AUT UNIVERSITY

Faculty of Business and Law

Department of Economics
Working Paper Series

Monkey see, monkey do? How do shifts in parental socio-economic class influence children's outcomes?

Jaimee Stuart, Mary Hedges, Gail Pacheco & Susan Morton

2013/07

Monkey see, monkey do? How do shifts in parental socio-economic class influence children's outcomes?

Jaimee Stuart*, Mary Hedges*, Gail Pacheco#, and Susan Morton*
*Centre for Longitudinal Research, University of Auckland, New Zealand.
#Department of Economics, Auckland University of Technology, Auckland, New Zealand.

Abstract

This paper utilises the Aberdeen Children of the 1950s (ACONF) cohort to investigate how both perinatal factors and changes in a child's environment impacts on IQ development between the ages of 7 and 11 years. Two methodological frameworks were utilised; (1) linear and logistic regression, the latter of which enabled calculation of odds ratios to predict likelihood of IQ growth above or below the population average, and (2) latent growth curve modelling (LGCM) which permitted estimation of determinants of two latent factors: an intercept and slope (which in this case equated to IQ at age 7 and the predicted growth trajectory in IQ between age 7 and 11).

Results from both approaches were consistent. All of the perinatal factors were found to predict initial levels of IQ and some (mother's age, parity, gestational age, and gender) were found to predict change in IQ over time. Interestingly, after controlling for relevant perinatal factors, we found the effect of a downward trajectory in socio-economic status (SES) was related to lower IQ at age 7, whereas upward mobility in SES was associated with the converse. Consequently, our results illustrate that while perinatal factors are important in determining IQ in early childhood, growth in intelligence does appear to be responsive to changes in a child's environment, in this case proxied by mobility of paternal SES.

Key words; intelligence, socio-economic mobility, childhood, life-course

This research was funded by Gravida as part of the International Healthy Start to Life Project

1. Introduction and Literature overview

Cognition and health status are interrelated concepts that develop concurrently across the life-course, with cognitive ability and mental health in particular being influenced by similar underlying biological and psycho-social development processes (Richards & Hatch, 2012). For example, they are both predicted by genetic influences, the uterine environment, and / or early childhood development. Research by Case et al (2005) emphasizes that deprivation during the crucial period of perinatal and childhood growth can have lasting effects on adult health, particularly via reduced educational attainment and opportunities. It is further documented that there is a strong correlation between education and health, with cognitive ability playing a significant role in the relationship between these two outcomes (Auld & Sidhu, 2005). Therefore, understanding the perinatal determinants of cognitive ability during childhood is key to improving a number of health outcomes later in life.

Recently, Heckman (2012) indicated that research into developmental origins of health is a key knowledge frontier in the field of health economics. However, very little research has attempted to bring together theories of life-course epidemiology into the study of cognition and health from an economics view point. With this in mind, the following study aims to combine approaches from the disciplines of epidemiology, psychology, and economics to provide an integrated framework for understanding the determinants of changes in cognitive ability (proxied by IQ scores) for children aged 7 to 11.Our analysis consequently focuses on both perinatal characteristics, as well as key predictors of a child's environment (such as paternal socio-economic status), with regard to better understanding their role in determining childhood IQ and the growth trajectory in IQ. We are motivated by the knowledge that both cognitive ability and health outcomes (whether during childhood and/or adult years) are inextricably linked during the life-course, and that assessing determinants of the former, is a small step towards better understanding the complex web of relationships that impact on the latter.

Epidemiological studies that investigate the pre- and postnatal determinants of intelligence and associated later life health outcomes can essentially be split into three broad categories. The first of these investigates perinatal determinants such as birth weight, gestational age and birth order[1]. For example, Alderman and Behrman (2004) found that individuals who had low birth weight (<2500 grams) were more likely to be at risk of a number of negative economic and health outcomes related to cognition later in life. At the other end of the spectrum, Cesur and Kelly (2010) found that high birth weight (>4500 grams) also results in adverse impacts on intelligence. In terms of gestational age, Kirkegaard, Obel, Hedegaard, and Henriksen (2006) found that a lower gestational age has a negative effect on certain school performance indicators, such as spelling and reading. A similar result was found by Villarroel *et al* (2013), specifically, they found that normal gestational age (37-<41 weeks gestation), higher birth weight, and greater birth length were associated with higher test scores whereas above average gestational age was associated with lower test scores. A noteable finding of Villarroel *et al's* (2013) study was that all of the birth measurements had a lower strength of association to intelligence than socio-economic factors. Birth order is another perinatal characteristics that appears to play a role in cognition, with research showing that first born children tend to be more intelligent at the age of 5 and to have a lower risk of developmental retardation than later born children (Boat, Campbell & Ramey, 1986). Furthermore, using the same cohort data as this current study, Lawlor *et al* (2005) found that gravidity, maternal age, intrauterine growth and father's social class around the time of birth were all associated with childhood intelligence.

---

[1] See for example: Alderman & Behrman, 2004; Boardman, et al., 2002; Breslau, et al., 1996; Cesur & Kelly, 2010; Lawlor et al., 2005; Richards, et al 2001, 2002; Shenkin, Starr, & Deary, 2004; Shenkin, et al., 2001; Villarroel, Karzulovic, Manzi, Eriksson, & Mardones, 2013.

A second group of studies investigating intelligence and health outcomes looks at postnatal determinants and/or interventions that may moderate or amplify perinatal predictors of intelligence. Included in this research cluster are early intervention studies and those that emphasize the socio-economic interactions within the child's early environment. Many of these studies find that socio-economic status at birth has a large influence on childhood intelligence that is independent of perinatal factors[2]. Guo and Harris (2000) extended upon this line of research by investigating the mediating effects of poverty through characteristics of the social environment on children's intellectual development. They found that the impact of poverty was fully mediated by factors such as cognitive stimulation, parenting styles and the physical environment of the home. These studies indicate that while early biological factors are important for the development of cognitive functioning, the social environment has undeniable influences on the expression of intelligence in children.

The final group of studies worth discussing here investigates whether the effects of perinatal and postnatal predictors of intelligence continue into adulthood and how this manifests in later life outcomes[3]. Many of these studies find that childhood intelligence plays a significant role in adult cognition and health (Batty & Deary, 2004; Batty, Deary, & Macintyre., 2007). For instance Starr, et al. (2004) found that lower childhood intelligence is associated with increased hypertension later in life, and Taylor, et al. (2003) illustrated that lower childhood intelligence often leads to an increased chance of smoking as an adult. This final group of studies is growing rapidly as more longitudinal panel data sets become available, including the Aberdeen Children of the Nineteen-fifties (ACONF), which is used in the current study.

---

[2] Examples include: Gomez-Sanchiz, et al., 2003 (About breasfeeding effects on IQ); Guo & Harris, 2000; Jefferis, Power, & Hertzman, 2002; Kramer, Allen, & Gergen, 1995; McLoyd, 1998; O'Callaghan, et al., 1995; Osler, et al., 2003; Rowe, Jacobson, & Van den Oord, 1999; Turkheimer, et al., 2003.

