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Andy Dickerson
Gurleen Popli

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Persistent Poverty and Children's Cognitive Development: Evidence from the UK Millennium Cohort Study

Andrew Dickerson and Gurleen K. Popli*
Department of Economics
University of Sheffield

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ABSTRACT

We use data from the four sweeps of the UK Millennium Cohort Study (MCS) of children born at the turn of the century to document the impact that poverty, and in particular persistent poverty, has on their cognitive development in their early years. Using Structural Equation Modelling (SEM), we show that children born into poverty have significantly lower test scores at age 3, age 5 and age 7, and that continually living in poverty in their early years has a cumulative negative impact on their cognitive development. For children who are persistently in poverty throughout their early years, their cognitive development test scores at age 7 are almost 20 percentile ranks lower than children who have never experienced poverty, even after controlling for a wide range of background characteristics and parental investment.

Keywords: child poverty, cognitive development
JEL classification codes: I32, J13, J62

*Address for correspondence: Gurleen Popli, Department of Economics, University of Sheffield, 9 Mappin Street, Sheffield, S1 4DT, UK. Email: g.popli@sheffield.ac.uk. T: +44 (0)114 222 3485. F: +44 (0)114 222 3458.

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"Give me a child until he is seven and I will give you the man." (attrib.) St. Francis Xavier (1506 – 1552)

1 Introduction

In this paper we investigate the impact of persistent poverty on the cognitive development of children in the very early years of their lives. We use the UK Millennium Cohort Study (MCS) which is a sample of 19,000 children born in the UK around the turn of the century. We trace their cognitive development as measured in a series of standard tests up until they are 7 years old. Our focus is on the impact of living in poverty on their cognitive development. We assess the impact of both *episodic* (period-by-period) poverty and *persistent* poverty, in order to examine the cumulative impact of multiple and continuous periods of deprivation.

It has become increasingly apparent that there is a strong link between children's development and educational attainment, and their family background (Blanden et al., 2007; Feinstein, 2003; Heckman and Masterov, 2007; Gregg and Macmillan, 2009). Specifically, there is a large literature exploring the impact of poverty and low income on the development of children. Brooks-Gunn and Duncan (1997) review evidence from numerous national longitudinal data sets for the US (such as the Panel Study of Income Dynamics (PSID), National Longitudinal Study of Youth (NLSY), and Children of NLSY) focusing on the consequences of poverty across a range of outcomes for children, and the pathways through which poverty might operate. Much of the evidence they describe points towards the negative impact of poverty on child development.

The link between early educational attainment and socio-economic status (SES) of families has also been emphasised by policy makers. Coupled with his administration's emphasis on education, in 1999 Prime Minister Tony Blair also famously pledged to end child poverty 'within a generation': "*Our historic aim will be for ours to be the first generation to end child poverty,*" (Tony Blair, Beveridge Lecture, 1999). This commitment was accompanied by a range of reforms and initiatives designed to tackle what had become a crisis, with one quarter of all children in Britain living in poverty in 1999. The following decade saw significant reductions in the child poverty rate measured in both relative and absolute income terms (Waldfogel, 2010). However, the rate of progress slowed somewhat after 2003/04, and progress towards the intermediate target of cutting the child poverty rate in half by 2010 was missed. Subsequently, the prospect of 'eliminating' child poverty by 2020 looks increasingly difficult. However, in March 2010, the UK Child Poverty Act enshrined in law the commitment to end child poverty by 2020. Explicit targets have been set in terms of relative income, material deprivation and absolute income measures. In addition, and as a late addition to the legislation, the significance of 'persistent poverty' was recognised, with a target to prescribed by regulation before 2015 (at the time of writing, this target was yet to be set).

More recently, the Field review (Field, 2010) on 'Poverty and Life Chances' called into question the focus on income poverty. Instead, the review recommended greater attention be paid to the problem of the intergenerational transfer of poverty. The role of family background, the quality of parenting, and children's opportunities for learning and development were argued to be crucially significant in determining adult outcomes because of their importance in children's development before age 5 ('Foundation Years' in the terminology of the review). Consequently, the review argued that supporting parents and their children in these early years through directed government spending should be the priority. Thus, rather than making income transfers to poorer families through the tax credit system, the Field review recommends that consideration should always be given to whether that income would be more effectively spent in improving early years provision of services such as Sure Start (a programme similar to Head Start in the US) in order to improve the outcomes that children from poor families might achieve in their adult lives. Such recommendations represent a clear change in focus.

