (human capital) based on the expected returns to education (Wilson, 2001). Becker (1962, 2009) started the trend of research on estimating returns to education and stress the significance of the rate of return for assessing the effectiveness of human capital investment. Card (1999) summarises major theoretical and empirical findings on the causal relationship between education and earnings. Empirically, higher education is shown to result in significant wage returns in the UK (Blundell et al., 2000). Weisbrod (1962) argues that every year of education completed provides a chance for further education as well as other life opportunities. In addition to simply raising labour earnings, a higher level of education boosts personal participation in financial markets, improves savings and investment decisions, and in turn increases overall income (Cole et al., 2014).

Cognitive ability is one of the factors in the earnings function. The initial research dates back to when Mincer (1974) published the seminal earnings function, which posits that higher educational attainment boosts economic outcomes, increasing earnings, employment opportunities and gross domestic product. Since then, labour economists have adopted and modified this model to explore the returns to education in many areas. Glewwe (1996) shows that, controlling for total years of schooling completed, higher cognitive skills more crucially affect wage determination and employment options. Using two American longitudinal data sets, Murnane and Willett (1995) find that early adult cognitive ability positively influences wage, while this return to cognitive ability increases by age. However, Glewwe et al. (2017) report that, after controlling for years of schooling, there is no strong evidence that childhood cognitive and non-cognitive abilities significantly influence wages in early adulthood.

People tend to subconsciously process and filter information through personal experiences and preferences. This difference in systematic ways of thinking reflects the heterogeneity of individual cognition, which is known as 'cognitive bias'. Cognitive ability is one of the traits valued by employers. For practical experience, people with high cognitive ability tend to be more educated and gain above-average earnings. However, a well-educated person may have higher innate abilities which enable them to make more money even with less schooling. In labour economics, when estimating returns to education, failure to control for cognitive ability leads to ability bias in the results. Given that both education and cognitive ability have associations with income, Griliches (1977) explains that the correlation between income determinants and schooling is the source of ability bias. Using data from the United States, previous studies have discovered that an additional year of schooling results in about 7-11% returns in earnings, while one standard deviation in cognitive ability test scores is associated with 10-15% in extra earnings (Hanushek and Woessmann, 2008; Murnane et al., 2000). After systematically reviewing of the literature, Ozawa et al. (2022) argue that greater cognitive ability is correlated with more school enrolment, higher academic achievement and more employment opportunities in low-and middle-income countries. Similar results also are found in high-income countries (Heckman and Vytlacil, 2001). These studies reinforce the importance of early cognitive ability in income returns to education but neglect the potential impact of adult cognitive ability.

4.2.2 Cognitive ability and health returns to education

The non-pecuniary effect of education is an important component of the return on education in addition to the market return. One of the most typical non-pecuniary returns is health. Abundant empirical evidence shows that disparities in health and life expectancy between educational groups are persistent and substantial (Mazumder, 2012). People with secondary education live on average four years longer than those who completed only primary education conditional on other circumstances (Bijwaard et al., 2015). Cutler and Lleras-Muney (2006) find that the monetary value of the health return to education is nearly half of the return to education on earnings. However, the mechanisms of how education affects health remain unclear.

Some literature consistently demonstrates that the association between education and health is mostly causal (Bijwaard et al., 2015). For example, Jürges et al. (2013) find a positive correlation not only between education and self-reported health but also between education and health biomarkers (blood fibrinogen and C-reactive protein levels). In their study, Courtin et al. (2019) discover a clear educational gradient in health biomarkers. They find that people who only finished primary education have significantly higher biological risk than those with secondary or higher education. Most research in this field focuses on education up to university and how it affects adult health, particularly longevity (Eide and Showalter, 2011).

Compared with the emphasis on controlling ability bias in labour economics, it is surprising that scant attention has been paid to such bias in the context of estimating health return to education. Auld and Sidhu (2005) argue that the regression results from most of the past literature are not credible if they do not deal with ability bias. The causal effect of education on health can be estimated without bias with proper instrument variable; even personal ability is unobserved. Using selected parental characteristics as instruments, Berger and Leigh (1989) show a large causal effect of schooling on health. Goldman and Lakdawalla (2001) adopt quarter-of-birth dummies as instruments and find greater effects of education on health than those from traditional OLS regressions. A natural experiment is another popular method. Using changes in compulsory education laws in England which raise the minimum school leaving age from 15 to 16, Davies et al. (2018) report that staying in school causally lowers the risk of death and diabetes from regression discontinuity design analysis. Similarly, Courtin et al. (2019) find that French compulsory school reform which increases the average school leaving age by about three months improves levels of biological risk, especially diastolic blood pressure and white blood cell count.

Additionally, using data from two national surveys (University of Michigan's Quality of Employment Surveys for 1973 and 1977), Leigh (1983) suggests that the indirect effect of education on health dominates the direct effect. Education has many indirect pathways of influence on health. One common route is through income since higher income often means greater accessibility to better health care. However, Cutler and Lleras-Muney (2006) show that the association between education and income can only explain part of health returns to education. They suggest that the main reason for this is that higher levels of education can influence different thinking and decision-making patterns. For example, educated individuals are more likely to make wiser use of health services, adopt recently developed pharmaceuticals, have healthy living habits, and make careful choices of occupation (Leigh, 1983; Lleras-Muney and Lichtenberg, 2005). In addition, Brunello et al. (2016) find that about a quarter of the short-term effect of education on health and about a third in the long term is mediated by health behaviours which are measured by smoking, alcohol consumption, exercise and body mass index, even though Kenkel (1991) suggests that the majority of improvements in health related to higher education cannot be attributed to changes in health behaviours associated with higher education.

Early cognitive ability is an important factor for health differences in adults (Conti et al., 2010). Wrulich et al. (2014) report that childhood intelligence is a valid predictor of adult health across 40 years. With birth cohort data from Scotland, Calvin et al. (2017) find that higher intelligence scores in childhood are associated with lower risk of mortality from coronary heart disease, stroke, smoking-related cancers, respiratory diseases, digestive diseases, trauma and dementia. However, Hatch et al. (2007b) report that higher early cognitive ability puts both men and women at higher risk of potential alcohol abuse.

Grossman (1972) suggests that the correlation between education and health may be because education enhances health production efficiency, which means that under the same conditions (including education achievements), individuals with higher cognitive ability are healthier as they can deal with diverse information on the relationships between health behaviours and treatments and potential health outcomes. Dohmen et al. (2018) point out that cognitive ability tends to be positively associated with avoidance of harmful or risky situations, but negatively associated with risk aversion in advantageous situations. Empirical evidence shows that individuals with higher cognitive ability tend to prosess healthful behaviours, such as less consumption of stimulant drinks, delayed initiation of smoking and a higher likelihood of quitting in adulthood (Ciarrochi et al., 2012; Daly and Egan, 2017). Using several different data sets from the US and UK respectively, Cutler and Lleras-Muney (2010) investigate the relationship between education and health behaviours and report that knowledge and measures of cognitive ability explain 30% of the education gradient.

Due to limitations in data collection, only a limited amount of literature includes both cognitive ability and education in health regressions. Hartog and Oosterbeek (1998) find that mathematical ability is associated with better self-reported health status after controlling schooling using ordered probit estimates. Auld and Sidhu (2005) investigate the role of cognitive ability in the health-education nexus and find that the causal effect of schooling on health is large only for respondents with low levels of schooling and low cognitive ability. By developing a structural equation model, Conti et al. (2010) and Heckman et al. (2014a,b) demonstrate that half of the association between education and health is explained by the causal effect of education on health, and the other half stems from cognitive and non-cognitive abilities and early childhood social background. They conclude that people with poor early cognition and a disadvantaged family background can benefit most from education. Similarly, Bijwaard et al. (2015) explain that cognitive ability and family SES contribute about half of the raw differences in mortality across educational groups (selection effect), and they confirm the importance of the causal effect of education on health even after controlling cognitive ability and other socioeconomic background variables.

Conversely, based on other natural experiments, some literature demonstrates the estimated direct causal effects of education on health, mortality and health behaviours are small (Lleras-Muney, 2005; Oreopoulos, 2006; Van Kippersluis et al., 2011) and even insignificant (Albouy and Lequien, 2009; Arendt, 2005; Braakmann, 2011; Clark and Royer, 2013). This indicates that in addition to the direct causal effect of education on health, the significant association between education and health may be driven by ‘reverse causality’, that poor health in childhood can constrain adulthood educational attainment (Behrman and Rosenzweig, 2004; Case et al., 2005), and confounding factors, which can simultaneously affect education and health outcomes. Fuchs (1982) discusses how time preference is such a confounding factor that people with high discount rates are less likely to invest in health and education.

In general, both education and cognition affect adult outcomes. There is a strong correlation between adult cognitive ability and adult outcomes, especially health outcomes. We have discussed the effect of educational decisions on midlife cognitive ability in the previous chapter. This prior knowledge supports our hypothesis that midlife cognitive ability is very likely to be a mediator in midlife returns to education. We will extend the structural modelling of the previous chapter and focus on analysing the mediation effect of midlife cognition on returns to education, which remains a research gap in a related field.

4.3 Methods

This paper aims to explore the mediation effect of midlife cognitive ability in the returns to educational decisions, with a modelling framework of returns to education modified from Heckman et al. (2018).

4.3.1 A structural model for defining returns to educational decisions

We consider three sequential educational decisions ($D_j, j \in \{1,2,3\}$) that a person faces following compulsory education in Britain[1]. The whole educational decision tree is presented in Figure 4.1.

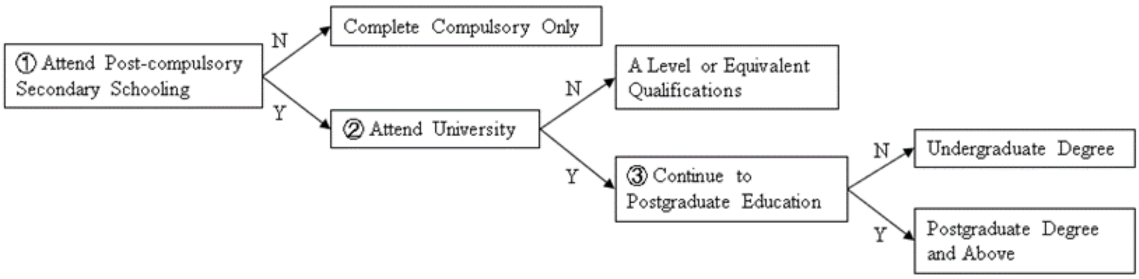

Fig. 4.1 A multistage sequential decision model modified from Heckman et al. (2018)

We assume that for a person who reaches stage j, he or she will continue education if the utility of doing so is not less than zero. Heckman et al. (2018) posit that this utility is determined by a vector of observed variables (X^D) and a vector of unobserved factors (U^D).

$$D_j = \begin{cases} 1, & I_j \geq 0 \\ 0, & I_j < 0 \end{cases}, \quad where \quad I_j = \phi_j(X^D) + U_j^D, \quad j \in \{1,2,3\}$$

Assume there is a set of outcomes $s \in S$. Once an individual makes a decision, they reach an outcome (Y_j^s), determined by a vector of observed variables (X^s) and a vector of unobserved factors (U^s). We then define the observed midlife outcome (Y^s) as

$$Y^s = \sum_{j=1}^{3} D_j Y_j^s, \quad where \quad Y_j^s = z_j(X^s) + U_j^s, \quad s \in S, j \in \{1,2,3\}$$

Following the identification strategy of Heckman et al. (2018), we assume the existence of a finite-dimensional vector of unobserved (by the analyst) factors θ, that account for all dependence between U_j^D and U_j^s. Thus,

$$U_j^D = -(\beta_j \theta - \eta_j), \quad j \in \{1,2,3\}$$

[1]We have shown the sequential educational decision model in section 2.3.3. To avoid too much repetition, we briefly recap the main elements.

and

$$\mathrm{U}_j^s = \rho_j^s \theta + \omega_j^s, \quad s \in S, j \in \{1,2,3\}$$

where η_j is an idiosyncratic error term for education stage j, and ω_j^s represents an idiosyncratic error term for outcome s after making decision at node j. After controlling for $\theta, \mathrm{X}^D, \mathrm{X}^s$, the model eliminates selection effects, so educational decisions and outcomes are statistically independent. Drawing on past literature, Heckman et al. (2018) suggested that the unobserved factors are latent early cognitive and non-cognitive abilities, which can be estimated them through a measurement model. We have introduced the measurement model in section 2.3.1. Based on our research questions, we distinguish cognitive (θ^C) and non-cognitive (θ^{NC}) abilities in the empirical model for ease of understanding and combine non-cognitive ability into the vector of control variables (X^D).

Empirically, in the structural model, we continue to use the function settings for educational decisions and midlife cognitive ability from the previous two chapters. Recall the education equations we presented in section 3.3.2[2]. The utility I_j is assumed to be linearly defined by early cognitive ability (θ^C) and a vector of exogenous covariates (X^D and X^s).

$$\mathrm{I}_j = \beta_j \theta^C + \pi_j \mathrm{X}_j^D + \eta_j, \tag{4.1}$$

where β_j captures the selection effect of early cognitive ability on the educational decision D_j. The error term η_j is normally distributed with mean zero and is assumed to be independent of cognitive abilities, exogenous covariates and measurement error e. Conditional on X^D, it is also independent across educational stages and individuals. We estimate this decision model by probit regression.

For midlife cognitive ability C_{46}, we adopt the same model identification shown in section 3.3.1.

$$\mathrm{C}_{46} = \gamma_{46} \theta^C + \lambda_{46} \mathrm{X}_{46}^C + \sum_{j=1}^{3} \delta_j \mathrm{D}_j + \varepsilon_{46} \tag{4.2}$$

[2]To avoid too much repetition, we briefly recap the main elements.

where γ_{46} captures the effect of early cognitive ability on midlife cognitive ability[3]. The error term ε_{46} is normally distributed and is assumed to be independent across individuals and over time. Conditional on observed covariates, the error term is independent of the lagged cognitive ability. δ_j refers to the marginal treatment effect of giving a positive response to educational decision D_j at stage j on midlife cognitive ability, while $\sum_1^j \delta_j \mathrm{D}_j$ denotes the cumulative treatment effect of educational decision up to stage j on midlife cognitive ability.

We also assume a linear formation and specify the following model:

$$\mathrm{Y}_{46}^s = \rho_5^s \mathrm{C}_5 + \rho_{46}^s \mathrm{C}_{46} + \sigma_{46}^s \mathrm{X}_{46}^s + \sum_{j=1}^{3} \tau_j^s \mathrm{D}_j + \omega_{46}^s \tag{4.3}$$

where ρ_{46}^s represents the effect of midlife cognitive ability on midlife outcome, while ρ_5^s indicates the selection effect of early cognitive abilities on midlife outcome. The parameter τ_j^s reveals the marginal direct effect of giving a positive response to educational decisions D_j at stage j on midlife outcomes Y_{46}^s. The error term ω_{46}^s is assumed to be independent across individuals and be independent of factors C, X^D, e and η, conditional on X_{46}^s. The independence assumption between ω and η indicates that conditional on cognitive abilities and exogenous covariates, educational decisions and midlife outcomes are statistically independent. As in Heckman et al. (2018), conditional on X_{46}^s, we assume that independence of latent abilities with respect to the observed covariates (X^D) in the Equation (4.1) and independence of the shocks (η,ω) with the latent abilities and the observables (X^D). Thus, any dependency assumed between η and ω can be captured by introducing latent abilities.

4.3.2 Decomposition

Given by Equations (4.1) and (4.3), we identify the marginal effect of educational decision D_j on midlife outcome Y_{46}^s, conditional on $\mathrm{D}_{j-1} = 1$, is:

$$\begin{aligned} \frac{d\mathrm{Y}_{46}^s}{d\mathrm{D}_j} &= \rho_{46}^s \frac{d\mathrm{C}_{46}}{d\mathrm{D}_j} + \tau_j^s \\ &= \underbrace{\rho_{46}^s \delta_j}_{\text{indirect effect}} + \underbrace{\tau_j^s}_{\text{direct effect}} \end{aligned} \tag{4.4}$$

[3]Unlike the previous chapter, we exclude post-compulsory school cognitive ability from the structural model to simplify it and preserve as much sample size as possible, given the large number of missing values in post-compulsory cognitive tests. Instead, we include non-cognitive ability as a control. As previously discussed, non-cognitive ability is likely to directly affect midlife cognitive ability in the absence of post-compulsory cognitive ability.

where $\rho^s_{46}\delta_j$ is the marginal mediation (indirect) effect on outcome Y^s_{46} via midlife cognition C_{46} of giving a positive response to the educational decision D_j, and τ^s_j indicates the marginal direct effect of giving a positive response to educational decisions D_j at stage j on midlife outcomes Y^s_{46}.

The cumulative direct effect of reaching educational state j on midlife outcome Y^s_{46} equals the cumulative sum of the effects of each positive response to the educational decisions up to state j:

$$\mathrm{EF}_j^{direct} = \sum_1^j \tau_j^s \tag{4.5}$$

Similarly, the cumulative mediation effect on outcome Y^s_{46} via midlife cognition C_{46} of reaching to educational state j is the cumulative sum of marginal indirect effects of each educational decisions up to state j:

$$\mathrm{EF}_j^{indirect} = \sum_1^j \rho_{46}^s \delta_j \tag{4.6}$$

Thus, the the total effect of reaching to educational state j on the outcome is:

$$\begin{aligned} \mathrm{EF}_j^{total} &= \mathrm{EF}_j^{direct} + \mathrm{EF}_j^{indirect} \\ &= \sum_1^j (\tau_j^s + \rho_{46}^s \delta_j) \end{aligned} \tag{4.7}$$

4.3.3 SEM framework

Figure 4.2 visualises our model which is estimated using the structural equation modelling approach. All observables are drawn in rectangles, while unobserved factors (including latent variables and error terms) are drawn wih ellipses. The single-headed arrows give us the unidirectional causal connections between two variables. The dashed rectangles present measurement models for cognitive ability across time[4]. The structural model is illustrated in the large rectangle (given by Equations (4.1), (4.2), and (4.3)). In the empirical analysis, we first estimated the measurement model to predict latent abilities. We then substituted the predicted abilities into the structural model for estimation. Given that the structural model

[4]To simplify the graph, not all measures are shown. We neglect the measurement model of latent non-cognitive ability and midlife health indicators as well.

estimation relied on these predicted abilities, we employed the bootstrap to estimate the standard errors[5].