[3] See for example: Batty & Deary, 2004; Batty, et al., 2007; Deary, Whiteman, Starr, Whalley, & Fox, 2004; Illsley, 2002 (focusses on educational attainment, rather than IQ); Starr, et al., 2004; Taylor, et al., 2003; Whalley & Deary, 2001;.

From an economics perspective there are a number of articles that link elements of the social environment, such as parental levels of education and/or income, to the development of intelligence and subsequently to later life outcomes. The methodological framework for much of this research is human capital theory (Becker, 1993). This theory has been used to explain the purchase patterns of education, health, job search, migration, training, addiction and, with the addition of a simple change in the unit of choice from the individual to the household, inter-generational poverty, marriage and family planning decisions. For instance, investigations of the relationship between family background and education have found parents' income, education levels, and socio-economic status are all positively related to participation in higher education (and also to each other) (Becker 1993). However, there is a lot of debate in the literature regarding 'nature vs. nurture' and the difficulty with regard to drawing causal inferences between pre- and post natal factors and childhood intelligence.

The relationship between biological predispositions to greater intelligence and the influence of the social environment have been discussed extensively in the field of developmental psychology using Bronfenbrenner's (1979) ecological model of development. This model suggests that the expression of genetic traits occurs in the interaction between the child and their environment (Bronfenbrenner & Ceci, 1994). Regarding the development of cognitive function, research has found that trait heritability of intelligence increases in more advantaged conditions (Rowe, Jacobson, & Van den Oord, 1999), meaning that the potential for a child to have a higher intelligence is greater when they have more resources such as greater parental education and higher socioeconomic status. Other research has found that environmental risk factors predict over a third of the variance in intelligence at age 4 and age 13, and after controlling for the effects of intelligence in childhood, environmental risk is still a significant predictor of intelligence during adolescence (Sameroff, Seifer, Baldwin, & Baldwin, 1993). These results suggest that regardless of the child's ability, lack of resources can undermine the development of cognitive functioning.

Combining the epidemiological, human capital and ecological development approaches to examine life-course trajectories is a relatively recent trend in the literature that is related to the increased availability of longitudinal panel data sets. A good example of this is the National Institute of Economics and Social Research (NIESR) that published a collection of research articles which utilise the British Birth Cohort Studies to investigate the links between early childhood and adult education and the labour market outcomes(see., Joshi, 2012). These research articles examine the influence of perinatal predictors such as age at motherhood and child development (Armstrong, 2012; Hawkes & Joshi, 2012), as well as early childhood educational, cognition, and primary school attainment (George, Stokes, & Wilkinson, 2012). In addition, the special issue investigates the relationship across generations between parents and their offspring. For instance, Armstrong (2012) outlines how parents' beliefs in the efficacy of investment in their children impacts on their children's cognition, and Hawkes and Joshi (2012) investigate the intergenerational transmission of advantage and disadvantage for women who have children at the extremes of the range (in their teens or over forty).

To our knowledge, even though there are clear links between the development of intelligence and the social environment of the child as well as a number of overlaps between epidemiological, economic and psychological literatures on this topic, there are no studies to date that examine how changes in family socio-economic status (SES) during early childhood impact on the development of intelligence. We believe this is predominantly due to the lack of studies that have multiple measures of both IQ and SES in addition to information on perinatal factors. Therefore, the following study employs the Aberdeen Children of the Nineteen-fifties ACONF data to investigate the interplay between perinatal factors, early environmental influences (particularly socio-economic status) and most importantly the change in some of these factors on determining IQ at age 7 and predicting the growth trajectory in IQ between ages 7 and 11.

There are two main contributions of this work. First, it is important to recognise that this study adopts a mixed-methods approach, by drawing on complementary methodologies from the disciplines of economics and psychology. This enables us to ensure the robustness of results, as well as showcase the value of latent growth curve modelling, which has received next to no attention in the field of health economics. The merit of this approach lies in its ability to simultaneously model determinants of the intercept (in the context of this research, IQ at age 7), and the slope (change in IQ between 7 and 11). For instance, let's posit that some environmental factors may have a substantial influence in the early years pre age 7, and then play a limited role in growth of cognitive ability post that age[4]. If traditional approaches are used that solely focus on determinants of the growth process, or the end point, then we may miss out on key information relevant to childhood development processes. A second contribution of this study is the empirical analysis of mobility in a key environmental factor during childhood – paternal socio economic status. While past empirical analyses on the determinants of intelligence have investigated the role of socio-economic status, this has often been via a measure at one time point. In contrast, this is the first study to pinpoint the influence of *change in socio-economic status* on both the initial measure of IQ at age 7, and on the change in IQ between 7 and 11. The ability to take this temporal slant with our analysis is afforded via the longitudinal panel data set at hand (ACONF).

The characteristics of the data set are detailed in the following section. Subsequently, section 3 then outlines the methods used in our analysis, which include logistic regression, and latent

[4] This is a very likely scenario as the two time periods in question (pre-birth to age 7, and age 7-11) encompass distinctly different phases of an individual's childhood, the latter of which may be dominated by primary school and peer relationships, and the former may be mostly influenced by the home environment and/or childcare.

growth curve modelling (LGCM). Section 4 presents the results, while the final section provides conclusions and indications of directions for future research.

2. Data

The ACONF dataset includes approximately 15,000 children who were born in Aberdeen between 1950 and 1956 and participated in a survey during 1962 when the children were between the ages of 7-12. For comprehensive details on the data collection methods, see Batty *et al.* (2004) and Leon *et al* (2006). The data used in the current study constitutes 7,647 children, and is made up of 4,043 males and 3,604 females. The sample is reduced (relative to the initial cohort surveyed) as it is the subset of individuals with full data from three separate sources - the 1962 survey, linked data from the Aberdeen Maternal and Neonatal Database (AMND), and school level records.

Measures

Cognitive ability

Childhood intelligence was measured three times, with information from routine cognitive tests administered through schools when children were aged 7, 9, and 11 years old. This data was then linked to their 1962 survey data and their perinatal hospital records. The tests conducted were the Moray House picture intelligence test at age 7 and the Schonell and Adams essential intelligence test at age 9. At age 11, there was a battery of Moray House tests: two ability tests (verbal reasoning 1 and 2) and two attainment tests (arithmetic, English). While four measures of cognitive ability were employed at age 11, there are sizeable gaps in the attainment test scores, which result in our decision to measure IQ at age 11, by constructing an average of the two verbal reasoning tests. These tests were mostly complete, and this is consistent with the findings by Lawlor *et al* (2005), who focus on birth characteristics as determinants of IQ at age 7.