The impact of persistence poverty remains a largely unexplored aspect of the importance of family background and other characteristics on children's cognitive development and educational attainment. Our paper is a contribution towards an investigation of this important issue. Specifically, we examine the relative importance of *both* family background (including parental investment) and income poverty – especially the persistence of poverty – for children's early cognitive development. This is one of the few papers to systematically and robustly examine the impact of persistent poverty on young children's cognitive development in contemporary Britain. Using a Structural Equation Modelling (SEM) approach, we show that children living in poverty have significantly lower cognitive test scores, even after controlling for a wide range of background characteristics and parental investment; and that the legacy of persistent poverty in their early years is a cumulative negative impact on their cognitive development.

The remainder of this paper is organised as follows. In the next section, we briefly review the relevant literature on cognitive development, family background and poverty. Section 3 presents the method that we employ to estimate the link between child poverty and cognitive development. Section 4 describes the data, and the tests that are used to measure children's cognitive development. Section 5 presents our main results, and section 6 draws some conclusions and implications.

2 Background literature

When discussing the impact of poverty on children, the timing and the duration of poverty is often highlighted (Duncan et al., 1998). There is growing evidence across various disciplines (neuroscience, development psychology, and economics among them) that the environment in the early years of a child's life has a significant impact on their development and ability formation (Knudsen et al., 2006). Thus it is not surprising that the impact of poverty is also found to be greater for poverty experienced in early childhood (usually defined as birth to 7 years) relative to late childhood or adolescence. Duncan et al. (2010) use the PSID and find significant and 'quantitatively large detrimental effects' of poverty in the early years (birth to 5 years) on a range of adult outcomes (earnings and hours worked). The theoretical explanation for these larger effects from early exposure of poverty comes from the 'self-productivity' argument given by Heckman and Masterov (2007), where development in later years is dependent upon development in early years.

Evidence also suggests that long exposure to low resources is more detrimental than transitory changes in family fortunes. Carneiro and Heckman (2002) use US data to study the relationship between family income and schooling of children. Their findings suggest that it is long-term factors such as better family resources throughout the child's formative years, rather than short-term liquidity constraints, that largely account for the family income gap in college enrolment. Findings by Cameron and Heckman (2001), again based on US data, also demonstrate that it is long-term influences associated with parental background and parental income throughout the child's adolescent years that largely account for the racial-ethnic college enrolment differential. Using data from Indonesia, Pakpahan et al. (2009) find that children who grow up in chronically (persistently) poor households have a 31 percentage point higher risk of continuing to live in poverty as adults relative to children from non-chronically poor households.

One key challenge in identifying the link between poverty and child development is in disentangling the effect of poverty from a range of factors associated with poverty which in themselves have a negative impact on children's development. For example, children in poor households often also have young, less educated, and single mothers. Each of these factors (young mother, less educated mother, single mother) by itself is associated with poorer outcomes for children (Mayer, 1997). Plug and Vivjerberg (2005) use adoptee data and show family income has a significant impact on schooling outcomes; adoptees with access to better family income have better educational outcomes. Dahl and Lochner (2012) use an instrumental variable approach to establish causality from family income to child development; even after controlling for numerous confounding factors they find that family income has an independent causal link to child development, more so for the low-income families.

There are a number of pathways via which poverty can impact child development: health and nutrition; home environment; parental interactions with children; parental health; neighbourhoods etc. (Corcoran, 1995; Duncan et al., 1998). An important pathway often stressed in the literature is the home environment, which is taken to include everything from the quality and quantity of time inputs by the parents, to the quality and quantity of goods (learning resources, toys, etc.) inputs provided by the parents to the child (Leibowitz, 1974). The home environment is often viewed as a mediating factor for most of the external factors impacting the children, such as the government programs or low income (Becker and Tomes, 1986; Todd and Wolpin, 2003; Gelber and Isen, 2013). Using the data for the US from the PSID and the Infant Health and Development Program, Brooks-Gunn et al. (1993) show that provision of learning experiences in the home can account for up to half of the effect of poverty on the IQ scores of five year olds. Similarly, a more recent study by Gelber and Isen (2013) analysing the Head Start program from the US finds that a significant part of the impact of the program on child development was via the increased parental investment in the child, as a result of participation in the program.