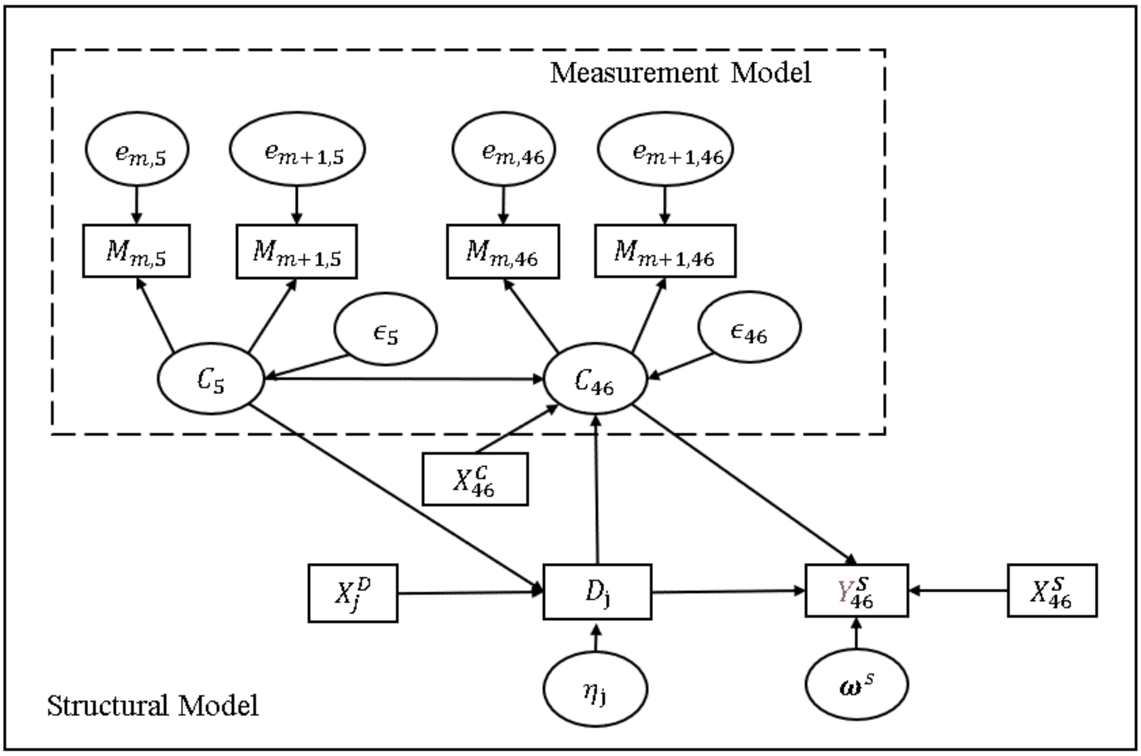

Fig. 4.2 Structural equation modelling framework

4.4 Data

The BCS70 is a multidisciplinary and longitudinal study of about 17,000 children born in one week of 1970 in Scotland, England, and Wales, and consists of 11 waves. We utilise data from the majority of the waves of the BCS70. The sample was constructed following the same steps as in the previous two chapters. Given the focus on the three midlife outcomes, we created separate samples for each to preserve as much information as possible. The sample sizes are 2,472 for physical health, 2,432 for mental health, and 2,111 for income.

Midlife outcomes: Our dependent variables are midlife financial and health outcomes measured at age 46. For the former, in the interview, respondents report their gross weekly earnings, which we transform by taking the logarithm prior to analysis[6]. For the latter,

[5]The one-step estimation did not feasible due to problems with model convergence. Instead, we applied the two-step estimation.

[6]One person reported a gross weekly earnings of £0.02, which is unrealistic. This outlier is likely to be due to a recording/coding error. We have re-coded this to a missing value.

Table 4.1 Descriptive statistics of midlife earnings and health measures

Variable	N	Mean	Std. dev.	Min	Max
Personal gross weekly earnings	2111	903.91	3823.85	12.69	132741.1
Physical health measures					
Physical functioning score	2472	90.17	18.06	0	100
Role-limitations due to physical health	2472	88.08	27.56	0	100
Pain score	2472	80.63	21.21	0	100
General health score	2472	69.99	20.22	0	100
Mental health measures					
Warwick Edinburgh Mental Well-Being Scale	2432	50.97	7.93	18	70

Source: BCS70 wave 10.

we consider both individual physical and mental health. To measure physical health, we use four physical test scores from the Short-Form Health Survey (SF-36). The SF-36 is a widely used multi-purpose health questionnaire comprised of 36 questions. We utilised four subscales that assess different aspects of physical health: The physical functioning score indicates functioning across a range of physical activities (e.g. running, climbing stairs). Role limitations represents lifestyle limitations as a result of physical health problems in the four weeks before the interview. The pain score reflects pain suffered and its impact on normal life. The general health score reflects overall health status. Each score ranges from 0 to 100. A higher score indicates better health. Mental health is measured using the Warwick Edinburgh Mental Well Being Scale, designed to assess an individual's mental well-being. Each of the 14 items is scored from 1 to 5, with a total score ranging from 14 to 70, where higher scores indicate better mental health. Related descriptive statistics are summarised in Table 4.1. Each health test score was standardised prior to estimation, and we calculated a weighted average of the four SF-36 tests to create a physical health indicator.

Educational decisions: To counter sample attrition and capture as much information as possible, we collect education data from the waves between ages 30 and 46 (including intermediate years). We use the general classification of three educational decisions faced after compulsory schooling, as presented in Section 3.4.1. For each dummy educational decision, a value of 1 indicates a positive response, while 0 indicates otherwise.

Figure 4.3 presents the kernel density curves of three midlife outcomes by (general) educational decisions. For each decision, individuals with positive responses exhibited better physical and mental health, as well as higher earnings, compared to those with negative responses. The distribution curves for both physical and mental health are left-skewed, indicating that a small percentage of the individuals experiences exceptionally poor health.

In contrast, the income distribution is right-skewed, meaning a small group has significantly higher incomes.

Abilities: Three latent abilities are assessed through the measurement model: preschool cognitive ability measured at age 5, midlife cognitive ability measured at age 46, and non-cognitive ability measured at age 10. The inclusion of early cognitive and non-cognitive abilities aims to control for unobserved selection bias. At age five, the BCS70 conducts five cognitive tests: the copying designs test, the English picture vocabulary test, the human figure drawing test, the complete-a-profile test, and the Schonell reading test. As for midlife cognitive ability, there is the animal naming task, letter cancellation task (accuracy and speed), and word-list recall test (immediate and delayed). Additionally, non-cognitive ability is assessed by six relative scales collected at age 10 based on Conti et al. (2010): the locus of control (caraloc) scale, the perseverance scale, the cooperativeness scale, the persistence scale, the attentiveness scale, and the completeness scale. Figure C.1 displays descriptive statistics for the above test scores[7]. Following Moulton et al. (2020), we standardise the total score for each test before estimating the measurement model.

The three scatter plots with fitted lines in Figure 4.4 show the correlation between midlife outcomes and midlife cognitive ability. The fitted line shows a positive correlation between midlife cognition and all three outcomes. That is, the higher the midlife cognition, the healthier the body and mind, and the higher the income. However, the scatter distribution is somewhat discrete, which means that this positive correlation is not very strong.

Covariates: We control for individuals' early backgrounds and adult socioeconomic status (SES). The former includes gender, number of siblings, parental education, and family income, while the latter includes marital status and occupation. These variables have been introduced in previous chapters. Descriptive statistics for these variables are summarised in Table C.2.

Table 4.2 outlines the control variables used in each structural equation. While our model, based on the selection on unobservables assumption, is theoretically free from endogeneity, number of siblings still serves as an exclusive restriction. Current literature largely agrees that family size does not directly influence adult income (Taubman and Behrman, 1986) or health Baranowska-Rataj et al. (2016)[8], with some suggesting that any potential effects are mediated through education and occupation (Black et al., 2005; Wijanarko and Wisana, 2019). Initially, we included number of siblings in the outcome equations, but the coefficients were

[7]We have introduced these tests in sections 2.4.2 and 3.4.1

[8]Using longitudinal data covering the entire Swedish population, Baranowska-Rataj et al. (2016) found that growing up in a large family has no causal effect on physical or mental health in midlife.

Table 4.2 Selection of control variables in each structural equation

	Education	Cognition	Outcomes
Gender	√	√	√
Parental education (age 5)	√	√	√
Number of siblings (age 5)	√		
Preschool cognitive ability (age 5)	√	√	√
Non-cognitive ability (age 10)	√	√	√
Family income (age 16)	√	√	√
Occupation (age 46)		√	√
Marital status (age 46)		√	√

very small and insignificant, likely because we already control for education and occupation. To streamline the model, we removed the number of siblings from the outcome equations.

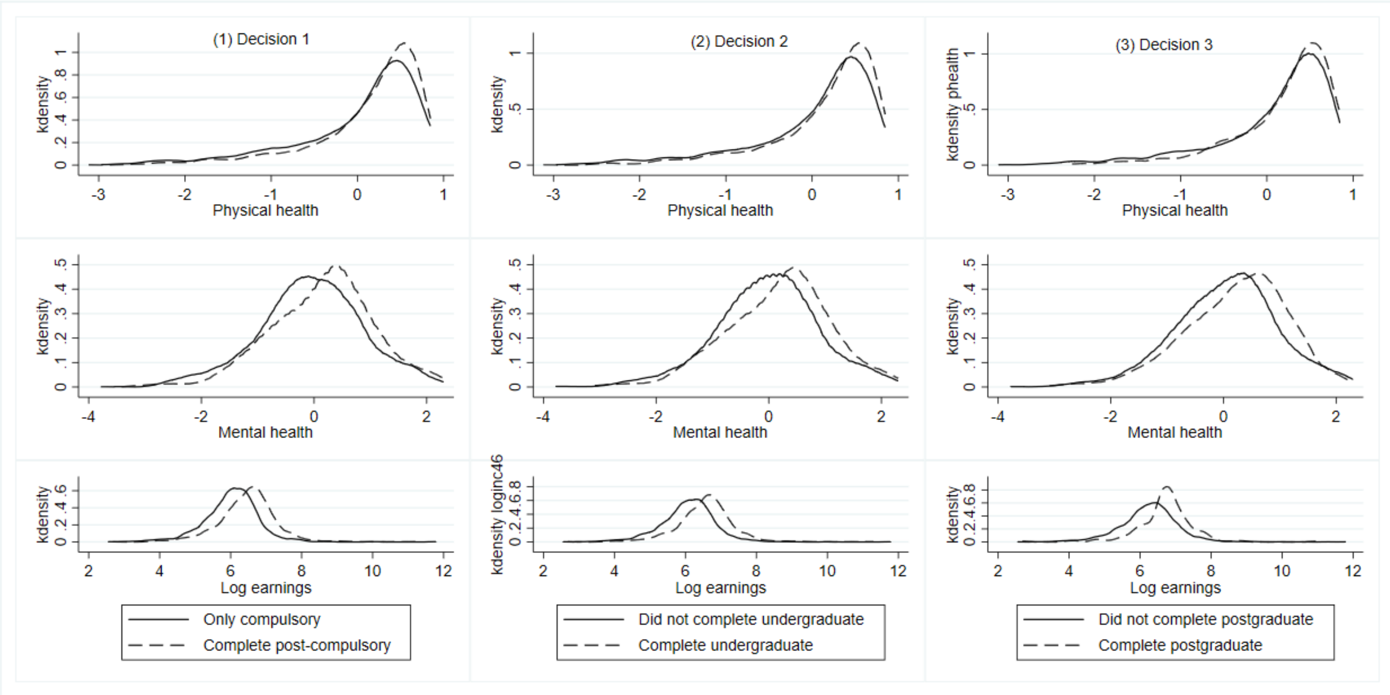

Fig. 4.3 Kernel density estimates for outcomes at the age 46, for the first educational decision (the left), the second educational decision (the middle) and the third educational decision (the right). These educational decisions are measured by general identification. The dashed line illustrates density for having a positive response for a given decision ($D_j = 1$), while the solid line presents density for having a negative response ($D_j = 0$).

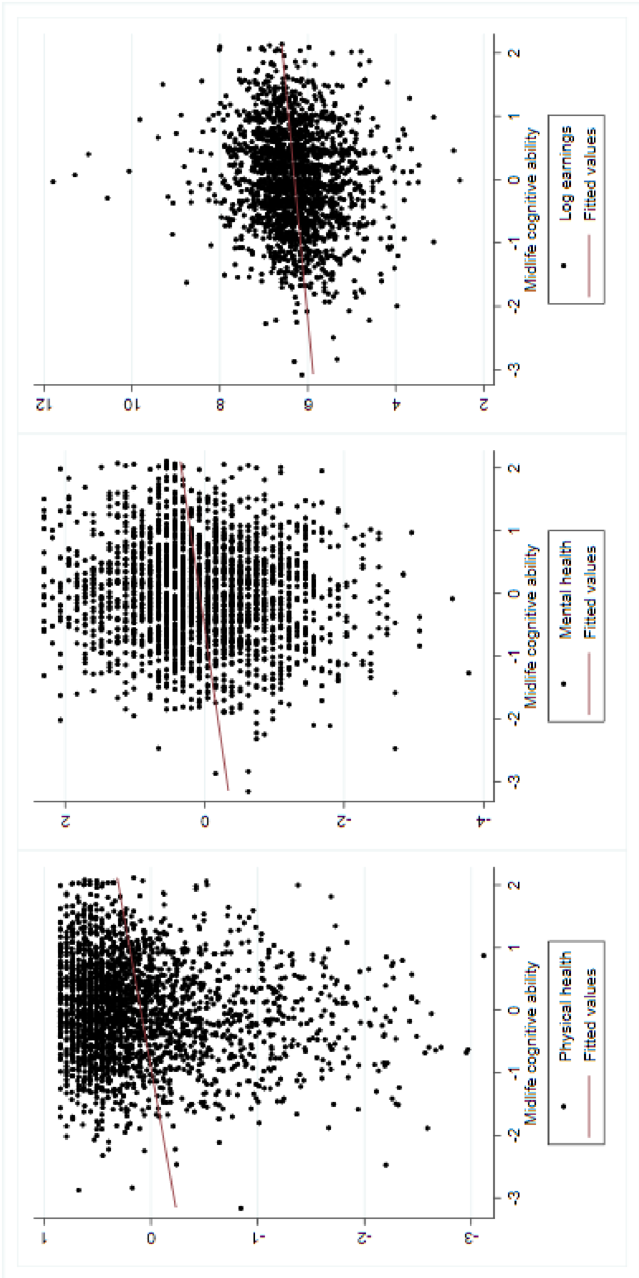

Fig. 4.4 Scatter plots for midlife outcomes

4.5 Results

Table 4.3 presents the estimates for midlife cognitive ability and outcomes. Consistent with the previous chapter, we find that preschool cognitive ability significantly impacts midlife cognitive ability[9]. This suggests that children with higher cognitive ability early in life maintain a lasting advantage in cognitive development. The treatment effects of educational decisions on midlife cognition are also remarkable. For instance, in the structural model for physical health, individuals with undergraduate or equivalent qualifications have an average of 0.099 standard deviations higher cognitive ability at midlife than those who only completed post-compulsory education. Compared to those who only completed compulsory education, the total effect of undergraduate education is 0.204. Pursuing postgraduate education results in an average increase of 0.113 standard deviations in midlife cognitive ability, with the total effect of completing a postgraduate degree being 0.317.

Table 4.3 shows that midlife cognitive ability positively affects both physical and mental health at the 1% significance level. Holding other factors constant, a one standard deviation increase in midlife cognitive ability is associated with a 0.062 standard deviation increase in physical health and a 0.072 standard deviation improvement in mental health. However, we do not observe any significant direct effect of educational decisions on health outcomes. Regarding log earnings, midlife cognitive ability has no significant influence, whereas completing an undergraduate education has a positive and significant marginal direct impact. People who completed undergraduate education have 17.5 percentage points higher earnings in midlife than those who did not.

Moreover, respondents with higher non-cognitive ability in childhood tend to be healthier in midlife. A one standard deviation increase in early non-cognitive ability is associated with a 0.101 standard deviation increase in physical health, holding other factors constant. Males tend to have poorer mental health (by approximately 0.115 standard deviations) but earn 66.6 percentage points more than females in midlife. Respondents from highly educated parents (above A level) and high-income families also have higher midlife earnings, with the latter group enjoying better physical health as well. Additionally, married individuals are in better physical and mental health than those who are unmarried. Finally, compared with manual workers, those in intermediate and professional occupations have significant advantages in both midlife health and earnings.