With 'single' measures of IQ at three points in an individual's childhood, we next considered whether differences in the measurement tools employed may influence the comparability across time. Our first step was exploratory descriptive analysis, where it appeared clear that the mean and standard deviation of the IQ measures varied in an unexpected fashion (M_{IQ7} = 107.60, SD_{IQ7} = 15.73; M_{IQ9} = 111.35, SD_{IQ9} = 16.90; M_{IQ11} = 104.14, SD_{IQ11} = 13.36). The inverted U-shaped trend in IQ is likely a reflection of the different tests utilised at each measurement check point. We therefore transformed the IQ scores, such that they were scaled to the international average, *M*= 100, *SD*= 15[5]. As a consequence to this transformation, changes in IQ over time should be interpreted and considered as a relative change in comparison to the sample mean, rather than an increase or decrease in IQ per se. The correlations between the transformed IQ measures were strong at each time point (r = 0.73 - 0.87, p < .001).

It is necessary to note that the transformation to normal distributions for the IQ measures is crucial to the analysis that follows. Prior to the transformation, raw IQ scores showed that across the entire sample average, IQ increased between 7 and 9 years of age and then fell between 9 and 11 years of age. In the only other study that makes use of ACONF data to investigate early life predictors of IQ (Lawlor *et al* (2005), this unexpected trend in IQ scores did not affect their analysis, as their empirical work focussed on IQ at age 7 as the dependent variable. They did replace the dependent variable with IQ at age 9, and IQ at age 11, but because they were concerned with the three IQ measures as separate endpoints, transforming the IQ measures to ensure comparability across time was not a major concern.

The general relationship between academic achievement (via IQ tests) and general intelligence is well established (Jensen, 1998). However, there is still much debate as to whether IQ is

[5] An alternative to scaling the IQ measures is to use z-scores. However, adoption of latent growth curve modelling in this research, means it is not feasible to make use of z-scores, due to their narrow distribution.

measuring cognitive function or a more measurable school aptitude (see Neisser et al, 1996). Nevertheless, there is a general consensus that these types of standardised tests do appear to have high statistical reliability. This implies that although test-takers may have varying scores when taking the same test on differing occasions, and they may have varying scores when taking different IQ tests at the same age, the scores generally agree with one another and across time within a margin of error (Hopkins & Bracht, 1975). More importantly they are often the only measure of cognitive function taken so offer the best available information on a child's cognitive ability.

Perinatal characteristics

Perinatal data was sourced from the Aberdeen Maternal and Neonatal Database (AMND) at the time of the 1962 survey. Seven variables are used in the forthcoming analyses to represent maternal and child characteristics at birth. These include maternal height and age at the time of birth, gravidity (number of pregnancies), birth order, child gender, gestational age at birth, and birth weight.

Socioeconomic Status

Socio economic status (SES) was derived from paternal occupation of the study participant at two points in time, birth (via AMND) and childhood (as reported by the study participant in 1962). At both of these time points, fathers' occupational data was classified into six categories according to the 1950 general register (General Register Office, 1951): I—professional; II—managerial; IIINM—non-manual, skilled non-manual; IIIM—manual, skilled manual; IV—manual, semi-skilled; and V—unskilled manual. In this study, the six occupational categories have been collapsed into four: (i) high SES (I – professional, and II – managerial); (ii) medium-high SES (IIINM – non-manual, skilled non-manual); medium-low SES (IIIM – manual, skilled manual, and IV – manual, semi-skilled); and (iv) low SES (V – unskilled manual). Observations where the father was unemployed, deceased or occupation unknown, were classed as missing.

The change in SES between birth and 1962 is a key indicator of change in a child's environment in those early years and is therefore the focus of our empirical analysis, with respect to its impact on childhood cognition. Change in SES during childhood was computed by subtracting social class at birth from social class at 1962 (low SES was coded as 1 and high SES as 4). The resulting change in SES scores ranged from -3 to 3, with 0 representing no change and other values indicating the direction and magnitude of change. Table 1 illustrates the movement across SES categories within our sample.

{Insert Table 1 here}

The shaded cells in Table 1 are indicative of the number and percentage of households that stayed in the same SES category. Overall, 72% of families stayed in the same social class between the birth of the participant in the study and 1962 – remembering that this is on average between 7 to 12 years time gap. The shading in Table 1 also makes it easy to visualize the number and percentage of households that shift SES class during that time period, with figures to the left of the shading illustrating how many households were downwardly mobile (16.58%), and those to the right of the shading, showcasing how many households were upwardly mobile (11.18%). Given that there are seven possibilities for movement (-3, -2, -1, 0, +1, +2, +3), to simplify the forthcoming analysis, we collapsed the two categories at each extreme. This resulted in five categories that were converted into dummy variables representing: no change (reference group), upward movement of one category (SES_pos1); upward movement of 2 or 3 categories (SES_pos2); downward movement of one category (SES_neg1); and downward movement of 2 or 3 categories (SES_neg2).

One caveat of our analysis is that it could be argued that father's occupational class may not be an ideal proxy for family SES in today's society. However, it is important to remember that the time period during which ACONF ran was the late 1950s and early 1960s. Additionally, the socio-cultural environment of Aberdeen at that time meant that very few mothers in this cohort were employed. This was evident in the data set, as information on mother's employment status was only asked with reference to mother's occupation category prior to marriage. Similarly there was very little variation in the sample across the mother's level of education achieved. The homogenous nature of maternal education and work characteristics therefore motivated the use of father's occupational class as an effective proxy for family SES.

Descriptive analysis

Definitions and descriptive statistics for all covariates described above (perinatal characteristics and SES), as well as the change in IQ from 7 to 11 (our dependent variable of interest) are provided in Table 2. IQ_change is a dummy variable that captures whether an individual's change in IQ from 7 to 11 (the transformed IQ scores were utilised to ensure comparability over time) was above the sample average. Therefore, this is a true reflection of change in cognitive ability, relative to an individual's peers. In general, the sub-sample with below average change in IQ between the ages of 7 and 11 were more likely to have older mothers, greater parity, be male and have had a higher gestation period, relative to the sub-sample with above average change in IQ. There appears to be minimal differences between column (2) and (3) in terms of shifts in SES. For instance, 1.7% of the below average change in IQ sub-sample experienced a drop in SES of 2 or more categories between birth and 1962; and the comparable figure for the above average change in IQ sub-sample was 1.3%; with a t-test revealing that the difference between the means not being statistically significant. Further t-tests (not reported here for the sake of brevity) reveal that in terms of SES shifts, only SES_pos2 had significantly different (at the 5% level) means between column (2) and (3). Descriptives point to those in the above average change in IQ sub-group being more likely to have experienced an upward shift in SES.