In our analysis we focus on the early years of children's development, as reflected in their cognitive development. We estimate the impact of both episodic (short term) and persistent (long term or chronic) poverty. We examine both the direct and the indirect impact of poverty on child development; for the indirect impact we specifically explore the pathway of home environment (which we call 'parental investment'). Finally, we also address two key empirical issues of measurement error and endogeneity of parental inputs.

First is the issue of measurement error, both in estimating cognitive ability and in measuring the parental investment in the child. In our framework, we assume that both the true ability of the child and the true investment in the child cannot be observed. Instead, what we have are a range of (imperfect) measures of cognitive ability and parental investment. Consider first the unobserved (latent) cognitive ability of the child. What we observe are test scores which are correlated with latent cognitive ability, but measure it with error. Cunha and Heckman (2008) discuss the issue in terms of 'measurement error' while Jerrim and Vignoles (2013) focus on the implications in terms of 'regression to the mean'. The basic argument is that the imperfection/randomness in testing means that classifying children as high or low ability on the basis of a single test is liable to be subject to error since getting a relatively high (low) score on a given day is likely to be followed by a less extreme score (i.e. will be lower (higher)) if they were tested on another day. To mitigate this problem we can use multiple tests at each age to estimate the latent cognitive ability of the child. A similar issue arises with the measurement of parental investment. However, we have numerous proxies available in our data which are related to the latent parental investment in the child.

Second is the issue of endogeneity of inputs, especially parental investment (see Todd and Wolpin, 2003, 2007, for details). The source of the problem is that there are inputs we do not observe but parents do, and that parents may modify their inputs based on what they observe of the child, leading to reverse causation. In our estimation framework we explicitly account for this potential endogeneity of inputs.

Next we briefly review studies using the UK data and put our work in the context of the UK specific literature.

2.1 Review of UK studies

For the UK, using data drawn from the 1970 British Cohort Study, Feinstein (2003) showed that parental SES has an important and long-lasting impact on children's development and attainment. While early cognitive development is a good predictor of educational qualification attainment 20 years later, children from low SES families are particularly disadvantaged. He also argued that children in low SES families are less likely to demonstrate high early scores, and even if they do show signs of good initial cognitive development, this advantage is soon eroded. Any upward mobility of children with low initial attainment is for children from medium and high SES families. Our paper has a number of parallels with Feinstein's study in that we are also interested in the impact of family background on children's early cognitive development, although our focus is on poverty and the persistence of poverty rather than differences over time by social status.

Gregg and Macmillan (2009) examine the impact of parental income on children's education and test scores (the youngest children they have are aged 7 years) using various UK cohort studies: National Child Development Study (born in 1958); British Cohort Study (born in 1970); three separate cohorts constructed from the British Household Panel Survey (for children born in the late 1970s, early 1980s, and late 1980s); Avon Longitudinal Study of Parents and Children (a Bristol-based birth cohort of children born in 1991/92); and the Longitudinal Study of Young People in England (a national sample of children born in England in 1989/90). They consistently find that children born into poorer families have a lifelong disadvantage.

Goodman and Gregg (2010) utilise the second and the third sweeps of the MCS. Their focus is on explaining the rich-poor gap in the cognitive ability of children by analysing the influence of aspirations and behaviour of parents on the outcomes of their children. However, they do not take into account the persistence of poverty in documenting or explaining the existence of the gap in ability. Blanden and Machin (2010) also utilise the second and the third sweeps of the MCS. They examine the connection between parental income and children's vocabulary and behaviour. Consistent with the previous literature, their findings also suggest that better child outcomes (in terms of vocabulary development and behaviours) are associated with higher income. For example, children from families in the top quintile in terms of income are more than one year ahead in vocabulary development at age 5 as compared to children from the bottom quintile.

None of the studies cited above examine the impact of persistent poverty. In contrast, Schoon et al. (2010) use the MCS data to look at the impact of persistent financial hardship (measured as the family being in receipt of state benefits) on the cognitive and behavioural development of children at age 5. Their findings suggest that persistent financial hardship has a large and negative impact on children's cognitive development, while the impact on children's behavioural adjustment is rather less. Further, this negative impact is mitigated by the 'protective factors' in the family environment. In a related paper using the same data, Schoon et al. (2012) examine the impact of persistent (income) poverty and 'family instability' (defined as changes in mothers' relationship status: married, cohabitating, or single) on children's cognitive ability. The results from this paper confirm their earlier findings and further illustrate that, after controlling for poverty, family instability has no significant association with the cognitive development of children.