We calculate the relative effects of each educational decision on midlife outcomes. Table 4.4 displays the cumulative impact of educational decisions on midlife outcomes. From the

[9] The magnitude of the estimated coefficients varies due to differences in sample sizes across the structural models.

indirect effect column, we find that all educational decisions, when mediated by midlife cognition, have a significant and positive effect on physical and mental health. For example, individuals who completed undergraduate education gained more midlife cognitive skills than those who did not, resulting in a 0.014 standard deviation improvement in mental health. In comparison, the gap between those with postgraduate education and those without was 0.022 standard deviations. However, we do not observe any significant direct effect of educational decisions on health outcomes, except for the positive association between completing undergraduate education and mental health. In contrast, higher education has a significant direct impact on weekly earnings at age 46. Respondents with an undergraduate degree earn 22.7 percentage points more than those who only completed compulsory education, while those with a postgraduate degree earn 31.7 percentage points more. We do not find any significant mediation effect of education on midlife earnings. The last column shows a positive and significant total effect of higher education on mental health, but not on physical health. The total effect of higher educational decisions on midlife earnings is primarily driven by direct effects, with mediation effects contributing less than 3%.

Table 4.5 summarises the key results of the robustness checks[10]. We considered four different scenarios. Column (1) presents the case where adult cognition is excluded, estimating only the direct effect of educational decisions on midlife outcomes. Column (2) assumes midlife cognition to act as a mediator in the midlife returns to education, as discussed in Table 4.3. Column (3) addresses potential sample attrition bias, applying the Inverse Probability Weighting (IPW) method to make the estimates as representative as possible. Column (4) reports results from a simple OLS regression. Comparing columns (1) and (2), we find that even without accounting for cognitive ability, there is still no direct effect of educational decision on (physical and mental) health outcomes, although the direct effect of higher education on earnings remains significant. This suggests that education influences health primarily through mediating factors, such as midlife cognition, rather than directly. However, the effect of education on earnings appears to be mostly direct. When comparing columns (2) and (3)[11], while the magnitude of the coefficients shifts slightly, our overall conclusions remain unchanged. The point estimates in columns (2) and (4) are consistent, with only minor differences in standard deviations. This is due to our model's assumption that, after controlling for latent (early cognitive and non-cognitive) abilities, there is no omitted variable bias, meaning that the error terms for educational decisions and midlife

[10] Full estimation results are provided in Tables C.4, C.5, and C.6

[11] A small number of individuals did not participate in the British birth wave for some reasons, making them ineligible for IPW weighting. However, as this group is relatively small, it is unlikely to introduce significant bias into the estimates.

outcomes are independent. Therefore, it is not surprising the maximum likelihood estimates and OLS results for outcome equations are quite similar.

Table 4.3 All outcomes: SEM regression results

	(1)		(2)		(3)	
	C46	Physical health	C46	Mental health	C46	Earnings
Midlife cognitive ability (C46)		0.062***		0.072***		0.025
		(0.017)		(0.025)		(0.020)
Whether finish post-compulsory schooling (D_1)	0.105**	0.017	0.102**	0.073	0.091*	0.052
	(0.044)	(0.043)	(0.043)	(0.055)	(0.047)	(0.042)
Whether to complete undergraduate education (D_2)	0.099**	0.012	0.099**	0.014	0.129***	0.175***
	(0.046)	(0.043)	(0.046)	(0.058)	(0.050)	(0.044)
Whether to obtain postgraduate education (D_3)	0.113*	0.007	0.108*	0.011	0.065	0.091
	(0.059)	(0.042)	(0.058)	(0.066)	(0.063)	(0.056)
Preschool cognitive ability	0.197***	0.024	0.194***	0.021	0.187***	0.044
	(0.032)	(0.031)	(0.032)	(0.040)	(0.035)	(0.028)
Early non-cognitive ability	0.263***	0.101*	0.264***	0.078	0.280***	0.082
	(0.058)	(0.053)	(0.057)	(0.073)	(0.065)	(0.057)
Gender (baseline = female)	-0.049	0.036	-0.051	-0.115***	-0.019	0.666***
	(0.031)	(0.028)	(0.031)	(0.039)	(0.035)	(0.030)
Parental education at age 5 (baseline = no qualification)						
lower than A level	0.027	-0.004	0.034	-0.041	0.033	0.095***
	(0.034)	(0.033)	(0.034)	(0.042)	(0.037)	(0.032)
A level and above	0.060	0.032	0.066	-0.120**	0.059	0.084*
	(0.047)	(0.040)	(0.048)	(0.059)	(0.052)	(0.050)
Family income at age 16 (baseline = low-income)						

(To be continued on the next page)

(table continued)

middle-income	0.011	0.049	0.009	0.063	-0.013	-0.002
	(0.035)	(0.035)	(0.037)	(0.046)	(0.039)	(0.033)
high-income	0.136***	0.125***	0.131***	0.086	0.090	0.121**
	(0.050)	(0.043)	(0.051)	(0.062)	(0.055)	(0.050)
Marital status (baseline = never married)						
Divorced/legally separated/widowed	0.174***	-0.043	0.173***	-0.017	0.164***	0.075
	(0.051)	(0.051)	(0.052)	(0.067)	(0.057)	(0.051)
Married	0.179***	0.083**	0.174***	0.192***	0.147***	0.014
	(0.040)	(0.038)	(0.039)	(0.048)	(0.044)	(0.038)
Occupation (baseline = manual)						
Intermediate	0.188***	0.102**	0.186***	0.062	0.219***	0.102*
	(0.043)	(0.044)	(0.044)	(0.058)	(0.051)	(0.053)
Professional	0.170***	0.117***	0.171****	0.205***	0.166***	0.579***
	(0.040)	(0.038)	(0.040)	(0.053)	(0.041)	(0.038)
N	2472		2432		2111	
AIC	18062.63		19303.03		15385.56	
BIC	18428.84		19668.21		15741.82	

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. All the structural models include the education equations, but only the results for the cognition and outcome equations are summarised here. All models were estimated using the two-step approach.

Table 4.4 All outcomes: decomposing effects of educational decisions

	Marginal Direct Effect	Direct Effect	D/T	Marginal Indirect Effect	Indirect Effect	M/T	Marginal Total Effect	Total Effect
Physical health								
Completed post-compulsory education	0.017	0.017	72.34%	0.006**	0.006**	27.66%	0.023	0.023
	(0.042)	(0.042)		(0.003)	(0.003)		(0.042)	(0.042)
Completed undergraduate degree	0.012	0.029	69.90%	0.006*	0.013***	30.10%	0.018	0.042
	(0.043)	(0.035)		(0.003)	(0.004)		(0.043)	(0.035)
Completed postgraduate degree or above	0.007	0.036	65.01%	0.007*	0.020***	34.99%	0.014	0.056
	(0.042)	(0.046)		(0.004)	(0.007)		(0.042)	(0.046)
Mental health								
Completed post-compulsory education	0.073	0.073	90.83%	0.007*	0.007*	9.17%	0.080	0.080
	(0.055)	(0.055)		(0.004)	(0.004)		(0.055)	(0.055)
Completed undergraduate degree	0.014	0.087*	85.77%	0.007*	0.014**	14.23%	0.022	0.102**
	(0.058)	(0.049)		(0.004)	(0.006)		(0.058)	(0.049)
Completed postgraduate degree or above	0.011	0.098	81.53%	0.008	0.022**	18.47%	0.019	0.121*
	(0.066)	(0.073)		(0.005)	(0.009)		(0.066)	(0.072)
Log earnings								
Completed post-compulsory education	0.052	0.052	95.89%	0.002	0.002	4.11%	0.054	0.054
	(0.042)	(0.042)		(0.002)	(0.002)		(0.042)	(0.042)
Completed undergraduate degree	0.175***	0.227***	97.68%	0.003	0.005	2.32%	0.178***	0.232***
	(0.044)	(0.037)		(0.003)	(0.005)		(0.043)	(0.037)
Completed postgraduate degree or above	0.091	0.317***	97.85%	0.002	0.007	2.15%	0.092	0.324***
	(0.056)	(0.059)		(0.002)	(0.006)		(0.056)	(0.059)

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. D/T refers to direct effect/ total effect. M/T refers to mediation effect/total effect. Inside the brackets is the standard deviation.

Table 4.5 Robustness checks

Phealth	(1)	(2)		(3)		(4)
	Phealth	C46	Phealth	C46	Phealth	Phealth
Midlife cognitive ability (age 46)			0.062***		0.065***	0.062***
			(0.017)		(0.018)	(0.018)
Whether finish post-compulsory schooling	0.023	0.105**	0.017	0.136***	0.001	0.017
	(0.042)	(0.044)	(0.042)	(0.050)	(0.044)	(0.043)
Whether to complete undergraduate education	0.018	0.099**	0.012	0.096*	0.012	0.012
	(0.043)	(0.046)	(0.043)	(0.056)	(0.044)	(0.043)
Whether to obtain postgraduate education	0.014	0.113*	0.007	0.120	0.012	0.007
	(0.042)	(0.059)	(0.042)	(0.080)	(0.041)	(0.043)
N	2472	2472		2408		2472
AIC	12554.79	18062.63		125248.3		4996.474
BIC	12822.18	18428.84		125612.8		5089.478
Mhealth	(1)	(2)		(3)		(4)
	Mhealth	C46	Mhealth	C46	Mhealth	Mhealth
Midlife cognitive ability (age 46)			0.072***		0.054*	0.072***
			(0.025)		(0.030)	(0.024)
Whether finish post-compulsory schooling	0.080	0.102**	0.073	0.134***	0.089	0.073
	(0.056)	(0.043)	(0.055)	(0.052)	(0.056)	(0.056)
Whether to complete undergraduate education	0.022	0.099**	0.014	0.096*	0.060	0.014
	(0.058)	(0.046)	(0.058)	(0.058)	(0.070)	(0.058)
Whether to obtain postgraduate education	0.019	0.108*	0.011	0.111	-0.061	0.011

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(table continued)

	(0.067)	(0.058)	(0.066)	(0.076)	(0.077)	(0.067)
N	2432	2432		2370		2432
AIC	13886.29	19303.03		136756		6452.227
BIC	14152.93	19668.21		137119.6		6544.971
Earnings	(1)	(2)		(3)		(4)
	Earnings	C46	Earnings	C46	Earnings	Earnings
Midlife cognitive ability (age 46)			0.025		0.003	0.025
			(0.020)		(0.020)	(0.020)
Whether finish post-compulsory schooling	0.054	0.091*	0.052	0.185***	0.023	0.052
	(0.041)	(0.047)	(0.042)	(0.065)	(0.044)	(0.043)
Whether to complete undergraduate education	0.178***	0.129***	0.175***	0.105*	0.192***	0.175***
	(0.044)	(0.050)	(0.044)	(0.061)	(0.046)	(0.045)
Whether to obtain postgraduate education	0.092*	0.065	0.091	0.076	0.097*	0.091
	(0.056)	(0.063)	(0.056)	(0.072)	(0.056)	(0.057)
N	2111	2111		2053		2111
AIC	10710.17	15385.56		125692.4		4196.305
BIC	10970.3	15741.82		126046.9		4286.783

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. The full regression results are summarised in Tables C.4, C.5 and C.6.

4.6 Conclusion

This paper addresses the question of whether midlife cognitive ability acts as a mediator in the midlife returns to educational decisions made following compulsory schooling, using a SEM approach. With data from the BCS70, we consider pecuniary return (weekly earnings) and non-pecuniary returns (physical and mental health) to educational decisions at age 46, where abilities are treated as latent factors and measured via the measurement model. Building on the previous framework, we include midlife outcome equations in the structural model and identify mediation effects.

Existing literature (Calvin et al., 2017; Carneiro et al., 2007; Furnham and Cheng, 2016; Hatch et al., 2007b; Sun et al., 2018; Wrulich et al., 2014) has shown that early cognitive ability positively influences later financial and health outcomes. However, conditional on education and adult SES, we do not find a significant direct effect of early cognitive ability on health and weekly earnings in midlife. After controlling early cognitive abilities, we find that midlife cognitive ability positively impacts physical and mental health but not earnings. This may be due to the fact that most of the diseases associated with midlife cognition are psychiatric (e.g. cognitive decline and Alzheimer's disease); and mental health and physical health tend to interact. Contrary to the findings in the existing literature, our results suggest that cognitive ability — whether in childhood or adulthood — does not have a significant impact on midlife earnings, once education and adult socioeconomic status (SES) are taken into account.

Next, we find that, through midlife cognitive ability, all education decisions have a significant positive influence on physical and mental health. This is not unexpected. Since cognitive ability is strongly correlated with health literacy (Wolf et al., 2012)[12], we expected that people with higher levels of education were more likely to have higher midlife cognitive abilities (and corresponding health literacy), which enables them to make more effective health decisions and achieve higher levels of health outcomes.

Furthermore, our study suggests that educational decisions have no significant direct effect on mental health, which is consistent with the literature (Albouy and Lequien, 2009; Arendt, 2005; Braakmann, 2011; Clark and Royer, 2013; Grossman, 2015). However, after accounting for the mediation effect, we find that the overall impact of education on mental health is significant and positive. Chevalier and Feinstein (2006) report that education

[12] Health literacy usually refers to an individual's ability to understand and use information to make decisions about their health. A person with low health literacy often has difficulty: reading and understanding health information, knowing how to act on this information, and knowing which health services to use and when to use them. Source: $https://service-manual.nhs.uk/content/health-literacy$

can reduce the transition to depression and improve mental health, especially for women, individuals with mid-level qualifications, and individuals at greater risk of mental illness. However, their study did not consider the effect of cognitive ability in midlife. Our findings suggest that the effects of education on mental health may be fully mediated through effects on cognitive ability in midlife. But, studying in higher education can be a stressful challenge for some. For example, Evans et al. (2018) find that graduate students are more than six times as likely to suffer from mental illness (depression and anxiety) than the general population, a phenomenon that has been referred to as a 'mental health crisis' in the postgraduate population.

In addition, our undergraduate and graduate education decisions positively affect midlife earnings, with the direct effect of education dominating. We find no significant mediating effects of midlife cognition. The effect of education on earnings through midlife cognition can be seen as a productivity effect, while the direct effect of education on earnings reflects more of a signalling effect. Our findings suggest that the signalling value of higher education is more important than its productivity effect (the value of education in promoting cognitive ability in terms of determining midlife earnings). We also do not find a significant effect of completing post-compulsory schooling on earnings. Arcidiacono et al. (2010) propose a view of ability revelation to explain the wage gap between college graduates and high school graduates. College graduates are paid by their ability from the beginning of their careers, since their ability is observed nearly perfectly. However, high school graduates' ability is revealed to the labour market gradually so that their wages are initially unrelated to their ability. Our findings suggest that the earnings gap between undergraduates and non-undergraduates persists through midlife.

In examining the returns to educational decisions, our model set-up and related assumptions draw heavily on Heckman et al. (2018)'s model. We assume that the source of endogeneity in the education variables is primarily an ability bias. As long as we introduce cognitive ability and non-cognitive ability indicators in our regressions, our model will theoretically be free of endogeneity. Consistent with Heckman et al. (2018), we find that early cognitive and non-cognitive abilities positively influence educational decisions. However, aside from a positive association between early non-cognitive ability and midlife physical health, we did not observe any significant associations between early abilities and midlife outcomes.

Some may be concerned that there is a possibility of reverse causality since both midlife cognitive ability and the outcomes we use were measured at age 46. We do not think that this is a problem, as health is not a prevalent factor in the literature related to cognitive function and research has focused more on the impact of adult cognitive ability on several cognitively related diseases, such as Alzheimer's disease. Rodriguez et al. (2021) have shown that personal income impacts adult cognitive ability. Their sample is a group of people over the age of 50, whereas our sample group is relatively young. There is no evidence we are aware of that income impacts the cognitive ability of people under 50.

Chapter 5

Conclusions

This thesis focuses on investment and returns to human capital, proposing a potential path mechanism to discuss the role of cognitive ability in midlife returns to educational decisions. In this path framework, we hypothesise that early cognitive abilities have a selection effect on educational decisions and midlife outcomes, while midlife cognitive ability acts as a mediator in the returns to educational decisions. These relationships are tested via a SEM approach. The validity of estimating causal effects using SEM is largely based on prior knowledge of the relevant disciplines. We then divide the verification process into three chapters, review the relevant literature for each relationship, start with a simple single relationship, and discuss it step by step. Chapter 2 explores the selection effect of early cognitive abilities on educational decisions. Chapter 3 analyses the treatment effect of educational decisions on midlife cognitive ability. Chapter 4 investigates the mediation effect of midlife cognitive ability on midlife returns to education.

Chapter 2 finds that higher preschool cognitive ability (measured at age five) makes individuals more likely to choose to complete post-compulsory education and undergraduate education, but it has no significant impact on the choice of postgraduate education. This confirms the importance of early cognitive development before the age of five. Research from Case and Kraftman (2022) propose that inequalities in early health and cognitive development are related to health inequalities in adulthood. It is important to understand the determinants of early childhood cognitive development (Burger, 2010). We find that children with lower birth weight, multiple siblings, and young, uneducated mothers were in a disadvantaged position in early cognitive development. To mitigate these early negative life difficulties, policies should target such children and their families. For example, policies can develop programs to address the unmet nutritional needs of at-risk mothers and children (e.g. see DiGirolamo et al. (2020) and its reference). In addition, we find that after controlling for preschool cognition, individuals with higher levels of post-compulsory school cognition still have a positive selection effect on all educational decisions, and this effect is significant and longer-lasting than the effect of preschool cognition. This means that if policymakers aim to improve the educational attainment of the population, then public policy should prioritise interventions for cognitive development during adolescence. Our findings indicate that children with higher cognitive abilities in preschool, higher parental education, and higher family income have more advantages for cognitive development during adolescence than others. This also requires policies that reduce inequalities in adolescent cognitive development based on socioeconomic background. For individuals born in the 1970s in the UK, government investment in early cognitive development was limited compared to today's standards. The focus on early cognitive development and related intervention policies primarily emerged after 1998, with initiatives like Sure Start (Sure Start Children's Centres) and 30 Hours Free Childcare. These programs was aimed to reduce early cognitive development gaps among disadvantaged children from low-income families by providing high-quality early educational opportunities and childcare services before the age of five. From ages 5 to 16, the UK government's interventions for cognitive development mainly centred on educational policy reforms aimed at raising academic standards and mitigating educational inequality. This included the introduction of the GCSE and A-level systems, as well as financial support for students from low-income families. However, current government policy tends to prioritise broader interventions for early cognitive development over those targeting adolescent cognitive development.