Prior to proceeding with the econometric analyses, it was deemed prudent to examine our sample with respective excluded versus included cases, i.e. comparing our final linked sample of 7,647 versus the initial cohort of 15,000 observations. This was carried out using the Mann-Whitney test. Significant differences were found on several independent variables - Mother's age at birth of the child (z= -3.59, p > .01), birth weight (z= -3.07, p > .01), gravidity (z= -5.94, p > .01), , gender (z= -3.35, p > .01), birth order (z= -5.78, p > .01), social class at birth (z= -3.91, p > .01), and social class in 1962 (z= -2.39, p > .01). Similar findings were also made with the dependent variables which are the focus of this study - IQ at age 7, 9, and 11 (z_{IQ7}= -14.02, z_{IQ9}= -12.03, z_{IQ11} = -14.99, p > .01). These results may reflect characteristics of the sampling process, where children who were well below the average IQ level may not have completed the required IQ tests at school, and where students who were more disadvantaged in general were over represented in missing values for the linked data. These differences between included and excluded cases mean that results of the forthcoming data analysis should be interpreted with a caveat in mind – that our sample may be underrepresented with respect to the most disadvantaged families.

Another potential caveat of this analysis is that we are unable to control for school quality. Nonetheless, we are confident that Aberdeen schooling during the period relevant to this study was relatively homogeneous. Private education was uncommon in Scotland at this time and most children attended their local primary school. Furthermore teacher selection of a or by a school was uncommon with the vast majority being trained at the Aberdeen Teacher's Training college and then being appointed to a school by the Local Education Authority (Illsley, 2006). We therefore believe this policy created relative homogeneity in teacher quality and thus school quality across our population based dataset (which included children from 44 different schools).

3. Methodology

The aim of this analysis is to bring together methodologies from different disciplines – specifically economics, epidemiology and psychology. We therefore begin the empirical journey with common tools for an economist - least squares regression and logistic modelling, both of which are used to examine the influence of perinatal characteristics and SES mobility on changes in childhood IQ over time. The regression models were conducted in two steps, where the 1st model included all perinatal characteristics (including SES level at birth), and the 2nd step, which was incremental in nature, also included the change in SES between birth and 1962. As explained earlier, change in SES is categorised as either a movement up (down) of 2 or more categories, or a movement up (down) of 1 category; with no change in SES being the reference group. The logistic regression was permitted via dichotomization of the change in IQ variable into above and below average change in IQ. To our knowledge, this is the first time a change in a child's environment, via change in SES is investigated with regard to its influence on changes in a child's cognitive ability.

In the second part of our empirical analysis, we undertake latent growth curve modelling (LGCM) to ensure we make full use of the unique longitudinal data at hand. This type of analysis is well placed to assess growth trajectories over time. It has been widely used in the fields of behavioural and social science, but to date has not featured prominently in the health economics literature. This is likely due to the lack of longitudinal data, with multiple measurements of the same variable, required for such a methodology to be effective.

As early as the 1960s, growth curve models have been utilised to model repeated measurements for dependent variables (see Potthoff & Roy, 1964). LGCM is a form of structural equation modelling, which offers a number of benefits; it permits investigation of inter-individual differences in change, as well as antecedents of change. The relative standing of an individual at each point in time is modelled as a function of an underlying growth process, and the best parameter values for that growth trajectory are then fitted to each individual. Curran and Willoughby (2003, p. 603) argue that LGCM resides "at an intersection between variable – centered and person-centered analysis".

LGCM accounts for both within and between person variance (Duncan & Duncan, 1995), provides group-level statistics such as mean intercept and growth rate, and can include both time-varying and time-invariant covariates. Specifically, this methodology allows two latent variables to be constructed, the intercept and the slope. In the context of this study, the intercept represents the average value of IQ when the growth curve begins (7 years old), and the slope represents the average change in IQ over time. In matrix notation, equation (1) details the relationship between the repeated measurements (y) over time, intercepts (τ), latent factors (η) factor loadings (Λ) and the disturbance variance of ε:

$$y = \tau_y + \Lambda_y \eta + \varepsilon \qquad (1)$$

The latent factors are initial status of IQ at age 7 (η_1) and slope of IQ change between 7 and 11 (η_2). As τ_y is usually set to zero for identification purposes, we can represent the model with time (t) and individual (i) points of observation. Therefore equation (1) is expanded to:

$$y_{ti} = \lambda_{1t}\eta_{1i} + \lambda_{2t}\eta_{2i} + \varepsilon_{ti} \qquad (2)$$

As shown in the following growth equations, we are modelling the latent means *(α1, α2)* and their respective variances *(ζ)* around these means:

$$\eta_{1i} = \alpha_1 + \zeta_{1i} \qquad (3) \quad \text{and}$$

$$\eta_{2i} = \alpha_2 + \zeta_{2i} \qquad (4)$$

We can also further break down the variance–covariance and mean structures of the model. The variance–covariance matrix (Σ) is a function of the factor variances and covariances (Ψ), the factor loadings (Λ), and the disturbance variances and covariance (Θ_ε).The following equations represent the population variance–covariance matrix (Σ) along with the population means of the observed variables (μ_y) :

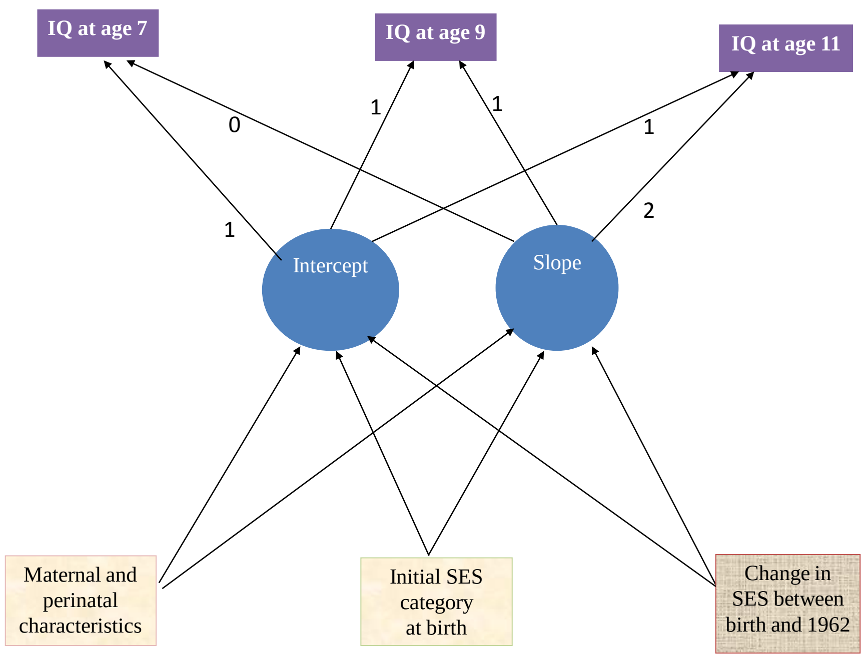
$$\Sigma = \Lambda_y \Psi \Lambda_y' + \Theta_\varepsilon \qquad (5) \quad \text{and}$$

$$\mu_y = \tau_y + \Lambda_y \alpha \qquad (6)$$

It is necessary to note that the covariances between the disturbances are assumed to be zero, and the variances are assumed to be invariant across time points. The expectation of this model is that it produces a mean structure with population observed means *(μ)*, which are a function of both the intercepts *(τ)* and the latent variable means *(α)*.