Kiernan and Mensah (2009) also use the MCS data and investigate the impact of persistent poverty, maternal depression, and 'family status' (defined as mothers' relationship status) on the cognitive and behavioural development of children, at age 3. Their findings also suggest that poverty has a negative impact on the development of children and, once poverty is taken into account, the effects of both maternal depression and family status are weak. In a related paper, Kiernan and Mensah (2011) look at the impact of parenting and persistent poverty on cognitive development of children at age 5. Their findings echo those of Schoon et al. (2012): the negative impact of persistent poverty is mitigated by positive parenting.

Our paper is different from Schoon et al. (2010, 2012) and Kiernan and Mensah (2009, 2011) in number of important aspects. First, we explicitly address the issues of measurement error and endogeneity of inputs. Second, we consider a longer time horizon by examining children's development at age 3, age 5 and age 7. This gives us an important advantage in modelling the persistence in cognitive development, and also allows us to include a period when the children have been attending school. Third, we explicitly model the 'parental investment' in children; the so called 'protective factors' in Schoon et al. (2010), and the 'index of parenting' in Kiernan and Mensah (2011).

Barnes et al. (2010) examine the impact of persistent poverty (defined as being in poverty for at least 3 of the 4 annual interviews of the Growing up in Scotland study) on young children in Scotland. They note that poverty is multi-dimensioned and that many, if not most, of its effects can be captured through correlated characteristics such as low parental education, poor health etc. Indeed, low income is not statistically significantly correlated with child outcomes (such as being overweight, poor language, social and emotional development etc) once all of these other family and various environmental factors are taken into account. Of course, this does not mean that income is not important for child outcomes, but rather that its impact is indirect, through its effect on other factors which are correlated with outcomes. In our analysis, we are able to capture and distinguish between both the direct and the indirect impact of income poverty.

3 Estimation method

In our framework, we adopt a *value added plus lagged inputs* model of ability formation (Todd and Wolpin, 2007), where child's current cognitive ability depends on the previous ability of the child and the past inputs (parental investments). Further, as in Cunha and Heckman (2008) we assume both the child's cognitive ability and the parental investment in the child are latent. The true ability of the child and the true investment in the child cannot be observed. Instead what we have are a range of (imperfect) measures of cognitive ability and parental investment. So, for example, the reading test score is just one measure of a child's cognitive ability; similarly a parent reading to the child is just one measure of the parental investment in the child. To understand the link between poverty and the cognitive development of the child, mediated by parental investment, we use SEM. The SEM has two components – a structural model and a measurement model.

3.1 Structural model

Let θ_t be the stock of latent cognitive skill (ability) of the child at time t. A child's ability at time t, θ_t, depends on past ability stock, θ_{t-1}, and past parental investment, λ_{t-1}; it also depends on some exogenous covariates X_t^θ, poverty being one such covariate. Evolution of ability over time is thus given by:

$$\theta_t = \gamma_{1t}\theta_{t-1} + \gamma_{2t}\lambda_{t-1} + \gamma_{3t}X_t^\theta + \eta_t \tag{1}$$

where $t = 1, \ldots T$, represent the different time periods of childhood, with $t = 0$ representing the initial endowments that a child is born with; γ_{1t}, γ_{2t}, and γ_{3t} are time-varying parameters to be estimated; and η_t is the normal error term, assumed to be independent across individuals and over time.

Parental investment is also assumed to be latent, and is influenced by some (exogenous) covariates, X_t^λ (including poverty),

$$\lambda_t = \gamma_{4t}X_t^\lambda + \nu_t \tag{2}$$

where γ_{4t} is the vector of time-varying parameters to be estimated; and ν_t is the normal error term, assumed to be independent across individuals and over time.