Based on the results of Chapter 2, Chapter 3 finds that completing graduate education, respectively, has a positive marginal treatment effect on midlife cognitive ability (measured at age 46), while there is a limited effect of post-compulsory education and undergraduate education on midlife cognition. In addition to early cognition and education, we also find that partnered individuals have higher midlife cognition than unpartnered individuals. Our results demonstrate a bidirectional relationship between cognition and education, whereby early cognition influences educational decisions, and educational decisions subsequently influence midlife cognition and also re-emphasise the importance of early cognitive development. Adult cognition is closely related to many aspects of people's lives and determines their quality of life (Anstey et al., 2013b). Our findings suggest that tertiary education can help people achieve higher cognitive abilities in midlife, which may also be one of the ways to alleviate cognitive impairment in later life. It also suggests that policies should take action (such as academic loans or tuition fee concessions) to encourage people to complete higher education.

Chapter 4 finds that midlife cognitive ability positively impacts midlife health. Completing education through midlife cognitive ability has a positive mediation effect on physical and mental health, but the direct effect is negligible. Our midlife health outcomes consider general health and do not place additional weight on certain conditions or diseases. In the existing literature arguing that education has a causal effect on health, health indicators are mostly obesity (Kemptner et al., 2011), self-reported health (Jürges et al., 2013), longevity (Eide and Showalter, 2011), depression (Chevalier and Feinstein, 2006) and specific biomarkers (Courtin et al., 2019), and the focus group is mostly people over 50 years old (e.g Brunello et al., 2016). However, we do not observe a significant causal effect of education on midlife health in terms of overall effects. This may be because the effects of education on health are only significant later in life, or because the effects of education are more prominent on specific diseases. This is a potentially rich area for future research. In addition, completing undergraduate education and postgraduate education has a significant effect on midlife earnings, with the direct effect of education dominating and the mediation effect being negligible. Our results suggest that, for adult outcomes that are closely related to midlife cognition, midlife cognitive ability is very likely to be an important mediator for studying the relationship between education and these adult outcomes. In contrast, midlife cognition is less important for educational returns that are not strongly related to midlife cognition. For example, for midlife earnings, the role of cognition is more reflected in the selection effect of early cognition rather than the mediator role of midlife cognition.

In terms of UK policy, individuals born in the 1970s have benefited from the Adult Education Funding and Lifelong Learning Strategy initiatives implemented in the 2000s, which aimed to enhance vocational skills and cognitive abilities. As the UK gradually transitions into an aging society, there will be a significant increase in the demand for healthcare services related to chronic diseases (such as diabetes, heart disease, and Alzheimer's disease) and mental health issues (like depression and anxiety) among the elderly population. At the same time, however, the NHS is struggling with healthcare resource scarcity and workforce shortages. Our findings indicate that active intervention in cognitive development during midlife can effectively improve health outcomes, thereby alleviating the social burden associated with healthcare. While current policies, such as the National Mental Health Plan in the UK, aim to raise public awareness of mental health issues and enhance psychological well-being through education and training, there remains an insufficient emphasis on cognitive development for older adults. We recommend that policies promoting lifelong learning also introduce more educational and training programs was tailored specifically for older adults. Furthermore, pension reform policies should include provision for adequate workplace and social support to help workers manage the mental health pressure of postpone retirement to late years.

In summary, our study confirms that cognitive abilities at different points in time play different roles in midlife returns to education that are closely related to cognitive abilities. For example, we find that early cognitive ability has a positive selection effect on educational decisions and midlife earnings, while midlife cognitive ability mediates the impact of educational decisions on midlife health. Our results find that completing undergraduate education and postgraduate education significantly contributes to midlife cognitive ability and midlife earnings. Our findings suggest that policies should give more attention to cognitive development in adolescence and adulthood and encourage higher education, which would help boost economic growth, reduce healthcare expenditures, and mitigate income and health inequalities. In Chapters 3 and 4, we are more interested in the average impact of education and assume that the returns to education are homogeneous. Future research could try to relax this assumption depending on the purpose of the study. At the same time, when studying returns to education, many studies tend to assume that education is endogenous because individuals' preferences for discount rates affect education choices and returns to education. We use non-cognitive ability to proxy these preferences and assume that education is exogenous after controlling for cognitive and non-cognitive abilities. Since people in our sample were born in the same period, many commonly used instrumental variables (e.g. month of birth and changes in compulsory schooling laws) do not apply to our case. Future studies may relax this assumption if valid instrumental variables (e.g. genes) can be found.

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Appendix A

Appendix to Chapter 1

A.1 Modelling the production function for cognitive ability

The idea of function framework was derived by Ben-Porath (1967) and extended by Leibowitz (1974) to applied for analysing family investment in children. Todd and Wolpin (2007) then gave a systematic review of conventional approaches to modelling and estimation of cognitive achievement production function. This section briefly introduces the value-added specification on modelling the production function of cognitive ability, which is largely based on the descriptions in Todd and Wolpin (2007), except for some notation differences. We use the same notation as in the main text.

We assume that the acquisition of knowledge is an cumulative process. People are born with an innate cognitive capacity which may be determined by a combination of genetic endowment and maternal conditions of conception. This initial ability, coupled with all past and present inputs, collectively drives a cognitive outcome.

Let C_t refers to the level of cognitive ability for a child at age t, and υ_0 denotes the initial capacity. A vector of all inputs given at ant time up to age t is denoted by $\mathrm{Z}_t(t)$. According to the above assumption, the level of cognitive ability at age t is a function of all prior inputs and initial endowment:

$$\mathrm{C}_t = f_t(\mathrm{Z}_t(t), \upsilon_0).$$

For ease of empirical interpretation, this production function is assumed to have a linear formation [1]. We assume that input effects do not depend on child's age, however, it could rely on the age at which they were applied relative to the current age. We further subdivide the inputs at age t into observed inputs X_t and unobserved inputs μ_t. In empirical, cognitive ability is a latent trait that cannot be observed. It is normally proxied by relevant test score $\widehat{C_t}$ that measures cognition with error ξ_t. Therefore, we have:

$$\begin{aligned}\widehat{C_t} &= (\lambda_1 X_t + \lambda_2 X_{t-1} + ... + \lambda_t X_1) \\ &\quad + (\iota_1 \mu_t + \iota_2 \mu_{t-1} + ... + \iota_t \mu_1) + \kappa_t \upsilon_0 + \xi_t.\end{aligned} \tag{A.1}$$

The specification of the Equation (A.1) indicates the 'true' structure which is hard to achieve empirically. There are a few challenges for the empirical implementation. First, the heritable endowment υ_0 is unable to observed. Next, the investment data sets are always partly missing [2]. Furthermore, Some chosen inputs may be endogenously with respect to unobserved factors [3]. It is because of these data limitations that researchers often need to make additional assumptions to their studies in order to make formulas (A.1) estimable.

The value added specification is one of the traditional approaches, which suits for the case that data on lagged inputs are missing or incomplete [4]. It identifies that the current cognitive measure is related to a lagged (previous) cognitive measure and inputs in current period.

$$\widehat{C_t} = \lambda X_t + \gamma \widehat{C}_{t-1} + \varepsilon_t. \tag{A.2}$$

Let us do some maths to convert Equation (A.1) into a similar value-added form. Based on the Equation (A.1), we can easily derive the equation for the lagged cognition.

$$\begin{aligned}\widehat{C}_{t-1} &= (\lambda_1 X_{t-1} + \lambda_2 X_{t-2} + ... + \lambda_{t-1} X_1) \\ &\quad + (\iota_1 \mu_{t-1} + \iota_2 \mu_{t-2} + ... + \iota_{t-1} \mu_1) + \kappa_{t-1} \upsilon_0 + \xi_{t-1}\end{aligned}$$

[1] Cunha and Heckman (2008) extend this linear value-added specification by allowing latent non-cognitive skills to affect latent cognitive skills, which suits for data with historical input and repeated cognitive measures. Cunha et al. (2010) further develop the model to allow for the nonlinear format.

[2] For example, some inputs may be missing, or some inputs may have incomplete historical data.

[3] For instance, when estimating the effect of parental investments on cognitive ability, parental investment could be endogenous as parents may perceive their children's (partial) ability and choose investment depends on this perception (Dickerson and Popli, 2016)

[4] For other specifications, see Todd and Wolpin (2007)

Then by subtracting $\gamma\widehat{C}_{t-1}$ from both sides of Equation (A.1), we have:

$$\begin{aligned}\widehat{C}_t - \gamma\widehat{C}_{t-1} = {} & (\lambda_1 X_t + \lambda_2 X_{t-1} + ... + \lambda_t X_1) + (\iota_1\mu_t + \iota_2\mu_{t-1} + ... + \iota_t\mu_1) + \kappa_t \upsilon_0 + \xi_t \\ & - \gamma[(\lambda_1 X_{t-1} + \lambda_2 X_{t-2} + ... + \lambda_{t-1} X_1) + (\iota_1\mu_{t-1} + \iota_2\mu_{t-2} + ... + \iota_{t-1}\mu_1) \\ & + \kappa_{t-1}\upsilon_0 + \xi_{t-1}] \\ = {} & \lambda_1 X_t + (\lambda_2 - \gamma\lambda_1)X_{t-1} + ... + (\lambda_t - \gamma\lambda_{t-1})X_1 + \iota_1\mu_t \\ & + (\iota_2 - \gamma\iota_1)\mu_{t-1} + ... + (\iota_t - \gamma\iota_{t-1})\mu_1 + (\kappa_t - \gamma\kappa_{t-1})\upsilon_1 + (\xi_t - \gamma\xi_{t-1}).\end{aligned}$$

Next, by moving $\gamma\widehat{C}_{t-1}$ from the left to the right, we obtain:

$$\begin{aligned}\widehat{C}_t = {} & \lambda_1 X_t + \gamma\widehat{C}_{t-1} + [(\lambda_2 - \gamma\lambda_1)X_{t-1} + ... + (\lambda_t - \gamma\lambda_{t-1})X_1] + (\kappa_t - \gamma\kappa_{t-1})\upsilon_1 \\ & + [\iota_1\mu_t + (\iota_2 - \gamma\iota_1)\mu_{t-1} + ... + (\iota_t - \gamma\iota_{t-1})\mu_1] + (\xi_t - \gamma\xi_{t-1}).\end{aligned} \tag{A.3}$$

In order for Equation (A.3) to become Equation (A.2), following constraints are required [5]:

1. For all $t \in T$, $\lambda_t = \gamma\lambda_{t-1}$. It assumes that the coefficients associated with the observed inputs change proportionally with age (or other measured distance) and at the same rate for each input.

2. For all $t \in T$, $\kappa_t = \gamma\kappa_{t-1}$. It assumes that the influence of initial endowment changes at the same rate as input effects.

3. For all $t \in T$, $\iota_t = \gamma\iota_{t-1}$. It assumes that the coefficients associated with the omitted inputs also change proportionally with age (or other measured distance) and at the same rate for each input.

4. All omitted inputs are uncorrelated with observed inputs and with the lagged cognitive ability (test score).

5. The shock $(\xi_t - \gamma\xi_{t-1})$ has an independent and identical distribution. It assumes that the residual ξ_t is serially correlated with the same rate as input effects.

[5] More details and discussions can be found in Boardman and Murnane (1979).

A.2 Appendix figures

Fig. A.1 Mean of abilities by response to each educational decision, for the negative response ($D_j = 0$, the left) and the positive response ($D_j = 1$, the right)

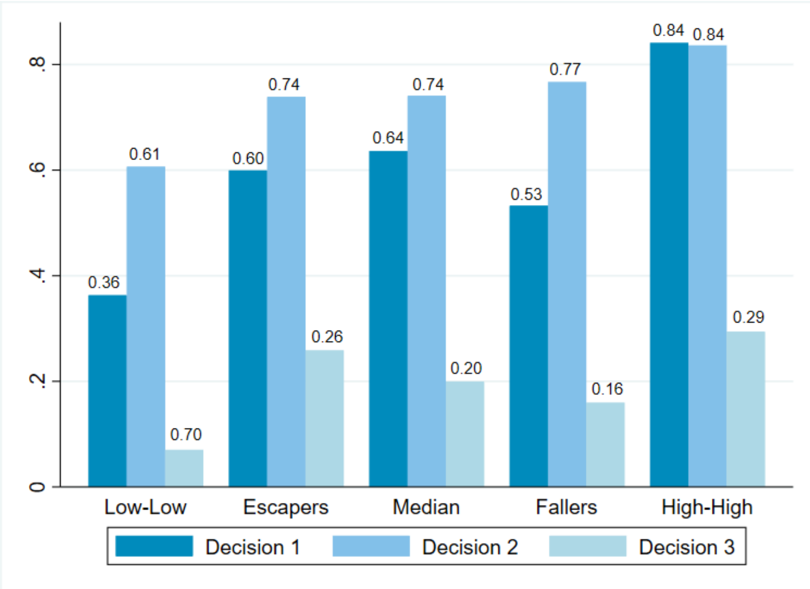

Fig. A.2 Correlations between early cognitive ability and sequential educational decisions

A.3 Appendix Tables

Table A.1 Compare distributions of control variables in sample and in original dataset

Variable	Sample	Original wave
Initial birth conditions		
Mother's age at birth	2363	13135
mean	26.04	25.97
Birth weight	2363	13135
mean	3.34	3.27
Gender	2363	13135
female	1384 (59%)	6327 (48%)
male	979 (41%)	6808 (52%)
Early family circumstances		
Number of siblings at age 5	2363	13135
none	258 (11%)	1352 (10%)
one sibling	1275 (54%)	6378 (49%)
two or more siblings	830 (35%)	5405 (41%)
Parental education at age 5	2363	12873
no qualification	1080 (46%)	7090 (55%)
lower than A level	898 (38%)	4248 (33%)
A level and above	385 (16%)	1535 (12%)
Family income at age 16	2363	7185
low-income group	692 (29%)	2639 (37%)
medium-income group	1289 (55%)	3523 (49%)
high-income group	382 (16%)	1023 (14%)

Source: the BCS70 wave 1, 2, and 4. T tests showed that the mean of controls in sample group was significantly different from the mean of controls in population group (except for mother's age at birth).

Table A.2 The correlation between non-cognitive measures at the age ten

	loc10	Pes10	Cop10	Com10	Att10	Pet10
Locus of control scale	1					
Perseverance scale	0.251	1				
Cooperativeness scale	0.136	0.393	1			
Completeness scale	0.136	0.581	0.293	1		
Attentiveness scale	0.221	0.624	0.351	0.593	1	
Persistence scale	0.212	0.713	0.326	0.564	0.617	1

Source: the BCS70 wave 3.

Table A.3 IPW: Results of cognitive development models

	Cognitive ability at age 5		Cognitive ability at age 16	
	Coef.	Std. Err.	Coef.	Std. Err.
Preschool cognitive ability (age 5)			0.747***	(0.071)
Mother's age at delivery	0.024***	(0.004)		
Birth weight	0.206***	(0.033)		
Gender (baseline = female)	-0.054	(0.037)	-0.172***	(0.047)
Number of siblings at age 5 (baseline = no sibling)				
one sibling	-0.008	(0.053)	-0.094	(0.075)
two or more siblings	-0.327***	(0.057)	-0.176**	(0.080)
Parental education at age 5 (baseline = no qualification)				
lower than A level	0.281***	(0.038)	0.144***	(0.055)
A level and above	0.466***	(0.052)	0.302***	(0.076)
Family income at age 16 (baseline = low-income)				
middle-income			0.233***	(0.0509)
high-income			0.425***	(0.075)

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$.

Table A.4 IPW: Results of sequential educational decision models

	post-compulsory schooling		undergraduate education		postgraduate education	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Preschool cognitive ability (age 5)	0.120	(0.083)	0.170	(0.110)	-0.062	(0.129)
Post-compulsory school cognitive ability (age 16)	0.322***	(0.049)	0.167***	(0.063)	0.201**	(0.081)
Non-cognitive ability (age 10)	0.518***	(0.137)	0.494***	(0.180)	0.894***	(0.234)
Gender (baseline = female)	0.131**	(0.060)	-0.070	(0.077)	0.020	(0.091)
Number of siblings (baseline = no sibling)						
one sibling	-0.058	(0.098)	0.069	(0.123)	-0.062	(0.151)
two or more siblings	-0.227**	(0.103)	0.022	(0.131)	-0.131	(0.165)
Parental education (baseline = no qualification)						
lower than A level	0.264***	(0.066)	0.175**	(0.087)	0.124	(0.112)
A level and above	0.464***	(0.099)	0.349***	(0.122)	0.442***	(0.134)
Family income (baseline = low-income)						
middle-income	0.050	(0.070)	-0.038	(0.095)	-0.116	(0.121)
high-income	0.159	(0.103)	0.084	(0.133)	0.012	(0.146)

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. Number of observations: 2363.