Similar to the OLS regression and logit model, the LGCM was conducted in two steps; step 1 assessed the predictive effects of perinatal characteristics and SES variables at birth on the intercept and slope of IQ, and step 2 assessed the additional predictive influence of SES mobility between birth and 1962 on the intercept and slope of IQ. Figure 1 provides a useful visual impression of the analysis conducted via LGCM. First, the lightly shaded boxes of independent variables (perinatal characteristics and initial SES categories at birth) are used to predict the latent factors of intercept and slope; before the darker shaded box of SES movement is added to assess its influence on the predictive capabilities of this model.

Figure 1: Pathways in assessing determinants of change in childhood IQ.



Note: Intercept factor loadings set to 1 and slope factor loading set to 0=IQ7, 1=IQ9, 2=IQ11.
Residuals and covariances not shown for ease of interpretation.

4. Results

Least squares and logistic regressions

Initially least squares regression was employed, where the continuous variable of change in IQ between 7 and 11 years of age was the dependent variable. Table 3 presents the results of the first step of this analysis within the column labelled 'Model (1)'. In comparison, 'Model (2)' illustrates the impact once indicators for change in SES category were included in the regression. Under both models, many results are as expected. A higher birth order significantly reduces the change in IQ between age 7 and 11. Shenkin et al (2001) also find a negative association between birth order and cognitive ability at age 11, when they make use of the Scottish Mental Survey; as did Villarroel et al (2013) in their cohort study of Chilean children. We also find females significantly more likely to experience a rise in IQ, relative to males. This finding is corroborated by the epidemiology literature. Although, recent research by Cesur and Kelly (2010) find opposing results on cognitive outcome for gender, dependent on the cognitive test used. The authors employ standardised reading and math test scores as the outcome variables, and make use of longitudinal data from the U.S. (The Early Childhood Longitudinal Study Kindergarten Cohort). They find negative associations between being female and math scores, and at the same time also find positive associations between being female and reading test scores (although the former results were not statistically significant, and the latter findings were). Furthermore, another noteworthy and significant result from Table 3 showed that gestational age was negatively associated with growth in IQ. This result is in line with Villarroel et al's (2013) study which found that increased gestational age was related to lower mathematics and language test scores.

In model (2), the indicators for SES mobility, which proxy for changes in a child's environment between birth and pre-teen times (i.e. age 7 to 11) were added to the regression framework. It is useful to note that when comparing findings between column (1) and (2), many of the initial findings are robust to the inclusion of these indicators of change in SES. Consequently, birth order, gender, and gestation continue to be important drivers of changes in childhood cognitive ability. It appears from the OLS regression that changes in paternal SES only play a significant role in influencing childhood cognitive outcomes, when the change is substantial (2 or more SES categories) and positive in nature. This is exhibited by the large and strong significance attached to the estimate on SES_pos2 in column (2).

{Insert Table 3 here}

To check robustness of results, we also conduct logistic regression, where we have dichotimized the change in IQ variable, such that 1 represents change above the mean, while 0 represented those that experienced a change in IQ below the mean. This analysis is useful in the sense that we are comparing individuals relative to their peers. In terms of perinatal characteristics, similar findings (as described above) remain intact, with an odds ratio for birth order and gestation below 1, and the female dummy having an odds ratio greater than 1 (although all these results have fallen in significance level, except for gestation age). The odds ratio for SES_pos2 illustrates that children in families that moved 2 or more categories up the SES ladder were 29.1% more likely to experience an increase in IQ between age 7 and 11 above the average change, relative to families that experienced stationary SES over the sample time frame.

While many of these results are intuitive and corroborate past literature (especially in terms of the influence of perinatal characteristics on cognitive ability), we unfortunately cannot ascertain from the models portrayed in Table 3, whether the independent variables are a significant and contributing force to both initial IQ at age 7, as well as the growth trajectory between age 7 and 11 (while controlling for the influence of the former). The estimates from LGCM in the following section will cover this important gap in the analysis.

Latent Growth Curve Model

LGCM begins with examination of a null, or unconditional model, where there are no predictors. It was estimated that the initial value for IQ at 7 was 100.43 (p < .01) and the mean value of change over time was non-significant (0.03, p = .58). The implied means calculated for IQ at age 9 and 11 were 101.40 and 101.37 respectively. This result indicates that without controlling for covariates average IQ does not significantly differ from 7 to 11. However, the variance of both the intercept (159.64 p < .01) and the slope (7.23, p <.01) were significant, indicating that potential predictors can be evaluated to account for the unexplained variance in the initial value of IQ and change in IQ over time (i.e., this variance shows that individuals are significantly different in terms of both their IQ at 7 and their growth trajectories). Additionally, the covariance between the slope and the intercept was non- significant (0.16, $p = 0.91$) meaning that change over time is not related to initial levels of IQ (i.e., those with higher versus lower initial IQ scores do not grow differently from one another over time).

Following common practice with LGCM, predictors were then added to make the model conditional, i.e., the intercept and slope were adjusted for the influence of predictors. The first conditional model, Model (1), was estimated (in a similar fashion to the previous linear and logit regressions) to include perinatal characteristics and SES status at birth. Furthermore, the correlations between these predictors were controlled for in the analyses, although only significant correlations were retained in the final model. After accounting for the predictive effects of the independent variables in Model (1), the estimated intercept (IQ at age 7) decreased to 85.59 and the slope became positive (1.08, $p < .01$). This indicates that, on average, after controlling for relevant birth information, childhood IQ increases over time. In terms of the significant effects, it was found that all of the perinatal factors significantly predicted IQ at age 7 (see Model (1), Table 4 for unstandardised coefficients), although only a few predicted change in IQ over time. The significant effects on initial values of IQ are as follows; mothers who are taller, older, and have had fewer pregnancies have children with relatively higher IQ at age 7. Also, female children, those who were heavier at birth, over 40 weeks gestation, were the third child or less had significantly higher IQ at 7. Furthermore, in comparison to those in the lowest SES category (SES=1), all other SES groups had higher initial values of IQ. The only significant positive effect found on change in IQ over time (slope) was if the child was female – and this effect was only significant at the 10% level. In terms of significant negative effects on the slope, these were apparent for birth order and gestation.

{Insert Table 4 here}

The second conditional (Model (2) in Table 4) also controls for SES mobility during childhood. We find that the initial average value of IQ at age 7 in this model was 85.43 and the average change over time was 1.10. The effects of all birth characteristics in Model (2) are similar to those found in the Model (1). All of the dummy variables representing change in social class between birth and 1962 (when children were between 7 and 12) had significant effects on IQ at 7. Results signal that upward SES mobility was related to increases in IQ at 7 and downward mobility was related to decreases in IQ at 7. Table 4 also indicates that to have a positive influence on both IQ at age 7 and the growth trajectory of IQ between 7 and 11, households needed to have increased at least two SES categories. SES_pos2 is the only change in SES dummy that is significant with regard to its influence on the slope for IQ change.