For period $t = 1$ equation (1) will be: $\theta_1 = \gamma_{11}\theta_0 + \gamma_{21}\lambda_0 + \gamma_{31}X_1^\theta + \eta_1$. In our empirical exercise we do not have specific measures to separately identify the initial endowments, θ_0, and initial parental investment in the child, λ_0, and hence we assume that these together depend in a linear fashion on a set of covariates, X_0. So for $t = 1$ we estimate:

$$\theta_1 = \gamma_{11}X_0 + \gamma_{31}X_1^\theta + \eta_1 \tag{3}$$

3.2 Measurement model

As both ability and parental investment are taken to be latent, we have a measurement model for each of them.

$$Y_{j,t}^\theta = \mu_{j,t}^\theta + \alpha_{j,t}^\theta\theta_t + \varepsilon_{j,t}^\theta \tag{4}$$

$$Y_{j,t}^\lambda = \mu_{j,t}^\lambda + \alpha_{j,t}^\lambda\lambda_t + \varepsilon_{j,t}^\lambda \tag{5}$$

where $Y_{j,t}^{k}$ (for $k \in \{\theta, \lambda\}$ and $j \in \{1, ..., m_t^k\}$) are the measures available for the latent ability and latent parental investment at time t. m_t^k are the number of measures available, such that $m_t^k \geq 2$. $\alpha_{j,t}^{k}$ are the factor loadings which can be interpreted as the amount of information that the measures $Y_{j,t}^{k}$ contain about the latent variables (θ_t and λ_t). $\varepsilon_{j,t}^{k}$ are the measurement errors, which capture the difference between the observed measures and the unobserved latent variables. $\mu_{j,t}^{k}$ and $\mu_{j,t}^{k}$ can depend on regressors as long as they are independent of the latent variables (θ_t and λ_t) and the error term ($\varepsilon_{j,t}^{k}$).

3.3 Identification

The factor loadings, in equations (4) and (5), can be identified only up to a scale, so we need to normalize them; the normalization we use here is: $\alpha_{1,t}^{\theta} = \alpha_{1,t}^{\lambda} = 1$. Further, we can not separately identify the mean of the latent variable, $E(\theta)$, and the intercepts $\mu_{j,t}^{\theta}$; we need to normalize one of them, we assume $E(\theta) = 0$ and identify $\mu_{j,t}^{\theta}$. Similarly we assume $E(\lambda) = 0$ and identify $\mu_{j,t}^{\lambda}$.

To be able to identify all the parameters of interest in equations (1) to (5) we need following assumptions:
Assumption 1: $\varepsilon_{j,t}^{k}$ is mean zero and independent across agents and over time for $t \in \{1, \ldots T\}$; $j \in \{1, ..., m_t^k\}$; and $k \in \{\theta, \lambda\}$.
Assumption 2: $\varepsilon_{j,t}^{k}$ is mean zero and independent of (θ_t, λ_t) for $t \in \{1, \ldots T\}$; $j \in \{1, ..., m_t^k\}$; and $k \in \{\theta, \lambda\}$.
Assumption 3: $\varepsilon_{j,t}^{k}$ is mean zero and independent from $\varepsilon_{i,t}^{l}$ for $t \in \{1, \ldots T\}$; $j \in \{1, ..., m_t^k\}$; and $l, k \in \{\theta, \lambda\}$ such that $l \neq k$.

In the empirical analysis to aid computation we further assume that $\varepsilon_{j,t}^{k}$, and η_t have a normal distribution, though this is not needed for identification. The assumptions we make here are the same assumptions as made by Cunha and Heckman (2008, page 747 and Appendix A2); see their paper for further details.

3.3.1 Identification of the factor loadings

Consider θ_t. Assume for simplicity that $m_t^{\theta} = 2$, i.e. we have only two measures for θ_t: $\{[Y_{j,t}^{\theta}]_{j=1}^{2}\}_{t=1}^{T}$. From the data available we can calculate the covariance between the different measures, which gives us the following set of equations (recall the normalization $\alpha_{1,t}^{\theta} = 1$):

$$Cov(Y_{1,t-1}^{\theta}, Y_{1,t}^{\theta}) = Cov(\theta_{t-1}, \theta_t) \tag{6}$$

$$Cov(Y_{2,t-1}^{\theta}, Y_{1,t}^{\theta}) = \alpha_{2,t-1}^{\theta} Cov(\theta_{t-1}, \theta_t) \tag{7}$$

$$Cov(Y_{1,t-1}^{\theta}, Y_{2,t}^{\theta}) = \alpha_{2,t}^{\theta} Cov(\theta_{t-1}, \theta_t) \tag{8}$$

$\alpha_{2,t-1}^{\theta}$ can be identified by taking the ratio of equation (7) to equation (6), and $\alpha_{2,t}^{\theta}$ can be identified by taking ratio of equation (8) to equation (6).