Appendix B

Appendix to Chapter 2

B.1 Additional adult cognitive measures

Cognitive ability tests at age 34: There were two cognitive tests. The first was a literacy assessment, consisting of both multiple-choice and open-response questions. In the multiple-choice section, participants were initially required to complete 10 screening questions at an introductory level. Those who answered fewer than six questions correctly proceeded to answer an additional 10 questions at the same level. Participants who correctly answered six to ten screening questions advanced to a higher level, where they completed 10 more challenging questions. Each correct answer was awarded one point. In calculating the total score, participants who did not pass the initial screening could achieve a score between 0 and 15, while those who passed were assumed to have answered all additional entry-level questions correctly, resulting in a possible score range of 16 to 30. The open-response section included 7 questions, with one point awarded for each correct answer.The second cognitive assessment focused on numeracy and consisted of 17 multiple-choice questions and 6 open-response questions. Each correct response was awarded one point. Given that there were only two tests, we obtained the cognitive indicator directly by averaging the test scores after normalising them.

Cognitive ability tests at age 42: At age 42, cohort members completed only a vocabulary test, designed to assess their understanding of word meanings. This task was a shortened version of the vocabulary test administered at age 16. Participants were presented with 20 sets of words (compared to 75 sets in the age 16 vocabulary test) and were required to select the word from each set of five that most closely matched the meaning of the target word within four minutes. One point was awarded for each correct selection. Since there was only one test, we directly used the scores that were standardised as an indicator of 42-year-old cognition.

B.2 Appendix tables

Table B.1 Descriptive statistics of cognitive test scores in baseline sample

	N	Mean	s.d.	Min	Max
Cognitive ability tests at age 5					
Copying designs test	2830	5.15	1.92	0	8
Complete a profile test	2751	7.07	3.93	0	16
English picture vocabulary test	2129	34.97	8.58	5	51
Human figure drawing test	2805	10.80	3.03	1	23
Shortened Edinburgh reading test	1409	3.93	6.13	0	50
Cognitive ability tests at age 16					
Shortened Edinburgh reading test	1427	56.54	12.04	12	75
BAS matrices test	1459	9.05	1.55	1	11
Arithmetic test	1685	38.49	11.23	0	60
Spelling test	2684	164.97	26.16	0	198
Vocabulary test	2674	43.99	12.19	0	72
Cognitive ability tests at age 46					
Immediate word-list recall test	2830	6.79	1.39	0	10
Delayed word-list recall test	2827	5.74	1.76	0	10
Animal naming task	2828	24.26	5.95	1	52
Letter cancellation task - speed	2764	352.30	82.01	128	780
Letter cancellation task - accuracy	2764	45.99	3.66	14	50

Source: BCS70 wave 2, 4 and 10.

Table B.2 Descriptive statistics of cognitive test scores in full sample

	N	Mean	s.d.	Min	Max
Cognitive ability tests at age 5					
Copying designs test	1537	5.17	1.92	0	8
Complete a profile test	1501	7.18	3.93	1	16
English picture vocabulary test	1140	35.33	8.15	6	51
Human figure drawing test	1527	10.84	3.02	1	21
Shortened Edinburgh reading test	794	4.10	6.25	0	48
Cognitive ability tests at age 16					
Shortened Edinburgh reading test	738	57.93	11.63	15	75
BAS matrices test	753	9.14	1.55	1	11
Arithmetic test	896	39.41	10.90	0	60
Spelling test	1456	166.45	25.26	0	197
Vocabulary test	1451	44.64	11.97	0	72
Cognitive ability tests at age 46					
Immediate word-list recall test	1537	6.79	1.38	1	10
Delayed word-list recall test	1535	5.75	1.75	0	10
Animal naming task	1536	24.34	5.97	2	52
Letter cancellation task - speed	1505	354.72	81.37	132	779
Letter cancellation task - accuracy	1505	46.01	3.68	14	50

Source: BCS70 wave 2, 4 and 10.

Table B.3 Descriptive statistics of non-cognitive test scores in full sample

	N	Mean	s.d.	Min	Max
Locus of control scale	1537	7.83	2.84	0	15
Perseverance scale	1501	31.64	10.47	1	47
Cooperativeness scale	1515	33.10	8.58	1	47
Completeness scale	1514	35.92	12.44	1	47
Attentiveness scale	1513	34.86	12.04	1	47
Persistence scale	1521	31.36	12.89	1	47

Source: BCS70 wave 3.

Table B.4 Compare distributions of selected variables in sample and in original dataset

Variable	Baseline Sample	Full Sample	Original wave
D1: Whether to complete post-compulsory schooling	2830	1537	13141
No	993 (35%)	501(33%)	6452(49%)
Yes	1837(65%)	1036(67%)	6689 (51%)
D2: Whether to finish undergraduate education	2830	1537	13141
No	1392(49%)	732(48%)	8291(63%)
Yes	1438 (51%)	805 (52%)	4850 (37%)
D3: Whether to complete postgraduate education	2830	1537	13141
No	2519 (89%)	1360 (88%)	12227 (93%)
Yes	311 (11%)	177 (12%)	914 (7%)
Initial birth conditions			
Gender	2830	1537	13135
female	1602 (57%)	898 (58%)	6327 (48%)
male	1228 (43%)	639 (42%)	6808 (52%)
Early family circumstances			
Number of siblings at age 5		1537	13135
none		173 (11%)	1352 (10%)
one sibling		850 (55%)	6378 (49%)
two or more siblings		514 (33%)	5405 (41%)
Parental education at age 5		1537	12873
no qualification		660 (43%)	7090 (55%)
lower than A level		606 (39%)	4248 (33%)
A level and above		271 (18%)	1535 (12%)

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(table continued)

Family income at age 16		1537	7185
low-income group		385 (25%)	2639 (37%)
medium-income group		878 (57%)	3523 (49%)
high-income group		274 (18%)	1023 (14%)
Marital status	2830	1537	8414
never married/ in a civil partnership	527 (19%)	278 (18%)	1739 (21%)
divorced/legally separated/widowed	431 (15%)	223 (15%)	1410 (17%)
married	1872 (66%)	1036 (67%)	5265 (63%)
Occupation	2830	1537	7373
manual	647 (23%)	317 (21%)	2010 (27%)
intermediate	615 (22%)	332 (22%)	1647 (22%)
professional	1568 (55%)	888 (58%)	3716 (50%)
Region (instrument)		1529	13071
England North		440 (29%)	3801(29%)
England Midlands		398 (26%)	2799(21%)
England South		465 (30%)	4557(35%)
Outside England		226 (15%)	1914(15%)

Source: the BCS70.

Table B.5 The correlation between cognitive test scores at age 5, 16 and 46 in baseline sample

	cd5	cp5	epvt5	hfd5	srt5	srt16	m16	vt16	at16	st16	iw46	dw46	an46	lcs46	lca46
Copying designs test (cd5)	1														
Complete a profile test (cp5)	0.195	1													
English picture vocabulary test (epvt5)	0.188	0.135	1												
Human figure drawing test (hfd5)	0.274	0.268	0.085	1											
Shortened Edinburgh reading test (srt5)	0.179	0.078	0.064	0.078	1										
Shortened Edinburgh reading test (srt16)						1									
BAS - matrices test (m 16)						0.488	1								
Vocabulary test (vt16)						0.745	0.373	1							
Arithmetic test (at16)						0.681	0.493	0.629	1						
Spelling test (st16)						0.505	0.307	0.528	0.492	1					
Immediate word-list recall test											1				
Delayed word-list recall test											0.710	1			
Animal naming task											0.264	0.242	1		
Letter cancellation task - speed											0.063	0.059	0.150	1	
Letter cancellation task - accuracy											0.097	0.131	0.060	-0.569	1

Source: BCS70 wave 2 and 4.

Table B.6 The correlation between cognitive test scores at age 5, 16 and 46 in full sample

	cd5	cp5	epvt5	hfd5	srt5	srt16	m16	vt16	at16	st16	iw46	dw46	an46	lcs46	lca46
Copying designs test (cd5)	1														
Complete a profile test (cp5)	0.169	1													
English picture vocabulary test (epvt5)	0.199	0.113	1												
Human figure drawing test (hfd5)	0.262	0.249	0.098	1											
Shortened Edinburgh reading test (srt5)	0.158	0.073	0.037	0.025	1										
Shortened Edinburgh reading test (srt16)						1									
BAS - matrices test (m16)						0.495	1								
Vocabulary test (vt16)						0.737	0.365	1							
Arithmetic test (at16)						0.662	0.472	0.620	1						
Spelling test (st16)						0.559	0.337	0.590	0.532	1					
Immediate word-list recall test											1				
Delayed word-list recall test											0.696	1			
Animal naming task											0.262	0.224	1		
Letter cancellation task - speed											0.030	0.029	0.122	1	
Letter cancellation task - accuracy											0.111	0.155	0.090	-0.566	1

Source: BCS70 wave 2 and 4.

Table B.7 Predicted cognitive abilities: Loading of cognitive measurement models in baseline sample

	Cognitive ability at age 5		Cognitive ability at age 16		Cognitive ability at age 46	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Copying designs test	1	constrained				
Complete a profile test	0.433***	(0.039)				
English picture vocabulary test	0.629***	(0.047)				
Human figure drawing test	0.756***	(0.044)				
Shortened Edinburgh reading test	0.482***	(0.058)				
Shortened Edinburgh reading test			1	constrained		
BAS - matrices test			0.614***	(0.028)		
Arithmetic test			0.844***	(0.025)		
Spelling test			0.583***	(0.022)		
Vocabulary test			0.846***	(0.021)		
Immediate word-list recall test					1	constrained
Delayed word-list recall test					0.991***	(0.030)
Animal naming task					0.384***	(0.024)
Letter cancellation task - speed					0.092***	(0.025)
Letter cancellation task - accuracy					0.153***	(0.025)

Note: ***$p \leq 0.01$.

Table B.8 Predicted cognitive abilities: Loading of cognitive measurement models in full sample

	Cognitive ability at age 5		Cognitive ability at age 16		Cognitive ability at age 46	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Copying designs test	1	constrained				
Complete a profile test	0.507***	(0.070)				
English picture vocabulary test	0.533***	(0.067)				
Human figure drawing test	0.844***	(0.095)				
Shortened Edinburgh reading test	0.369***	(0.081)				
Shortened Edinburgh reading test			1	constrained		
BAS - matrices test			0.625***	(0.040)		
Arithmetic test			0.842***	(0.037)		
Spelling test			0.639***	(0.031)		
Vocabulary test			0.839***	(0.032)		
Immediate word-list recall test					1	constrained
Delayed word-list recall test					0.956***	(0.071)
Animal naming task					0.341***	(0.034)
Letter cancellation task - speed					0.029	(0.033)
Letter cancellation task - accuracy					0.181***	(0.036)

Note: $^{***}p \leq 0.01$.

Table B.9 Descriptive statistics of predicted cognition from original sample

	N	Mean	s.d.	Min	Max
C5	13049	-0.001	0.56	-1.92	2.06
C16	6044	0.08	0.92	-3.66	2.16
C34	9522	-0.02	0.96	-6.72	1.15
C42	9433	0	1	-3.40	2.00
C46	8509	-0.0003	0.78	-3.22	2.44

Table B.10 Definition of groups indicating change or persistence in adulthood

<table>
<tr><td></td><td colspan="4">Quartile at age 46</td></tr>
<tr><td>Quartile at age 16</td><td>1 (Low)</td><td>2</td><td>3</td><td>4 (High)</td></tr>
<tr><td>1 (Low)</td><td>Group 1 (Low-Low)</td><td colspan="3">Group 2 (Escapers)</td></tr>
<tr><td>2</td><td colspan="4">Group 3 (Median)</td></tr>
<tr><td>3</td><td colspan="4">Group 3 (Median)</td></tr>
<tr><td>4 (High)</td><td colspan="2">Group 4 (Fallers)</td><td colspan="2">Group 5 (High-High)</td></tr>
</table>

Note: This table references the design of Feinstein and Bynner (2004).

Table B.11 The number of observations in each defined group (16 and 46)

	Married Status	Job	Complete post-compulsory	Complete undergraduate	Complete postgraduate	N	%
Group 1 (Low-Low)	2.30	1.84	0.38	0.25	0.01	287	10.14%
Group 2 (Escapers)	2.48	2.01	0.46	0.31	0.03	421	14.88%
Group 3 (Median) 2	2.51	2.36	0.67	0.50	0.10	1415	50.00%
Group 4 (Fallers)	2.36	2.53	0.76	0.62	0.16	242	8.55%
Group 5 (High-High)	2.55	2.70	0.88	0.80	0.25	465	16.43%

Note: Use of baseline sample.

Table B.12 Robustness checks: results of the 'baseline' model

	(1)	(2)	(3)	(4)	(5)
Whether finish post-compulsory schooling	0.057	0.052	0.052	0.104*	0.062
	(0.051)	(0.042)	(0.043)	(0.059)	(0.052)
Whether to complete undergraduate education	0.110**	0.093**	0.093**	0.126*	0.116**
	(0.051)	(0.044)	(0.044)	(0.066)	(0.052)
Whether to obtain postgraduate education	0.155***	0.129***	0.129***	0.130*	0.164***
	(0.055)	(0.048)	(0.049)	(0.075)	(0.056)
Preschool cognitive ability (age 5)	0.270***	0.233***	0.233***	0.277***	0.269***
	(0.043)	(0.028)	(0.029)	(0.044)	(0.043)
Post-compulsory school cognitive ability (age 16)	0.166***	0.164***	0.164***	0.163***	0.164***
	(0.026)	(0.017)	(0.017)	(0.033)	(0.026)
Gender (baseline = female)	-0.041	-0.031	-0.031	0.013	-0.042
	(0.033)	(0.027)	(0.028)	(0.057)	(0.034)
Marital status (baseline = never married)					
Divorced/legally separated/widowed	0.201***	0.171***	0.171***	0.221***	0.198***
	(0.056)	(0.048)	(0.047)	(0.060)	(0.057)
Married	0.206***	0.177***	0.177***	0.216***	0.204***
	(0.043)	(0.038)	(0.037)	(0.056)	(0.044)
Occupation (baseline = manual)					
Intermediate	0.101**	0.088**	0.088**	0.147**	0.104**
	(0.049)	(0.040)	(0.041)	(0.069)	(0.050)
Professional	0.142***	0.124***	0.124***	0.174***	0.138***
	(0.044)	(0.038)	(0.038)	(0.067)	(0.045)

(To be continued on the next page)

(table continued)

Approach	GSEM(one-step)	GSEM(two-step)	OLS	GSEM(IPW)	GSEM(one-step)
N	2830	2830	2830	2745	2745
AIC	94779.47	6187.896	6185.896	571445.1	91889.58
BIC	95112.56	6259.272	6251.324	571776.5	92220.96

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. For those model estimated by two-step approach, standard errors are further estimated by bootstrap (with 2000 repetitions).)

Table B.13 Robustness checks: OLS results of the ’full’ model

	D1	D2	D3	C46
Whether finish post-compulsory schooling (D1)				0.091
				(0.057)
Whether to complete undergraduate education (D2)				0.084
				(0.060)
Whether to obtain postgraduate education (D3)				0.132**
				(0.066)
Preschool cognitive ability (age 5)	0.071***	0.092***	0.016	0.165***
	(0.023)	(0.026)	(0.018)	(0.040)
Post-compulsory school cognitive ability (age 16)	0.096***	0.108***	0.041***	0.173***
	(0.015)	(0.016)	(0.008)	(0.025)
Noncognitive ability (age 10)	0.210***	0.217***	0.107***	
	(0.055)	(0.054)	(0.033)	
Gender (baseline = female)	0.029	0.004	-0.014	-0.007
	(0.023)	(0.024)	(0.016)	(0.038)
Number of siblings at age 5 (baseline = no sibling)				
one sibling	-0.031	0.007	0.027	
	(0.037)	(0.042)	(0.027)	
two or more siblings	-0.099**	-0.050	0.007	
	(0.039)	(0.044)	(0.027)	
Parental education at age 5 (baseline = no qualification)				
lower than A level	0.103***	0.088***	0.020	
	(0.027)	(0.028)	(0.017)	

(To be continued on the next page)

(table continued)

A level and above	0.158***	0.174***	0.102***	
	(0.033)	(0.038)	(0.028)	
Family income at age 16 (baseline = low-income)				
middle-income	-0.0003	-0.005	-0.019	
	(0.031)	(0.030)	(0.018)	
high-income	0.045	0.077*	0.018	
	(0.037)	(0.039)	(0.028)	
Marital status (baseline = never married)				
Divorced/legally separated/widowed				0.189***
				(0.067)
Married				0.232***
				(0.049)
Occupation (baseline = manual)				
Intermediate				0.090
				(0.056)
Professional				0.053
				(0.052)

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. C46 refers to midlife cognition. Standard errors are further estimated by bootstrap (with 2000 repetitions).)