5. Conclusion

This study makes use of a valuable historical dataset from Aberdeen, which provides multiple measurements of childhood IQ at ages 7, 9 and 11. Along with expected covariates that influence cognition, such as birth characteristics and socio economic status at birth, this data set also included pertinent information on change in a child's environment, via changes in paternal SES. Such information enabled empirical analysis that attempted to disentangle the role of different early childhood influences on an individual's cognitive ability at age 7, as well as the growth trajectory between age 7 and 11.

This research also aimed to showcase the value of LGCM in the field of health economics. This methodology provided a useful tool to simultaneously assess the predicted impact of relevant explanatory variables on IQ at age 7 (the intercept), as well as the growth trajectory forecast between age 7 and 11 (the slope). Overall, results from the LGCMs indicated that maternal and perinatal variables did influence cognition. Mother's age at birth, and height, birth order, birth weight, and gestational age all influenced the intercept of IQ, although these perinatal determinants had a markedly smaller effect, or no effect, on the slope of IQ during childhood. That is, they affected IQ at 7, but only birth order, gestation, and gender were found to influence growth in IQ between 7 and 11. These results highlight the developmental phase during which an individual's birth characteristics have greatest impact on their cognition.

It must also be noted, that while the significant covariates with regard to predicting the slope of IQ change in the LGCMs were similar to the results from the linear and logistic regression also conducted in this study, the LGCMs enabled us to see the influence of these variables on both the initial levels of IQ and IQ change over time. One interesting finding that is illuminated by the LGCMs is that gestational age has a significant positive effect on IQ at 7, but a significant negative effect on the slope. This indicates that greater gestational age is associated with higher cognition in early childhood, but that those who are above average gestation tend to regress towards the mean of cognition over time. Effectively, the positive impacts of intrauterine growth on cognition for those with greater gestational age are most likely achieved in very early childhood, and then diminish as the child ages.

Noteably, the impact of the majority of the perinatal determinants was smaller than that of the impact on SES at birth and SES change. Additionally, while both initial status for SES and mobility in this indicator of a child's environment important in determining initial levels of IQ, only a positive increase of two or more categories in SES had a significant impact on the growth curve for IQ.

Finally, it is important to note that the change in SES variable could be capturing a number of other aspects about the early home environment that we are unable to separate out in this analysis. For example, there is no measure of different parenting practices included in this dataset and how that may influence cognition. Armstrong (2012) found that belief in a just world was a strong predictor of early attainment and reduced the importance of parental income or SES as a determinant. Consequently future research could delve into the mediating relationships between SES, change in SES and childhood cognition outcomes.

References

Armstrong, A. (2012). Belief in a Just World and Children's Cognitive Scores. *National Institute Economic Review, 222*(1), R7-R19. 10.1177/002795011222200102

Alderman, H., & Behrman, J. (2004). Estimated Economic Benefits of reducing Low Birth Weight in Low-Income Countries. *Health, Nutrition and Population, World Health Organisation, 35548*, 34.

Auld, M. & Sidhu, N. (2005). Schooling, cognitive ability and health. *Health Economics*, 14: 1019-1034.

Batty, G. D., & Deary, I. J. (2004). Early life intelligence and adult health. Emerging associations, plausible mechanisms, and public health importance. BMJ2004;329:585–6. *British Medical Journal, 329*(7466), 2.

Batty, G. D., Deary, I. J., & Macintyre, S. (2007). Childhood IQ in relation to risk factors for premature mortality in middle-aged persons: the Aberdeen Children of the 1950s study. *J Epidemiol Community Health, 61*(3), 241-247. 10.1136/jech.2006.048215

Batty, G. D., Morton, S. M. B., Campbell, D., & et al., (2004). The Aberdeen children of the 1950s cohort study: background, methods, and follow-up information on a new resource for the study of life-course and intergenerational effects on health. *Paediatric and Perinatal Epidemiology, 18*(3), 18.

Becker, G. S. (1993). *Human Capital* (3rd ed.). Chicago: The University of Chicago Press.

Boardman, J. D., Powers, D. A., Padilla, Y. C., & al., e. (2002). Low birth weight, social factors, and developmental outcomes among children in the United States. . *Demography, 39*(2), 353-368.

Boat, B. W., Campbell, F. A., & Ramey, C. T. (1986). Preventive education and birth order as co-determinants of IQ in disadvantaged 5-year-olds. *Child: Care , Health and Development, 12*(1), 12.

Breslau, N., Chilcoat, H., DelDotto, J., & al., e. (1996). Low birth weight and neurocognitive status at six years of age. *Biological Psychiatry, 40*(5), 389-397.

Bronfenbrenner, U. (1979). *The ecology of human development: Experiments by nature and design*. Cambridge, MA: Harvard University Press.

Bronfenbrenner, U. (1994). Ecological models of human development. In M. Gauvain & M. Cole (Eds.), *Readings on the development of children* (2nd ed., pp. 37–43). Oxford: Elsevier.

Case, A., Fertig, A., and Paxson, C. (2005). The lasting impact of childhood health and circumstance. *Journal of Health Economics*, 24: 365-389.

Cesur, R., & Kelly, I. R. (2010). From Cradle to Classroom: High Birth Weight and Cognitive Outcomes. *Forum for Health Economics & Policy, 13*(2), 1-24. 10.2202/1558-9544.1189

Curran, P. and Willoughby, M. (2003). Implications of latent trajectory models for the study of developmental psychopathology. *Development and Psychopathology*, 15(3): 581-612.

Deary, I., Whiteman, M. C., Starr, J. M., Whalley, L. J., & Fox, H. C. (2004). The Impact of Childhood Intelligence on Later Life: Following Up the Scottish Mental Surveys of 1932 and 1947. *Journal of Personality and Social Psychology, 86*(1), 130-147.

Duncan, T. and Duncan, S. (2004). An Introduction to Latent Growth Curve Modeling. *Behavior Therapy, 35*, 333-363.

General Register Office. (1951). *Classification of occupations 1950*. London.

George, A., Stokes, L., & Wilkinson, D. (2012). Does Early Education Influence Key Stage 1 Attainment? Evidence for England from the Millennium Cohort Study. *National Institute Economic Review, 222*(1), R67-R80. 10.1177/002795011222200106

Gomez-Sanchiz, M., Canete, R., Rodero, I., & al., e. (2003). Influence of breast-feeding on mental and psychomotor development. . *Clinical Pediatrics, 42*(1), 35-42.

Guo, G., & Harris, K. M. (2000). The mechanisms mediating the effects of poverty on children's intellectual development. . *Demography, 37*(4), 431-447.