Similarly we can identify the factor loadings $\alpha_{j,t}^{\lambda}$ for the latent parental investment, up to the normalization $\alpha_{1,t}^{\lambda} = 1$, by exploiting the covariances between the measures of parental investment $Y_{j,t}^{\lambda}$.

3.3.2 Identification of the structural parameters

Once the factor loadings have been estimated we can use two-stage least squares to estimate the structural parameters. In the first-stage we take the weighted average of the measures to get the error-corrected estimates of the latent variables. For example, consider θ_t, we can use the estimated factor loadings to construct:

$$\widehat{\theta}_t = \sum_{j=1}^{m_t^{\theta}} \omega_{j,t} Y_{j,t}^{\theta} \qquad \text{where} \qquad \omega_{j,t} = \frac{\left(\widehat{\alpha}_{j,t}^{\theta}\right)^2}{\sum_{j=1}^{m_t^{\theta}} \left(\widehat{\alpha}_{j,t}^{\theta}\right)^2} \tag{9}$$

where $\widehat{\theta}_t$ is the error-corrected estimate of true latent ability θ_t. We can similarly construct $\widehat{\lambda}_t$, the error-corrected estimate of true parental investment λ_t. In the second-stage $\widehat{\theta}_t$, $\widehat{\theta}_{t-1}$ and $\widehat{\lambda}_{t-1}$ can be substituted in equations (1) to (3) to estimate the structural parameters. For details refer to the discussion in Cunha (2011).

3.4 Endogeneity

If we assume that η_t is independent of λ_t, then assumptions in section 3.3 fully identify the model. We call this as the '*baseline model*' in our empirical analysis. However, endogeneity of inputs is a concern: one way to think about this is reverse causation where parents observe some aspect of child's current ability which has an impact on their investment in the child, so that θ_t can be expected to impact λ_t. In equation (1) using lagged parental investment (λ_{t-1}) to explain child's current ability (θ_t) should solve the issue of reverse causation, as θ_t cannot impact λ_{t-1} (referred to as the *value added with lagged inputs* specification by Todd and Wolpin, 2007). However, we have a dynamic model where θ_{t-1} impacts θ_t and if the inputs are endogeneous then θ_{t-1} can also impact λ_{t-1}. This will then violate the assumption that η_t is independent of λ_t.

To address the issue of endogeneity of inputs in the most general way we specify a parental investment function, as suggested by Cunha et al. (2010):

$$\lambda_t = \phi_{1t}\theta_t + \phi_{2t}X_t^{\lambda} + \phi_{3t}R_t + \zeta_t \tag{10}$$

where ζ_t is the normal error term that is orthogonal to (θ_t, X_t^{λ}, R_t); and we assume that there exists at least one such variable, R_t, that impacts parental investment but not the ability of the child. R_t can be interpreted to reflect the family resources or constraints that limit the ability of the parents to invest in their children, but do not have a direct impact on child's ability. Cunha et al. (2010) discuss in detail the justification of the investment function given by equation (10); they further suggest that to estimate equation (10) we can use two-stage least squares where the past values of R_t are used as proxies for θ_t.

3.5 Direct versus indirect effects

The SEM approach allows us to capture and identify both the direct and the indirect effects of poverty on cognitive development. The direct effects are simply how poverty affects cognitive development, while the indirect effects capture how poverty affects parental investment and parenting style, which in turn impact upon cognitive development. Equation (1) gives us the direct impact of the exogenous variables (including poverty) on cognitive skills while equation (2) gives us the direct impact of exogenous variables on parental investment. Equations (1) and (2) together give us the indirect effects of the exogenous variables on cognitive skills through their impact on parental investment. Separately identifying the direct and indirect effects allows us to compute the total effect of each of the exogenous variables on children's cognitive development. We therefore identify three effects: (i) the direct impact of parenting inputs on children's ability, (ii) the direct impact of poverty on children's ability, and (iii) the indirect impact of poverty on children's ability, via its impact on parenting inputs.

3.6 Episodic versus persistent poverty

We estimate two different specifications using SEM. In the first specification, in vector X_t^{θ} in equation (1), we include a (1, 0) dummy only for the current poverty status (P_t). This captures the direct impact of episodic poverty on cognitive development (θ_t). Implicitly, it is assumed that the previous periods of poverty do not have any direct impact on current cognitive development. Any previous poverty episodes (P_{t-i}) only have an indirect impact on current cognitive development, via lagged cognitive development (θ_{t-1}), and lagged parental investment (λ_{t-1}). Similarly, X_t^λ only includes P_t.