Table B.14 Robustness: IPW weighted and unweighted results of the ’full’ model

	(1) Unweighted				(2) Weighted			
	D1	D2	D3	C46	D1	D2	D3	C46
Whether finish post-compulsory schooling				0.082				0.110*
				(0.058)				(0.060)
Whether to complete undergraduate education				0.102*				0.126*
				(0.060)				(0.075)
Whether to obtain postgraduate education				0.146**				0.133
				(0.068)				(0.086)
Preschool cognitive ability (age 5)	0.231***	0.267***	0.064	0.163***	0.087	0.104	0.0008	0.154***
	(0.078)	(0.076)	(0.100)	(0.039)	(0.112)	(0.119)	(0.092)	(0.039)
Post-compulsory school cognitive ability	0.277***	0.315***	0.308***	0.171***	0.248***	0.252***	0.338***	0.191***
	(0.046)	(0.049)	(0.073)	(0.025)	(0.062)	(0.074)	(0.080)	(0.029)
Noncognitive ability (age 10)	0.603***	0.625***	0.706***		0.749***	0.815***	0.672***	
	(0.163)	(0.160)	(0.238)		(0.257)	(0.276)	(0.250)	
Gender (baseline = female)	0.089	0.019	-0.082	-0.007	0.120	0.088	-0.165	0.034
	(0.073)	(0.072)	(0.095)	(0.038)	(0.107)	(0.107)	(0.106)	(0.061)
Number of siblings at age 5								
(baseline = no sibling)								
one sibling	-0.048	0.047	0.081		-0.064	0.044	0.067	
	(0.122)	(0.113)	(0.155)		(0.126)	(0.121)	(0.160)	
two or more siblings	-0.265**	-0.110	-0.037		-0.276**	-0.061	-0.014	
	(0.125)	(0.120)	(0.166)		(0.140)	(0.136)	(0.173)	

(To be continued on the next page)

(table continued)

Parental education at age 5								
(baseline = no qualification)								
lower than A level	0.292***	0.242***	0.134		0.303***	0.210**	0.143	
	(0.079)	(0.077)	(0.112)		(0.084)	(0.082)	(0.116)	
A level and above	0.536***	0.514***	0.471***		0.508***	0.517***	0.471***	
	(0.117)	(0.110)	(0.130)		(0.127)	(0.116)	(0.145)	
Family income at age 16								
(baseline = low-income)								
middle-income	-0.0003	-0.013	-0.065		-0.093	-0.141	-0.086	
	(0.088)	(0.087)	(0.122)		(0.119)	(0.125)	(0.133)	
high-income	0.144	0.219*	0.103		0.129	0.169	0.024	
	(0.123)	(0.118)	(0.145)		(0.145)	(0.141)	(0.163)	
Marital status (baseline = never married)								
Divorced/legally separated/widowed				0.186***				0.218***
				(0.070)				(0.073)
Married				0.236***				0.272***
				(0.052)				(0.061)
Occupation (baseline = manual)								
Intermediate				0.091				0.062
				(0.057)				(0.061)
Professional				0.046				0.045
				(0.053)				(0.058)
N		1496				1496		
AIC		7815.804				90232.45		

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(table continued)

BIC	8054.779	90471.43

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. All models were estimated by two-step GSEM approach.

Table B.15 Robustness checks: results of the 'full' model using region as one of exclusive restrictions

	D1	D2	D3	C46
Whether finish post-compulsory schooling				0.091
				(0.056)
Whether to complete undergraduate education				0.084
				(0.060)
Whether to obtain postgraduate education				0.132**
				(0.067)
Preschool cognitive ability (age 5)	0.240***	0.284***	0.100	0.165***
	(0.077)	(0.075)	(0.101)	(0.039)
Post-compulsory school cognitive ability (age 16)	0.281***	0.313***	0.326***	0.173***
	(0.046)	(0.050)	(0.075)	(0.025)
Noncognitive ability (age 10)	0.592***	0.603***	0.702***	
	(0.163)	(0.162)	(0.242)	
Gender (baseline = female)	0.082	0.005	-0.073	-0.007
	(0.074)	(0.071)	(0.094)	(0.039)
Number of siblings at age 5 (baseline = no sibling)				
one sibling	-0.093	0.008	0.098	
	(0.122)	(0.116)	(0.159)	
two or more siblings	-0.292**	-0.144	-0.035	
	(0.126)	(0.120)	(0.167)	
Parental education at age 5 (baseline = no qualification)				
lower than A level	0.302***	0.237***	0.127	
	(0.081)	(0.077)	(0.111)	

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(table continued)

A level and above	0.508***	0.477***	0.425***	
	(0.116)	(0.103)	(0.132)	
Family income at age 16 (baseline = low-income)				
middle-income	0.003	-0.003	-0.111	
	(0.090)	(0.087)	(0.122)	
high-income	0.183	0.251**	0.037	
	(0.124)	(0.117)	(0.150)	
Marital status (baseline = never married)				
Divorced/legally separated/widowed				0.189***
				(0.067)
Married				0.232***
				(0.050)
Occupation (baseline = manual)				
Intermediate				0.090
				(0.058)
Professional				0.053
				(0.052)
Region (baseline = England north)				
England midlands	-0.021	-0.077	-0.276**	
	(0.096)	(0.092)	(0.132)	
England south	-0.069	-0.083	0.115	
	(0.097)	(0.093)	(0.117)	
Outside England	0.269	0.200*	0.121	

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(table continued)

	(0.119)	(0.112)	(0.145)

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. AIC:8001.349; BIC:8289.579. Due to missing values in the region variable, the number of observations for the cognition equation (N:1537) includes eight more individuals than the education equation (N:1529). Given the small number of missing values, we do not expect missing values to introduce any significant bias into the estimates.

Table B.16 Extended analysis: the impact of education (completed before age 34) on different periods of adult cognition (complete results)

(1)	Age 34	Age 42	Age 46
Whether finish post-compulsory schooling	0.388***	0.402***	0.200***
	(0.043)	(0.085)	(0.052)
Whether to complete undergraduate education	0.096**	0.189**	0.151***
	(0.043)	(0.086)	(0.052)
Whether to obtain postgraduate education	0.219***	0.452***	0.283***
	(0.051)	(0.102)	(0.062)
Gender (baseline = female)	0.162***	0.101*	-0.091***
	(0.028)	(0.057)	(0.034)
Marital status (baseline = never married)			
Divorced/legally separated/widowed	0.139***	-0.071	0.213***
	(0.052)	(0.089)	(0.059)
Married	0.091***	0.040	0.221***
	(0.030)	(0.066)	(0.045)
Occupation (baseline = manual)			
Intermediate	0.340***	0.090	0.189***
	(0.041)	(0.076)	(0.051)
Professional	0.516***	0.373***	0.274***
	(0.037)	(0.067)	(0.046)
Educational equations			
One-step	√	√	√
N	3104	1088	2703
(2)	Age 34	Age 42	Age 46
Whether finish post-compulsory schooling	0.257***	0.218***	0.110**
	(0.040)	(0.069)	(0.051)
Whether to complete undergraduate education	0.017	-0.034	0.080
	(0.040)	(0.070)	(0.051)
Whether to obtain postgraduate education	0.101**	0.240***	0.199***
	(0.048)	(0.083)	(0.060)
Preschool cognitive ability (age 5)	0.297***	0.272***	0.274***
	(0.035)	(0.063)	(0.043)
Post-compulsory school cognitive ability (age 16)	0.377***	0.525***	0.171***
	(0.023)	(0.044)	(0.026)
Gender (baseline = female)	0.223***	0.160***	-0.062*

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(table continued)

	(0.026)	(0.046)	(0.034)
Marital status (baseline = never married)			
Divorced/legally separated/widowed	0.108**	-0.041	0.207***
	(0.049)	(0.072)	(0.057)
Married	0.088***	0.042	0.211***
	(0.028)	(0.054)	(0.043)
Occupation (baseline = manual)			
Intermediate	0.176***	-0.075	0.103**
	(0.039)	(0.061)	(0.050)
Professional	0.249***	0.134**	0.137***
	(0.036)	(0.055)	(0.045)
Educational equations			
One-step	√	√	√
N	3104	1088	2703
AIC	69812.09	24308.59	90569.85
BIC	70071.83	24523.25	90900.36
(3)	Age 34	Age 42	Age 46
Whether finish post-compulsory schooling	0.275***	0.154	0.096*
	(0.051)	(0.108)	(0.056)
Whether to complete undergraduate education	0.061	0.056	0.095*
	(0.041)	(0.099)	(0.057)
Whether to obtain postgraduate education	0.121**	0.293***	0.167**
	(0.038)	(0.079)	(0.071)
Preschool cognitive ability (age 5)	0.322***	0.329***	0.175***
	(0.034)	(0.068)	(0.040)
Post-compulsory school cognitive ability (age 16)	0.319***	0.451***	0.174***
	(0.034)	(0.052)	(0.026)
Gender (baseline = female)	0.191***	0.164***	-0.030
	(0.035)	(0.064)	(0.039)
Marital status (baseline = never married)			
Divorced/legally separated/widowed	0.030	0.040	0.212***
	(0.070)	(0.107)	(0.068)
Married	0.083**	0.089	0.252***
	(0.036)	(0.077)	(0.052)
Occupation (baseline = manual)			
Intermediate	0.143***	0.013	0.113*

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(table continued)

	(0.069)	(0.096)	(0.057)
Professional	0.222***	0.167**	0.071
	(0.056)	(0.075)	(0.054)
Educational equations	√	√	√
One-step			
N	1687	594	1477
AIC	8460.014	3065.999	7511.167
BIC	8704.396	3263.408	7749.567

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. As the variables included in the model vary, the corresponding sample size also changes. SES is measured in accordance with the update of adult cognition.

Table B.17 Compare distributions of educational decisions (completed before age 34) in different samples

Variable	Age 34	Age 42	Age 46	Archived obs
D1: Whether to complete post-compulsory schooling (by Age 34)	3104	1088	2703	11905
No	1139(37%)	431(40%)	977(36%)	5843 (49%)
Yes	1965 (63%)	657(60%)	1726(64%)	6062 (51%)
D2: Whether to finish undergraduate education (by Age 34)	3104	1088	2703	11905
No	1604(52%)	584(54%)	1380(51%)	7555(63%)
Yes	1500(48%)	504(46%)	1323(49%)	4350 (37%)
D3: Whether to complete postgraduate education (by Age 34)	3104	1088	2703	11905
No	2822(91%)	992(91%)	2458(91%)	11192(94%)
Yes	282 (9%)	96(9%)	245(9%)	713(6%)

Table B.18 Comparison of estimates using different educational variables

	Baseline		Full	
	(1)	(2)	(3)	(4)
Whether finish post-compulsory schooling (by age 34)	0.110**		0.096*	
	(0.051)		(0.056)	
Whether to complete undergraduate education (by age 34)	0.080		0.095*	
	(0.051)		(0.057)	
Whether to obtain postgraduate education (by age 34)	0.199***		0.167**	
	(0.060)		(0.071)	
Whether finish post-compulsory schooling (by age 46)		0.078*		0.105*
		(0.052)		(0.058)
Whether to complete undergraduate education (by age 46)		0.108**		0.079
		(0.051)		(0.061)
Whether to obtain postgraduate education (by age 46)		0.163***		0.133**
		(0.055)		(0.065)
Preschool cognitive ability (age 5)	0.274***	0.275***	0.175***	0.179***
	(0.043)	(0.043)	(0.040)	(0.039)
Post-compulsory school cognitive ability (age 16)	0.171***	0.171***	0.174***	0.178***
	(0.026)	(0.026)	(0.026)	(0.025)
Controls	√	√	√	√
N	2703	2703	1477	1477
Approach	one-step	one-step	two-step	two-step

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. Outcome variable is midlife cognition.

B.3 Appendix figures

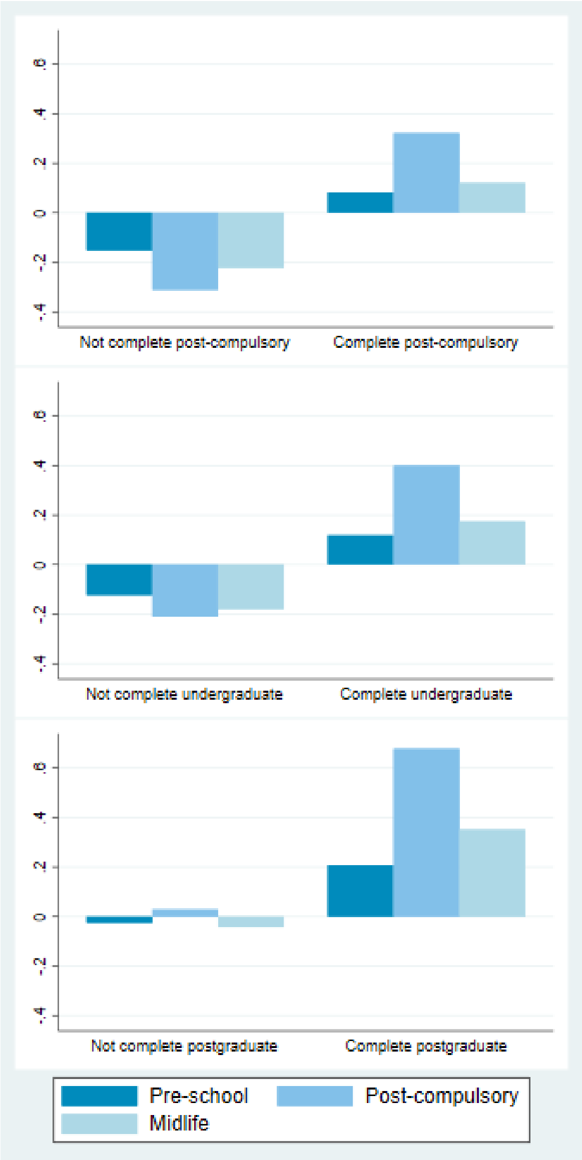

Fig. B.1 Mean of abilities by response to each general educational decision, for the negative response ($D_j = 0$, the left) and the positive response ($D_j = 1$, the right)

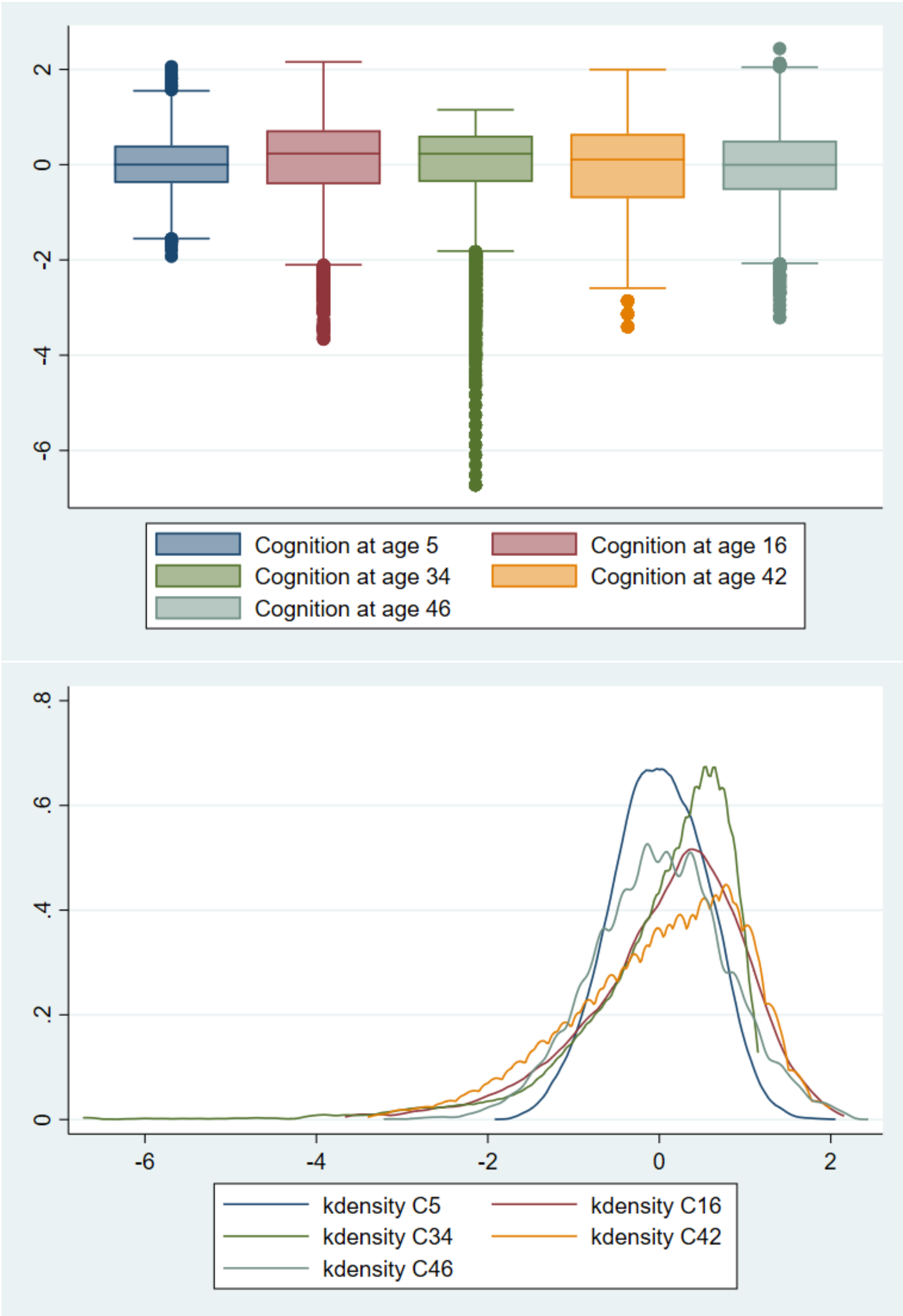

Fig. B.2 Distribution of predicted cognition from original sample

Appendix C

Appendix to Chapter 3

C.1 Appendix tables

Table C.1 Descriptive statistics of latent ability test scores by ages

	N	Mean	S.D.	Min	Max
Cognitive ability tests at age 5					
Copying designs test	2470	5.06	1.94	0	8
Complete a profile test	2395	7.16	3.98	1	16
English picture vocabulary test	1859	34.81	8.42	6	51
Human figure drawing test	2453	10.73	3.07	1	22
Shortened Edinburgh reading test	1222	3.70	5.71	0	48
Cognitive ability tests at age 46					
Immediate word-list recall test	2472	6.72	1.40	0	10
Delayed word-list recall test	2469	5.65	1.75	0	10
Animal naming task	2470	23.98	5.94	1	52
Letter cancellation task - speed	2424	349.68	82.81	120	780
Letter cancellation task - accuracy	2424	45.93	3.68	14	50
Noncognitive ability tests at age 10					
Locus of control scale	2441	7.60	2.92	0	15
Perseverance scale	2413	30.52	10.72	1	47
Cooperativeness scale	2430	32.85	8.54	1	47
Completeness scale	2429	34.60	12.81	1	47
Attentiveness scale	2423	33.58	12.22	1	47
Persistence scale	2441	29.86	13.15	1	47

Note: Since the sample sizes of the different outcomes are similar and the variable distributions show little variation, we present the descriptive statistics only for the largest sample. Source: BCS70 wave 2, 3 and 10.