Hawkes, D., & Joshi, H. (2012). Age at Motherhood and Child Development: Evidence from the UK Millennium Cohort. *National Institute Economic Review, 222*(1), R52-R66. 10.1177/002795011222200105

Heckman, J. (2012). The developmental origins of health. *Health Economics*, 21: 24-29.

Hopkins, K. D., & Bracht, G. H. (1975). Ten-year stability of verbal and nonverbal IQ scores. *American Educational Research Journal, 12*(4), 469-477.

Illsley, R. (2002). A City's Schools: From equality of input to inequality of outcome. *Oxford Review of Education, 28*(4), 427-445. 10.1080/0305498022000013607

Jefferis, B. J., Power, C., & Hertzman, C. (2002). Birth weight, childhood socioeconomic environment, and cognitive development in the 1958 British birth cohort study. *British Medical Journal, 325*(7359).

Jensen, A.R. (1998). The g factor: The science of mental ability. Westport, CT: Praeger.

Joshi, H. (2012). From Cradle to Career: Evidence from the British Birth Cohort Studies on the Family, Education and Employment – Introduction. *National Institute Economic Review, 222*(1), R1-R6. 10.1177/002795011222200101

Kirkegaard, I., Obel, C., Hedegaard, M., & Henriksen, T. (2006). Gestational Age and Birth Weight in Relation to School Performance of 10-Year-Old Children: A Follow-up Study of Children Born after 32 Completed Weeks. *Pediatrics, 118*(4), 1600-1606. 10.1542/peds.2005-2700

Kramer, R. A., Allen, L., & Gergen, P. J. (1995). Health and social characteristics and children's cognitive functioning: results from a national cohort. . *American Journal of Public Health, 85*(3), 312-318.

Lawlor, D. A., Batty, G. D., Morton, S. M. B., Deary, I. J., Macintyre, S., Ronalds, G., & Leon, D. A. (2005). Early Life Predictors of Childhood Intelligence: Evidence from the Aberdeen Children of the 1950s Study. *Journal of Epidemiology Community Health, 59*, 7. 10.1136

Leon, D. A. (2006). Cohort Profile: The Aberdeen Children of the 1950s Study. *International Journal of Epidemiology, 35*, 549-552. 10.1093/ije/dyi319

McLoyd, V. C. (1998). Socioeconomic disadvantage and child development. . *American Psychologist, 53*(2), 185-204.

Neisser, U., Boodoo, G., Bouchard, T. J. . J., Boykin, a. W., Brody, N., Ceci, S. J., … Urbina, S. (1996). Intelligence: Knowns and unknowns. *American Psychologist, 51*(2), 77–101. doi:10.1037/0003-066X.51.2.77

O'Callaghan, M., Williams, G. M., Andersen, M. J., & et al. (1995). Social and biological risk factors for mild and borderline impairment of language comprehension in a cohort of five-year-old children. *Developmental Medicine and Child Neurology, 37*(12), 1051-1061.

Osler, M., Andersen, A. M., Due, P., & et al. (2003). Socioeconomic position in early life, birth weight, childhood cognitive function, and adult mortality. A longitudinal study of Danish men born in 1953. *Journal of Epidemiology and Community Health, 57*(11), 681-686.

Potthoff, R. and Roy, S. (1964). A generalized multivariate analysis of variance model useful especially for growth curve problems. *Biometrika*, 51: 313-326

Richards, M., Hardy, R., Kuh, D., & Wadsworth, M. (2001). Birth weight and cognitive function in the British 1946 birth cohort: longitudinal population based study. *British Medical Journal, 322*(27 January), 199-203.

Richards, M., Hardy, R., Kuh, D., & al., e. (2002). Birthweight, postnatal growth and cognitive function in a national UK birth cohort. . *International Journal of Epidemiology, 31*(2), 342-348.

Richards, M., & Hatch, S. L. (2012). A Life course approach to the development of mental skills. *The Journals of Gerontology, Series B: Psychological Sciences and Social Sciences, 66*(Supp 1), i26-i35. 10.1093/geronb/gbr013

Rowe, D. C., Jacobson, K. C., & Van den Oord, E. J. (1999). Genetic and environmental influences on vocabulary IQ: parental education level as moderator. . *Child Dev, 70*(5), 1151-1162.

Sameroff, A. J., Seifer, R., Baldwin, A., & Baldwin, C. (1993). Stability of intelligence from preschool to adolescence: the influence of social and family risk factors. *Child development*, *64*(1), 80–97.

Shenkin, S. D., Starr, J. M., Pattie, A., & al., e. (2001). Birth weight and cognitive function at age 11 years: the Scottish mental survey 1932. *Archives of Disease in Childhood, 85*(3), 189-197.

Shenkin, S. D., Starr, J. M., & Deary, I. J. (2004). Birth weight and cognitive ability in childhood: a systematic review. *Psychological Bulletin, 6*(130), 989-1012.

Starr, J. M., Taylor, M. D., Hart, C. L., & et al. (2004). Childhood mental ability and blood pressure at midlife: linking the Scottish mental survey 1932 and the Midspan studies. . *Journal of Hypertension, 22*(5), 893-897.

Taylor, M. D., Hart, C. L., Davey Smith, G., & et al. (2003). Childhood mental ability and smoking cessation in adulthood: prospective observational study linking the Scottish mental survey 1932 and the midspan studies. *Journal of Epidemiology and Community Health, 57*(6), 464-465.

Turkheimer, E., Haley, A., Waldron, M., & al., e. (2003). Socioeconomic status modifies heritability of IQ in young children. *Psychological Science, 14*(6), 623-628.

Villarroel, L., Karzulovic, l., Manzi, J., Eriksson, J. G., & Mardones, F. (2013). Association of perinatal factors and school performance in primary school Chilean children. *Journal of Developmental Origins of Health and Disease, 4*(3), 232-238. http://dx.doi.org/10.1017/S2040174413000020

Whalley, L. J., & Deary, I. J. (2001). Longitudinal cohort study of childhood IQ and survival up to age 76. *British Medical Journal, 322*(7290), 819-823.

Table 1: SES movement between birth and 1962

		SES at birth				
		Low	Medium-low	Medium-high	High	Total
SES in the 1962 survey	Low	1473 (75.35)	401 (20.51)	63 (3.22)	18 (0.92)	1955
	Medium-low	643 (17.85)	2840 (78.82)	86 (2.37)	34 (0.94)	3603
	Medium-high	125 (12.28)	252 (24.75)	593 (58.25)	48 (4.72)	1018
	High	42 (3.92)	206 (19.23)	205 (19.14)	618 (57.70)	1071
	Total	2283	3699	947	718	7647

Note: Socio-economic status (SES) is proxied by paternal social class. The categories are defined as follows: Low = semi-skilled and unskilled manual (occupation class IV & V); Medium-low = skilled manual (occupation class IIIb & IIIc); Medium-high = non-manual (occupation class IIIa); and High = professional and intermediate (occupation class I & II).