To capture the impact of persistent poverty on the child's cognitive development, in the second specification we include dummies for all past poverty states in equation (1); i.e. X_t^θ now includes P_t, P_{t-1}, P_{t-2}, etc.. This allows us to identify the direct impact of persistent poverty on the cognitive development of the child by cumulating the estimated coefficients of P_t, P_{t-1}, P_{t-2}, etc.. The motivation for this specification comes from the wider literature on poverty which makes the case that the effect of a period of poverty on an individual is likely to be different depending on whether this period of poverty was preceded by poverty or relative affluence (i.e. not in poverty); see Foster (2009), Bossert et al. (2012) and Dutta et al. (2013). This specification thus allows us to distinguish between the direct effects of episodic and persistent poverty, where the latter has often been called the 'scarring' impact of poverty in the literature. The indirect impact of previous episodes of poverty via lagged cognitive development and lagged parental investment still exists. Similarly we also allow parental investment to be influenced by persistent poverty; X_t^λ now includes P_t, P_{t-1}, P_{t-2}, etc.

A diagrammatic representation of the estimated structural and measurement model is given in Figure 1. Estimation is performed using Mplus v7 (Muthen and Muthen, 2010).

4 Data and measurement

The UK Millennium Cohort Study (MCS) is following a large sample of around 19,000 babies born in 2000-01. The first sweep (MCS1) took place in 2001-02 when these babies were, on average, around 9 months old, and recorded details of their family background, mothers' pregnancy and birth, and the early months of their lives. The second sweep (MCS2) took place when the children were around 3 years old, while the third sweep (MCS3) was administered when the children had reached age 5 and had started school. Finally, the fourth sweep (MCS4) was undertaken in 2008 when the children were 7 years old. The age 11 survey, the fifth sweep, started in 2012. In our analysis we use the first four sweeps of the MCS.

Information is gathered in face-to-face interviews on a wide range of socioeconomic and demographic characteristics about the child, their family (parents and grandparents), parenting activities, cognitive assessments, and early education. The survey has a clustered stratified design, with oversampling of: ethnic minorities (Asian and Black families); children living in disadvantaged areas; and children from the three smaller countries of the UK (Scotland, Wales and Northern Ireland). Weights which take account of differential sampling, non-response and attrition have been used throughout the analysis – see Hansen (2012) for details.

4.1 Measuring child poverty

Household income data in the MSC is gathered using a banded question recording total net income from all sources. A large number of income bands are used (19 in MCS4 for example) with the top and bottom bands open-ended. Different sized bands were used for lone parent households, as compared to couples, given their lower household incomes in general. Rather than using the mid-point of the reported band as an estimate of household income, a continuous income measure is imputed using interval regression (Stewart, 1983), with predictors including age, labour market status, region, benefit recipient, ethnicity, highest education level, housing tenure and number of children. This imputation also facilitates predicting household income for non-respondents (either 'refusal' or 'don't know', representing about 10% of households in each sweep).

While there are several criteria currently in use for measuring child poverty, a commonly utilised measure is relative income poverty. This is the measure of poverty that is reported in the official Households Below Average Income (HBAI) statistics on poverty (HBAI, 2010), and is defined as living in a household with net equivalent income less than 60 percent of median UK household income. Equivalisation takes into account family size and composition by rescaling income by the number of 'equivalent adults'. As with the HBAI, the MCS uses the modified OECD household equivalence scale (OECD, 2009) which weights the first adult as 0.67, the second adult and each child over 14 as 0.33, and each child under 14 as 0.20. The MCS equivalised income is then compared to the official poverty thresholds from the HBAI for the appropriate year of the MCS sweep. Children living in households below the HBAI threshold for that year are defined as being in poverty for that sweep. We use this measure of child poverty, made available by MCS, in our analysis.

4.2 Cognitive test scores

It is difficult to capture the latent cognitive ability of a child at age 9 months (i.e. in MCS1) since there are no tests for cognitive ability for children that young. What we can measure at that age is their development – i.e. their physiological and psychological functioning – and in particular, whether they have reached particular age-specific 'developmental milestones' that most children can do at their age. The MCS uses the well-established Denver Developmental Screening Test (Frankenburg and Dodds, 1967; Frankenburg et al., 1992) with assessment based on the responses given by the main respondent. The version of the test used in MCS assesses children in three areas: fine motor function (picking, passing, etc.); gross motor function (sitting, standing, etc.); and communicative gesture (smiles, nods for yes, etc.) (Dezateux et al., 2004; Schoon et al., 2012). A child is classified as having a delay in a particular item if s/he is unable to perform a task that 90% of the children of their age can do.