Table C.2 Sample sizes of socioeconomic characteristics

Variable	Full Sample	Original wave
Educational decisions by the age of 46		
D1: Whether to complete post-compulsory schooling	2472	13141
No	959 (39%)	6452 (49%)
Yes	1513 (61%)	6689 (51%)
D2: Whether to finish undergraduate education	2472	13141
No	1337 (54%)	8291 (63%)
Yes	1135 (46%)	4850 (37%)
D3: Whether to complete postgraduate education	2472	13141
No	2236 (90%)	12227 (93%)
Yes	236 (10%)	914 (7%)
Covariates		
Gender	2472	13135
female	1270 (51%)	6327 (48%)
male	1202 (49%)	6808 (52%)
Number of siblings at age 5	2472	13135
none	251 (10%)	1352 (10%)
one sibling	1326 (54%)	6378 (49%)
two or more siblings	895 (36%)	5405 (41%)
Parental education at age 5	2472	12873
no qualification	1172 (47%)	7090 (55%)
lower than A level	923 (37%)	4248 (33%)
A level and above	377 (15%)	1535 (12%)
Family income at age 16	2472	7185
low-income group	691 (28%)	2639 (37%)
medium-income group	1361 (55%)	3523 (49%)
high-income group	420 (17%)	1023 (14%)
Marital status	2472	8414
never married/ in a civil partnership	483 (20%)	1739 (21%)
divorced/legally separated/widowed	379 (15%)	1410 (17%)
married	1610 (65%)	5265(63%)
Occupation	2472	7373
manual	637 (26%)	2010 (27%)
intermediate	497 (20%)	1647 (22%)
professional	1338 (54%)	3716 (50%)

Note: Since the sample sizes of the different outcomes are similar and the variable distributions show little variation, we present the descriptive statistics only for the largest sample. Source: BCS70.

Table C.3 Predicted latent abilities: Loading of measurement models

	Cognitive ability at age 5		Cognitive ability at age 46		Noncognitive ability at age 10	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Copying designs test	1	constrained				
Complete a profile test	0.536***	(0.053)				
English picture vocabulary test	0.593***	(0.055)				
Human figure drawing test	0.885***	(0.070)				
Shortened Edinburgh reading test	0.409***	(0.065)				
Immediate word-list recall test			1	constrained		
Delayed word-list recall test			0.952***	(0.054)		
Animal naming task			0.359***	(0.027)		
Letter cancellation task - speed			0.112***	(0.026)		
Letter cancellation task - accuracy			0.093***	(0.027)		
Locus of control scale					1	constrained
Perseverance scale					2.79***	(0.192)
Cooperativeness scale					1.499***	(0.119)
Completeness scale					2.313***	(0.164)
Attentiveness scale					2.512***	(0.175)
Persistence scale					2.698***	(0.187)

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. The sample used here is based on the physical health sample.

Table C.4 Physical health: Estimate results for different model settings

	(1)				(2)				
	D1	D2	D3	Phealth	D1	D2	D3	C46	Phealth
Midlife cognitive ability (age 46)									0.062***
									(0.017)
Whether finish post-compulsory schooling				0.023				0.105**	0.017
				(0.042)				(0.044)	(0.042)
Whether to complete undergraduate education				0.018				0.099**	0.012
				(0.043)				(0.046)	(0.043)
Whether to obtain postgraduate education				0.014				0.113*	0.007
				(0.042)				(0.059)	(0.042)
Preschool cognitive ability (age 5)	0.323***	0.300***	0.284***	0.036	0.323***	0.300***	0.284***	0.197***	0.024
	(0.058)	(0.057)	(0.083)	(0.030)	(0.060)	(0.058)	(0.080)	(0.032)	(0.031)
Non-cognitive ability (age 10)	0.873***	0.878***	0.752***	0.118**	0.873***	0.878***	0.752***	0.263***	0.101*
	(0.098)	(0.101)	(0.155)	(0.055)	(0.100)	(0.099)	(0.158)	(0.058)	(0.053)
Gender (baseline = female)	0.008	-0.053	-0.077	0.033	0.008	-0.053	-0.077	-0.049	0.036
	(0.055)	(0.053)	(0.076)	(0.028)	(0.056)	(0.054)	(0.074)	(0.031)	(0.028)
Number of siblings (baseline = no sibling)									
one sibling	-0.107	-0.008	0.145		-0.107	-0.008	0.145		
	(0.093)	(0.091)	(0.137)		(0.095)	(0.093)	(0.133)		
two or more siblings	-0.275***	-0.159*	0.072		-0.275***	-0.159	0.072		
	(0.097)	(0.095)	(0.139)		(0.101)	(0.098)	(0.137)		
Parental education (baseline = no qualification)									
lower than A level	0.296***	0.296***	0.221**	-0.002	0.296***	0.296***	0.221**	0.027	-0.004
	(0.062)	(0.060)	(0.089)	(0.033)	(0.062)	(0.062)	(0.089)	(0.034)	(0.033)
A level and above	0.474***	0.576***	0.559***	0.036	0.474***	0.576***	0.559***	0.060	0.032
	(0.091)	(0.087)	(0.105)	(0.040)	(0.091)	(0.085)	(0.104)	(0.047)	(0.040)

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(table continued)

Family income (baseline = low-income)									
middle-income	0.145**	0.118*	0.037	0.049	0.145**	0.118*	0.037	0.011	0.049
	(0.064)	(0.066)	(0.095)	(0.036)	(0.065)	(0.065)	(0.095)	(0.035)	(0.035)
high-income	0.324***	0.361***	0.193	0.133***	0.324***	0.361***	0.193*	0.136***	0.125***
	(0.092)	(0.088)	(0.118)	(0.043)	(0.091)	(0.088)	(0.117)	(0.050)	(0.043)
Marital status (baseline = never married)									
Divorced/legally separated/widowed				-0.032				0.174***	-0.043
				(0.052)				(0.051)	(0.051)
Married				0.094**				0.179***	0.083**
				(0.037)				(0.040)	(0.038)
Occupation (baseline = manual)									
Intermediate				0.114***				0.188***	0.102**
				(0.044)				(0.043)	(0.044)
Professional				0.128***				0.170***	0.117***
				(0.038)				(0.040)	(0.038)
N		2472					2472		
AIC		12554.79					18062.63		
BIC		12822.18					18428.84		

			(3)			(4)
	D1	D2	D3	C46	Phealth	Phealth
Midlife cognitive ability (age 46)					0.065***	0.062***
					(0.018)	(0.018)
Whether finish post-compulsory schooling				0.136***	0.001	0.017
				(0.050)	(0.044)	(0.043)
Whether to complete undergraduate education				0.096*	0.012	0.012
				(0.056)	(0.044)	(0.043)

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(table continued)

Whether to obtain postgraduate education				0.120	0.012	0.007
				(0.080)	(0.041)	(0.043)
Preschool cognitive ability (age 5)	0.206**	0.152	0.222***	0.200***	0.029	0.024
	(0.083)	(0.095)	(0.075)	(0.036)	(0.028)	(0.029)
Non-cognitive ability (age 10)	0.918***	0.929***	0.706***	0.227***	0.077	0.101*
	(0.138)	(0.146)	(0.158)	(0.064)	(0.054)	(0.054)
Gender (baseline = female)	-0.004	-0.033	-0.151*	-0.048	0.034	0.036
	(0.072)	(0.076)	(0.080)	(0.044)	(0.029)	(0.027)
Number of siblings (baseline = no sibling)						
one sibling	-0.088	0.008	0.138			
	(0.102)	(0.095)	(0.142)			
two or more siblings	-0.221**	-0.074	0.128			
	(0.108)	(0.107)	(0.146)			
Parental education (baseline = no qualification)						
lower than A level	0.326***	0.307***	0.250***	0.037	-0.020	-0.004
	(0.069)	(0.068)	(0.095)	(0.043)	(0.033)	(0.031)
A level and above	0.542***	0.644***	0.603***	0.169**	0.044	0.032
	(0.103)	(0.099)	(0.118)	(0.076)	(0.039)	(0.039)
Family income (baseline = low-income)						
middle-income	0.057	0.029	0.021	-0.012	0.082**	0.049
	(0.085)	(0.093)	(0.106)	(0.047)	(0.036)	(0.034)
high-income	0.272**	0.310***	0.137	0.171**	0.159***	0.125***
	(0.107)	(0.109)	(0.135)	(0.073)	(0.043)	(0.044)
Marital status (baseline = never married)						
Divorced/legally separated/widowed				0.221***	-0.014	-0.043
				(0.058)	(0.053)	(0.051)
Married				0.223***	0.116***	0.083**

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(table continued)

		(0.053)	(0.039)	(0.037)
Occupation (baseline = manual)				
Intermediate		0.215***	0.075*	0.102**
		(0.053)	(0.043)	(0.044)
Professional		0.198***	0.077**	0.117***
		(0.053)	(0.039)	(0.038)
N	2408			2472
AIC	125248.3			4996.474
BIC	125612.8			5089.478

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. All models were estimated by the two-step approach.

Table C.5 Mental health: Estimate results for different model settings

	(1)				(2)				
	D1	D2	D3	Mhealth	D1	D2	D3	C46	Mhealth
Midlife cognitive ability (age 46)									0.072***
									(0.025)
Whether finish post-compulsory schooling				0.080				0.102**	0.073
				(0.056)				(0.043)	(0.055)
Whether to complete undergraduate education				0.022				0.099**	0.014
				(0.058)				(0.046)	(0.058)
Whether to obtain postgraduate education				0.019				0.108*	0.011
				(0.067)				(0.058)	(0.066)
Preschool cognitive ability (age 5)	0.319***	0.303***	0.316***	0.035	0.319***	0.303***	0.316***	0.194***	0.021
	(0.057)	(0.059)	(0.085)	(0.039)	(0.058)	(0.059)	(0.084)	(0.032)	(0.040)
Non-cognitive ability (age 10)	0.890***	0.876***	0.731***	0.097	0.890***	0.876***	0.731***	0.264***	0.078
	(0.101)	(0.102)	(0.157)	(0.070)	(0.099)	(0.103)	(0.159)	(0.057)	(0.073)
Gender (baseline = female)	0.013	-0.051	-0.074	-0.118***	0.013	-0.051	-0.074	-0.051	-0.115***
	(0.054)	(0.054)	(0.075)	(0.038)	(0.053)	(0.053)	(0.075)	(0.031)	(0.039)
Number of siblings (baseline = no sibling)									
one sibling	-0.088	-0.0001	0.141		-0.088	-0.0002	0.141		
	(0.097)	(0.091)	(0.137)		(0.097)	(0.092)	(0.137)		
two or more siblings	-0.265***	-0.159*	0.048		-0.265***	-0.159	0.048		
	(0.101)	(0.095)	(0.142)		(0.099)	(0.098)	(0.142)		
Parental education (baseline = no qualification)									
lower than A level	0.293***	0.291***	0.227**	-0.038	0.293***	0.291***	0.227**	0.034	-0.041
	(0.063)	(0.062)	(0.090)	(0.043)	(0.061)	(0.061)	(0.089)	(0.034)	(0.042)
A level and above	0.460***	0.559***	0.573***	-0.115**	0.460***	0.559***	0.573***	0.066	-0.120**
	(0.091)	(0.089)	(0.106)	(0.059)	(0.092)	(0.087)	(0.107)	(0.048)	(0.059)

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(table continued)

Family income (baseline = low-income)									
middle-income	0.153**	0.130**	0.039	0.064	0.153**	0.130**	0.039	0.009	0.063
	(0.064)	(0.065)	(0.096)	(0.047)	(0.065)	(0.066)	(0.098)	(0.037)	(0.046)
high-income	0.337***	0.381***	0.181	0.095	0.337***	0.381***	0.181	0.131***	0.086
	(0.094)	(0.090)	(0.121)	(0.062)	(0.097)	(0.093)	(0.121)	(0.051)	(0.062)
Marital status (baseline = never married)									
Divorced/legally separated/widowed				-0.005				0.173***	-0.017
				(0.067)				(0.052)	(0.067)
Married				0.204***				0.174***	0.192***
				(0.050)				(0.039)	(0.048)
Occupation (baseline = manual)									
Intermediate				0.075				0.186***	0.062
				(0.059)				(0.044)	(0.058)
Professional				0.217***				0.171***	0.205***
				(0.052)				(0.040)	(0.053)
N		2432					2432		
AIC		13886.29					19303.03		
BIC		14152.93					19668.21		

	(3)				(4)	
	D1	D2	D3	C46	Mhealth	Mhealth
Midlife cognitive ability (age 46)					0.054*	0.072***
					(0.030)	(0.024)
Whether finish post-compulsory schooling				0.134***	0.089	0.073
				(0.052)	(0.056)	(0.056)
Whether to complete undergraduate education				0.096*	0.060	0.014
				(0.058)	(0.070)	(0.058)

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(table continued)

Whether to obtain postgraduate education				0.111	-0.061	0.011
				(0.076)	(0.077)	(0.067)
Preschool cognitive ability (age 5)	0.202**	0.156	0.253***	0.202***	-0.051	0.021
	(0.083)	(0.096)	(0.079)	(0.036)	(0.064)	(0.041)
Non-cognitive ability (age 10)	0.927***	0.919***	0.694***	0.229***	0.123	0.078
	(0.140)	(0.148)	(0.164)	(0.067)	(0.085)	(0.070)
Gender (baseline = female)	0.001	-0.029	-0.147*	-0.049	-0.062	-0.115***
	(0.074)	(0.077)	(0.082)	(0.044)	(0.047)	(0.038)
Number of siblings (baseline = no sibling)						
one sibling	-0.068	0.017	0.134			
	(0.101)	(0.097)	(0.140)			
two or more siblings	-209**	-0.073	0.106			
	(0.104)	(0.107)	(0.146)			
Parental education (baseline = no qualification)						
lower than A level	0.323***	0.303***	0.254***	0.043	-0.088*	-0.041
	(0.068)	(0.067)	(0.097)	(0.042)	(0.049)	(0.045)
A level and above	0.528***	0.625***	0.621***	0.176**	-0.155**	-0.120**
	(0.099)	(0.097)	(0.120)	(0.075)	(0.065)	(0.060)
Family income (baseline = low-income)						
middle-income	0.067	0.043	0.017	-0.016	0.032	0.063
	(0.086)	(0.092)	(0.108)	(0.050)	(0.064)	(0.046)
high-income	0.286***	0.331***	0.117	0.166**	0.077	0.086
	(0.107)	(0.110)	(0.137)	(0.074)	(0.073)	(0.060)
Marital status (baseline = never married)						
Divorced/legally separated/widowed				0.217***	-0.091	-0.017
				(0.060)	(0.086)	(0.067)
Married				0.216***	0.100	0.192***

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(table continued)

		(0.052)	(0.080)	(0.049)
Occupation (baseline = manual)				
Intermediate		0.214***	0.059	0.062
		(0.055)	(0.062)	(0.058)
Professional		0.198***	0.223***	0.205***
		(0.052)	(0.064)	(0.051)
N	2370			2432
AIC	136756			6452.227
BIC	137119.6			6544.971

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. All models were estimated by the two-step approach.