Figures in parenthesis represent percent of sub-sample.

Table 2: Descriptive Statistics

Variable	Definition	M (SD)	Below Average Change M (SD)	Above Average Change M (SD)
IQ_change	Dummy variable = 1 if individual's change in IQ from 7 to 11 is above sample average; 0 otherwise	0.502 (0.500)	-	-
Maternal height	Maternal height in inches 1= ≤ 60, 2=61, 3=62, 4=63, 5=64, 6=65, 7=≥65	3.161 (1.747)	3.137 (1.743)	3.184 (1.751)
Maternal age	Maternal age at birth in years 1=15-19, 2=20-24, 3=25-29, 4=30-34, 5=35-39, 6= 40+	3.097 (1.125)	3.120 (1.121)	3.075 (1.129)
Birth order	Maternal number of births 1=1, 2=2, 3=3, 4=4, 5=5+	2.076 (1.133)	2.131 (1.148)	2.022 (1.117)
Gender	0=Male, 1=Female	0.471 (0.499)	0.461 (0.499)	0.481 (0.500)
Gestation	Gestational age in weeks 1= < 37, 2=37-40, 3=41+	2.446 (0.572)	2.464 (0.568)	2.428 (0.576)
Birth weight	Birthweight in pounds 1= ≤ 5.4, 2=5.5-6.4, 3=6.5-7.4, 4=7.5-8.4, 5=8.5-9.4, 6=9.5+	3.316 (1.108)	3.334 (1.101)	3.299 (1.115)
Gravidity	Maternal number of pregnancies 1=1, 2=2, 3=3, 4=4, 5=5+	2.291 (1.252)	2.346 (1.259)	2.238 (1.244)
High SES	Dummy variable = 1 if social class of Father at birth = I and II professional and skilled technical; 0 otherwise	0.094 (0.292)	0.097 (0.296)	0.091 (0.288)
Medium high SES	Dummy variable = 1 if social class of Father at birth = III non-manual; 0 otherwise	0.124 (0.329)	0.117 (0.322)	0.131 (0.337)
Medium low SES	Dummy variable = 1 if social class of Father at birth = III manual; 0 otherwise	0.484 (0.500)	0.488 (0.500)	0.480 (0.500)
SES_neg2	Dummy variable = 1 if Father's social class in 1962 changed more than 1 category down; 0 otherwise	0.015 (0.122)	0.017 (0.130)	0.013 (0.113)
SES_neg1	Dummy variable = 1 if Father's social class in 1962 changed 1 category down; 0 otherwise	0.070 (0.255)	0.068 (0.251)	0.072 (0.259)
SES_pos1	Dummy variable = 1 if Father's social class in 1962 changed 1 category up; 0 otherwise	0.144 (0.351)	0.143 (0.350)	0.145 (0.352)
SES_pos2	Dummy variable = 1 if Father's social class in 1962 changed more than 1 category up; 0 otherwise	0.049 (0.215)	0.043 (0.203)	0.054 (0.227)
Sample size		7,647	3,808	3,839

Note: Below (Above) average change = individual's change in IQ from 7 to 11 is below (above) sample median.
Reference groups are Low SES, and no change in SES between birth and 1962.

Table 3: Change in IQ from 7 to 11

	OLS		Logit	
Variable	Model (1)	Model (2)	Model (1)	Model (2)
Intercept	2.105***	2.104***	1.473***	1.452***
	(0.718)	(0.733)	(0.197)	(0.198)
Maternal height	0.049	0.041	1.013	1.012
	(0.072)	(0.072)	(0.014)	(0.014)
Maternal age	0.068	0.046	1.007	1.005
	(0.129)	(0.130)	(0.024)	(0.024)
Birth order	-0.784***	-0.767***	0.920*	0.922*
	(0.228)	(0.229)	(0.040)	(0.040)
Gender	0.570**	0.582**	1.088*	1.090*
	(0.248)	(0.248)	(0.051)	(0.051)
Gestation	-0.629***	-0.635***	0.891***	0.890***
	(0.229)	(0.229)	(0.038)	(0.038)
Birth weight	0.054	0.044	1.002	1.001
	(0.121)	(0.121)	(0.023)	(0.023)
Gravidity	0.011	0.018	0.995	0.996
	(0.213)	(0.214)	(0.040)	(0.040)
High SES	-0.570	-0.373	0.897	0.933
	(0.480)	(0.505)	(0.080)	(0.087)
Medium high SES	0.624	0.854**	1.067	1.103
	(0.417)	(0.431)	(0.084)	(0.090)
Medium low SES	-0.369	-0.375	0.959	0.957
	(0.287)	(0.304)	(0.052)	(0.055)
SES_neg2	-	-1.324	-	0.749
		(0.970)		(0.147)
SES_neg1	-	0.0005	-	1.087
		(0.503)		(0.100)
SES_pos1	-	-0.239	-	1.005
		(0.365)		(0.070)
SES_pos2	-	1.856***	-	1.291**
		(0.596)		(0.140)
N	7,647			

Notes: Coefficients are reported for the OLS models, and odds ratios for the logit model.
Standard errors are in parenthesis and *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Table 4: Latent Growth Curve Model on IQ

	Model (1)		Model (2)	
	Intercept	Slope	Intercept	Slope
Maternal height	0.137***	0.006	0.123***	0.005
	(0.030)	(0.012)	(0.030)	(0.012)
Maternal age	2.051***	0.028	1.941***	0.018
	(0.148)	(0.060)	(0.147)	(0.060)
Birth order	-1.225***	-0.336***	-1.138***	-0.327***
	(0.250)	(0.101)	(0.248)	(0.101)
Gender	1.159***	0.223*	1.197***	0.228*
	(0.295)	(0.120)	(0.293)	(0.120)
Gestation	0.242**	-0.092**	0.240***	-0.091**
	(0.090)	(0.036)	(0.089)	(0.097)
Birth weight	0.589***	0.006	0.564***	0.003
	(0.074)	(0.030)	(0.074)	(0.030)
Gravidity	-1.210***	0.048	-1.176***	-0.049
	(0.213)	(0.087)	(0.212)	(0.087)
High SES	11.967***	-0.320	13.487***	-0.232
	(0.544)	(0.221)	(0.541)	(0.221)
Medium high SES	7.648***	0.118	8.832***	0.222
	(0.491)	(0.200)	(0.488)	(0.199)
Medium low SES	3.486***	-0.203	4.268***	-0.195
	(0.338)	(0.137)	(0.336)	0.137)
SES_neg2	-	-	-6.495***	-0.528
			(1.190)	(0.486)
SES_neg1	-	-	-3.148***	-0.092
			(0.572)	(0.234)
SES_pos1	-	-	1.482***	-0.099
			(0.418)	(0.170)
SES_pos2	-	-	3.452***	0.785***
			(0.677)	(0.276)

Standard errors are in parenthesis and *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.