Table C.6 Earnings: Estimate results for different model settings

	(1)				(2)				
	D1	D2	D3	Earnings	D1	D2	D3	C46	Earnings
Midlife cognitive ability (age 46)									0.025
									(0.020)
Whether finish post-compulsory schooling				0.054				0.091*	0.052
				(0.041)				(0.047)	(0.042)
Whether to complete undergraduate education				0.178***				0.129***	0.175***
				(0.044)				(0.050)	(0.044)
Whether to obtain postgraduate education				0.092*				0.065	0.091
				(0.056)				(0.063)	(0.056)
Preschool cognitive ability (age 5)	0.286***	0.320***	0.315***	0.048*	0.286***	0.320***	0.315***	0.187***	0.044
	(0.061)	(0.060)	(0.086)	(0.029)	(0.063)	(0.061)	(0.088)	(0.035)	(0.028)
Non-cognitive ability (age 10)	0.926***	0.848***	0.930***	0.088	0.926***	0.848***	0.930***	0.280***	0.082
	(0.116)	(0.119)	(0.191)	(0.055)	(0.119)	(0.121)	(0.192)	(0.065)	(0.057)
Gender (baseline = female)	-0.020	-0.060	-0.073	0.666***	-0.020	-0.060	-0.073	-0.019	0.666***
	(0.059)	(0.058)	(0.080)	(0.030)	(0.058)	(0.057)	(0.080)	(0.035)	(0.030)
Number of siblings (baseline = no sibling)									
one sibling	-0.082	-0.026	0.148		-0.082	-0.026	0.148		
	(0.104)	(0.101)	(0.138)		(0.105)	(0.103)	(0.143)		
two or more siblings	-0.248**	-0.216**	0.065		-0.248**	-0.216**	0.065		
	(0.108)	(0.105)	(0.142)		(0.107)	(0.104)	(0.148)		
Parental education (baseline = no qualification)									
lower than A level	0.304***	0.292***	0.270***	0.096***	0.304***	0.292***	0.270***	0.033	0.095***
	(0.066)	(0.067)	(0.094)	(0.032)	(0.067)	(0.064)	(0.094)	(0.037)	(0.032)
A level and above	0.420***	0.542***	0.618***	0.086*	0.420***	0.542***	0.618***	0.059	0.084*
	(0.095)	(0.091)	(0.110)	(0.047)	(0.096)	(0.090)	(0.110)	(0.052)	(0.050)

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(table continued)

Family income (baseline = low-income)									
middle-income	0.154**	0.111	0.040	-0.002	0.154**	0.111	0.041	-0.013	-0.002
	(0.067)	(0.068)	(0.102)	(0.032)	(0.069)	(0.070)	(0.103)	(0.039)	(0.033)
high-income	0.393***	0.380***	0.166	0.123**	0.393***	0.380***	0.166	0.090	0.121**
	(0.100)	(0.096)	(0.125)	(0.051)	(0.098)	(0.094)	(0.125)	(0.055)	(0.050)
Marital status (baseline = never married)									
Divorced/legally separated/widowed				0.079				0.164***	0.075
				(0.051)				(0.057)	(0.051)
Married				0.018				0.147***	0.014
				(0.037)				(0.044)	(0.038)
Occupation (baseline = manual)									
Intermediate				0.107**				0.219***	0.102*
				(0.054)				(0.051)	(0.053)
Professional				0.583***				0.166***	0.579***
				(0.037)				(0.041)	(0.038)
N		2111					2111		
AIC		10710.17					15385.56		
BIC		10970.3					15741.82		

	(3)					(4)
	D1	D2	D3	C46	Earnings	Earnings
Midlife cognitive ability (age 46)					0.003	0.025
					(0.020)	(0.020)
Whether finish post-compulsory schooling				0.185***	0.023	0.052
				(0.065)	(0.044)	(0.043)
Whether to complete undergraduate education				0.105*	0.192***	0.175***
				(0.061)	(0.046)	(0.045)

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(table continued)

Whether to obtain postgraduate education				0.076	0.097*	0.091
				(0.072)	(0.056)	(0.057)
Preschool cognitive ability (age 5)	0.285***	0.311***	0.254***	0.197***	0.048	0.044
	(0.062)	(0.061)	(0.087)	(0.037)	(0.030)	(0.029)
Non-cognitive ability (age 10)	0.850***	0.743***	0.864***	0.294***	0.024	0.082
	(0.141)	(0.127)	(0.170)	(0.081)	(0.051)	(0.056)
Gender (baseline = female)	-0.139*	-0.139**	-0.118	-0.063	0.689***	0.666***
	(0.077)	(0.069)	(0.083)	(0.052)	(0.031)	(0.030)
Number of siblings (baseline = no sibling)						
one sibling	-0.122	-0.044	0.134			
	(0.124)	(0.115)	(0.150)			
two or more siblings	-0.240**	-0.164	0.110			
	(0.120)	(0.116)	(0.157)			
Parental education (baseline = no qualification)						
lower than A level	0.377***	0.353***	0.275***	0.075	0.082**	0.095***
	(0.089)	(0.079)	(0.099)	(0.060)	(0.034)	(0.033)
A level and above	0.490***	0.610***	0.694***	0.143**	0.080	0.084*
	(0.107)	(0.098)	(0.119)	(0.068)	(0.051)	(0.047)
Family income (baseline = low-income)						
middle-income	0.089	0.078	0.006	-0.114	0.007	-0.002
	(0.092)	(0.084)	(0.113)	(0.075)	(0.036)	(0.031)
high-income	0.369***	0.368***	0.140	0.014	0.142***	0.121**
	(0.109)	(0.103)	(0.137)	(0.074)	(0.055)	(0.050)
Marital status (baseline = never married)						
Divorced/legally separated/widowed				0.193***	0.094*	0.075
				(0.062)	(0.054)	(0.050)
Married				0.114*	0.046	0.014

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(table continued)

		(0.066)	(0.041)	(0.038)
Occupation (baseline = manual)				
Intermediate		0.297***	0.120**	0.102*
		(0.078)	(0.055)	(0.053)
Professional		0.256***	0.573***	0.579***
		(0.078)	(0.042)	(0.038)
N	2053			2111
AIC	125692.4			4196.305
BIC	126046.9			4286.783

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. All models were estimated by the two-step approach.

Table C.7 Extension analysis: Using educational decisions by age 34 and cognition at age 42

	(1)		(2)		(3)	
	C42	Physical health	C42	Mental health	C42	Earnings
Midlife cognitive ability (C42)		0.012		-0.002		0.023
		(0.033)		(0.041)		(0.030)
Whether finish post-compulsory schooling (by age 34)	0.173*	0.075	0.201**	0.093	0.225**	0.081
	(0.092)	(0.080)	(0.095)	(0.107)	(0.104)	(0.088)
Whether to complete undergraduate education (by age 34)	0.124	0.051	0.099	0.102	0.085	0.239***
	(0.090)	(0.080)	(0.092)	(0.107)	(0.102)	(0.090)
Whether to obtain postgraduate education (by age 34)	0.242***	-0.010	0.207**	-0.171	0.279***	0.055
	(0.088)	(0.086)	(0.089)	(0.133)	(0.096)	(0.114)
Preschool cognitive ability	0.461***	0.091	0.468***	-0.006	0.418***	0.088
	(0.064)	(0.057)	(0.066)	(0.076)	(0.077)	(0.061)
Early non-cognitive ability	0.882***	0.141	0.907***	0.057	0.956***	-0.055
	(0.128)	(0.118)	(0.136)	(0.150)	(0.158)	(0.115)
Gender (baseline = female)	0.158***	0.050	0.158***	-0.132*	0.161**	0.643***
	(0.058)	(0.054)	(0.059)	(0.071)	(0.068)	(0.055)
Parental education at age 5 (baseline = no qualification)						
lower than A level	0.305***	-0.005	0.301***	0.008	0.315***	0.098
	(0.065)	(0.059)	(0.065)	(0.078)	(0.069)	(0.062)
A level and above	0.446***	-0.045	0.441***	-0.050	0.493***	0.091
	(0.092)	(0.086)	(0.094)	(0.110)	(0.100)	(0.099)
Family income at age 16 (baseline = low-income)						

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(table continued)

middle-income	-0.133*	0.049	-0.145**	0.073	-0.117	-0.001
	(0.072)	(0.066)	(0.070)	(0.087)	(0.077)	(0.059)
high-income	-0.012	0.140*	-0.012	0.072	-0.018	-0.068
	(0.101)	(0.082)	(0.100)	(0.113)	(0.111)	(0.095)
Marital status (baseline = never married)						
Divorced/legally separated/widowed	0.005	-0.042	0.009	0.064	-0.038	0.198
	(0.107)	(0.092)	(0.112)	(0.122)	(0.126)	(0.102)
Married	0.023	0.099	0.052	0.166*	0.055	-0.031
	(0.071)	(0.069)	(0.075)	(0.087)	(0.087)	(0.064)
Occupation (baseline = manual)						
Intermediate	0.031	0.067	0.002	0.003	0.061	0.253***
	(0.087)	(0.073)	(0.086)	(0.096)	(0.102)	(0.082)
Professional	0.268***	0.092	0.250***	0.240***	0.252***	0.535***
	(0.074)	(0.066)	(0.073)	(0.088)	(0.080)	(0.077)
N	812		796		650	
AIC	6204.908		6512.355		4983.393	
BIC	6500.976		6807.17		5265.442	

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. All the structural models include the education equations, but only the results for the cognition and outcome equations are summarised here. All models were estimated using the two-step approach.

Table C.8 Extension analysis: Using educational decisions by age 34 and cognition at age 42 (IPW)

	(1)		(2)		(3)	
	C42	Physical health	C42	Mental health	C42	Earnings
Midlife cognitive ability (C42)		-0.038		-0.055		0.031
		(0.055)		(0.060)		(0.033)
Whether finish post-compulsory schooling (by age 34)	0.170*	0.115	0.229**	0.118	0.243**	0.087
	(0.104)	(0.085)	(0.096)	(0.112)	(0.106)	(0.092)
Whether to complete undergraduate education (by age 34)	0.126	0.075	0.084	0.114	0.100	0.218**
	(0.097)	(0.082)	(0.092)	(0.113)	(0.104)	(0.097)
Whether to obtain postgraduate education (by age 34)	0.193**	0.006	0.152	-0.137	0.227**	0.106
	(0.098)	(0.085)	(0.097)	(0.147)	(0.099)	(0.116)
Preschool cognitive ability	0.342***	0.127**	0.352***	0.058	0.418***	0.093
	(0.064)	(0.063)	(0.064)	(0.076)	(0.079)	(0.066)
Early non-cognitive ability	0.868***	0.132	0.869***	0.027	0.914***	-0.158
	(0.143)	(0.126)	(0.144)	(0.155)	(0.140)	(0.124)
Gender (baseline = female)	0.072	0.105	0.064	-0.065	0.159**	0.653***
	(0.080)	(0.074)	(0.078)	(0.086)	(0.070)	(0.065)
Parental education at age 5 (baseline = no qualification)						
lower than A level	0.268***	0.009	0.271***	0.008	0.319***	0.090
	(0.074)	(0.072)	(0.069)	(0.090)	(0.073)	(0.067)
A level and above	0.454***	-0.008	0.451***	-0.059	0.512***	0.064
	(0.095)	(0.095)	(0.097)	(0.122)	(0.100)	(0.117)
Family income at age 16 (baseline = low-income)						

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(table continued)

middle-income	0.220**	0.135	-0.240**	0.182*	-0.117	-0.051
	(0.104)	(0.084)	(0.100)	(0.106)	(0.081)	(0.065)
high-income	-0.062	0.248**	-0.068	0.168	-0.008	-0.110
	(0.119)	(0.098)	(0.118)	(0.126)	(0.113)	(0.106)
Marital status (baseline = never married)						
Divorced/legally separated/widowed	-0.005	0.002	0.007	0.073	-0.065	0.225**
	(0.111)	(0.102)	(0.112)	(0.129)	(0.130)	(0.107)
Married	0.094	0.067	0.126	0.090	0.053	-0.009
	(0.100)	(0.089)	(0.099)	(0.101)	(0.090)	(0.074)
Occupation (baseline = manual)						
Intermediate	-0.063	0.148	-0.101	0.113	0.070	0.296***
	(0.110)	(0.099)	(0.111)	(0.114)	(0.105)	(0.087)
Professional	0.185*	0.186**	0.161*	0.346***	0.258***	0.566***
	(0.096)	(0.092)	(0.096)	(0.107)	(0.082)	(0.082)
N	785		769		627	
AIC	128532		136763.8		123979.1	
BIC	128825.9		137029.4		124258.9	

Note: *$p \leq 0.1$, **$p \leq 0.05$, ***$p \leq 0.01$. All the structural models include the education equations, but only the results for the cognition and outcome equations are summarised here. All models were estimated using the two-step approach.

Table C.9 Extension analysis: Using educational decisions by age 34 and cognition at age 34

	(1)		(2)		(3)	
	C34	Physical health	C34	Mental health	C34	Log earnings
Midlife cognitive ability (34)		0.058**		0.054*		0.075***
		(0.024)		(0.030)		(0.019)
Whether finish post-compulsory schooling (by age 34)	0.221***	0.011	0.227***	0.015	0.227***	0.098**
	(0.047)	(0.048)	(0.046)	(0.064)	(0.055)	(0.048)
Whether to complete undergraduate education (by age 34)	0.036	0.008	0.029	0.105	0.071	0.144***
	(0.043)	(0.047)	(0.042)	(0.066)	(0.047)	(0.051)
Whether to obtain postgraduate education (by age 34)	0.153***	0.005	0.147***	-0.013	0.158***	0.099
	(0.039)	(0.052)	(0.039)	(0.081)	(0.040)	(0.066)
Preschool cognitive ability	0.356***	-0.013	0.359***	0.011	0.367***	0.016
	(0.032)	(0.034)	(0.033)	(0.047)	(0.034)	(0.032)
Early non-cognitive ability	0.655***	0.031	0.644***	0.087	0.654***	0.053
	(0.069)	(0.065)	(0.066)	(0.083)	(0.083)	(0.065)
Gender (baseline = female)	0.213***	0.035	0.201***	-0.070	0.226***	0.590***
	(0.033)	(0.032)	(0.033)	(0.044)	(0.036)	(0.032)
Parental education at age 5 (baseline = no qualification)						
lower than A level	0.079**	0.004	0.083**	-0.036	0.124***	0.070**
	(0.037)	(0.037)	(0.038)	(0.051)	(0.040)	(0.034)
A level and above	0.143***	0.044	0.141***	-0.065	0.180***	0.100*
	(0.043)	(0.045)	(0.045)	(0.066)	(0.049)	(0.052)
Family income at age 16 (baseline = low-income)						

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(table continued)

middle-income	0.073*	0.080**	0.065	0.083	0.054	0.003
	(0.042)	(0.041)	(0.043)	(0.055)	(0.047)	(0.037)
high-income	0.086*	0.131***	0.084*	0.109	0.091*	0.116**
	(0.050)	(0.050)	(0.050)	(0.070)	(0.054)	(0.058)
Marital status (baseline = never married)						
Divorced/legally separated/widowed	-0.014	-0.068	-0.021	0.094	0.013	0.098
	(0.063)	(0.065)	(0.065)	(0.081)	(0.071)	(0.070)
Married	0.098***	0.101***	0.106***	0.174***	0.084**	-0.002
	(0.036)	(0.033)	(0.036)	(0.048)	(0.040)	(0.034)
Occupation (baseline = manual)						
Intermediate	0.198***	0.080	0.181***	0.015	0.173***	0.172***
	(0.057)	(0.052)	(0.059)	(0.065)	(0.063)	(0.050)
Professional	0.366***	0.181***	0.362***	0.048	0.332***	0.419***
	(0.047)	(0.045)	(0.048)	(0.061)	(0.052)	(0.043)
N	2140		2107		1750	
AIC	15778.71		16797.73		12677.55	
BIC	16135.83		17153.87		13021.99	

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. All the structural models include the education equations, but only the results for the cognition and outcome equations are summarised here. All models were estimated using the two-step approach.

Table C.10 Extension analysis: Using educational decisions by age 34 and cognition at age 34 (IPW)

	(1)		(2)		(3)	
	C34	Physical health	C34	Mental health	C34	Log earnings
Midlife cognitive ability (C34)		0.054**		0.069**		0.079***
		(0.025)		(0.032)		(0.019)
Whether finish post-compulsory schooling (by age 34)	0.191***	-0.006	0.206***	0.012	0.149*	0.079
	(0.060)	(0.049)	(0.056)	(0.066)	(0.077)	(0.050)
Whether to complete undergraduate education (by age 34)	0.066	0.007	0.050	0.177**	0.104*	0.146***
	(0.052)	(0.051)	(0.048)	(0.082)	(0.057)	(0.053)
Whether to obtain postgraduate education (by age 34)	0.179***	0.018	0.169***	-0.069	0.207***	0.110*
	(0.046)	(0.051)	(0.046)	(0.089)	(0.050)	(0.066)
Preschool cognitive ability	0.306***	0.001	0.305***	-0.073	0.344***	0.023
	(0.031)	(0.031)	(0.030)	(0.068)	(0.033)	(0.032)
Early non-cognitive ability	0.591***	0.020	0.582***	0.133	0.457***	0.007
	(0.070)	(0.063)	(0.072)	(0.093)	(0.096)	(0.055)
Gender (baseline = female)	0.246***	0.028	0.230***	-0.024	0.280***	0.607***
	(0.040)	(0.032)	(0.039)	(0.056)	(0.054)	(0.033)
Parental education at age 5 (baseline = no qualification)						
lower than A level	0.040	-0.018	0.051	-0.080	0.043	0.065*
	(0.049)	(0.037)	(0.047)	(0.055)	(0.066)	(0.035)
A level and above	0.091*	0.051	0.092*	-0.093	0.113*	0.090
	(0.050)	(0.046)	(0.051)	(0.074)	(0.067)	(0.055)
Family income at age 16 (baseline = low-income)						

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(table continued)

middle-income	0.089	0.104**	0.073	0.028	0.148*	-0.001
	(0.059)	(0.041)	(0.059)	(0.068)	(0.087)	(0.038)
high-income	0.098	0.167***	0.091	0.097	0.168**	0.123**
	(0.061)	(0.048)	(0.061)	(0.079)	(0.078)	(0.063)
Marital status (baseline = never married)						
Divorced/legally separated/widowed	-0.005	-0.055	-0.011	0.054	0.023	0.088
	(0.070)	(0.066)	(0.071)	(0.087)	(0.075)	(0.068)
Married	0.126***	0.109***	0.135***	0.145***	0.164***	0.013
	(0.044)	(0.035)	(0.045)	(0.056)	(0.062)	(0.034)
Occupation (baseline = manual)						
Intermediate	0.181**	0.044	0.167**	0.061	0.099	0.195***
	(0.072)	(0.053)	(0.071)	(0.098)	(0.090)	(0.052)
Professional	0.341***	0.157***	0.341***	-0.002	0.274***	0.428***
	(0.058)	(0.045)	(0.059)	(0.060)	(0.084)	(0.047)
N	2088		2056		1702	
AIC	125583.4		136329.1		122387	
BIC	125939		136683.7		122729.7	

Note: $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$. All the structural models include the education equations, but only the results for the cognition and outcome equations are summarised here. All models were estimated using the two-step approach.