The MCS records a number of standard tests of cognitive development at ages 3 (MCS2), 5 (MCS3) and 7 (MCS4) years. In each case, these are age-appropriate tests administered to the children themselves. We focus on the children's performance across all of these tests since they reflect different cognitive abilities and educational concepts and performance, and provide different indicators of ability. There are two tests in MCS2, and three in each of MCS3 and MCS4. These tests are described briefly below while Connelly (2013) and Hansen (2012) provide full details of the implementation of these tests in the MCS.

The British Ability Scales (BAS) are a set of standard age-appropriate individually-administered tests of cognitive ability and educational achievements suitable for use with young children – see Elliott et al. (1996, 1997) for further information. Six different BAS tests have been administered across the MCS sweeps. The difficulty of the tests is changed dynamically to reflect the child's performance in the initial set of items in order to present the child with the most appropriate test for their ability. The BAS Naming Vocabulary test (BAS-NV) assesses expressive verbal ability and vocabulary, as well as language development. The children are shown a series of coloured pictures of objects one at a time which they are asked to name. The raw scores are then adjusted to take account of the difficulty of the item set administered and the age of the child (in 3 month bands) using a set of standard look-up tables. This test was administered in MCS2 and MCS3. In the BAS Pattern Construction test (BAS-PC), the child replicates a design by putting together flat squares or solid cubes with black and yellow patterns on each side. The child's score is based on both speed and accuracy in the task. This test assesses spatial problem solving, but also dexterity and coordination. Once again, the raw scores are adjusted for age and the difficulty of the test items with reference to a set of standard tables. This test was administered in MCS3 and again in MCS4. The BAS Picture Similarity test (BAS-PS) was administered in MCS3. This test assesses non-verbal reasoning or problem solving: the child is shown 4 pictures and asked to identify a further related/congruent picture. Finally, in the BAS Word Reading test (BAS-WR) which was administered in MCS4 (age 7), the child reads a series of words presented on a card. This assesses the child's educational knowledge of reading.

In addition to the six BAS-based tests, two further tests were administered. First, in MCS2, the Bracken School Readiness Assessment (BSRA) is used to assess the 'readiness' of young children for formal education by testing their knowledge and understanding of a range of basic concepts – see Bracken (2002). MCS2 employs six of the subtests which specifically evaluate: colours; letters; numbers/counting; sizes; comparisons; and shapes. The BSRA test result is a composite score based on the total number of correct answers across all six subtests. Second, in MCS4, children's numerical and analytical skills are assessed using a variant of the National Foundation for Educational Research (NFER) standard Progress in Maths (PiM) test in which a range of tasks covering number, shape, space, measures and data are assessed.

For each of the tests, we use the age-standardised scores, and construct the child's percentile ranking across all children in the MCS who complete the test to take account of differences in scale and dispersion between the tests. The percentile rankings record on a scale of 0 to 100 the percentage of children in the sample completing the test who are ranked below the child's score. Thus a child's ranking of 90 on a particular test indicates that 90 percent of children scored lower in the test; the child is thus in the top 10% of the specific test score distribution. Percentile rankings also provide a convenient and informative metric against which to record the influence of poverty on the different cognitive skills assessed in each of the tests.

4.3 Independent variables

There is considerable evidence in the literature that children's cognitive outcomes are influenced by the SES and other characteristics of their family, including parents' (especially mothers') education and family structure, as well as parental investment (see, for example, Field, 2010; Ermisch, 2008; Kiernan and Huerta, 2008; Kiernan and Mensah, 2011; Schoon et al., 2010, Melhuish et al., 2008). Thus, we include a range of variables in our empirical model which may impact on children's cognitive development. Identical questions are not asked in every sweep of the MCS since the focus is on making the survey questionnaire age-relevant.

4.3.1 Parental investment

The measures used for capturing parental investment are motivated by the Melhuish et al. (2008) paper; where the authors discuss the different home learning variables (like reading to the child) and the variables that capture the social/routine activities (like regular bed time) which constitute the home environment of (input into) the child. The measures used here are similar to those in the 'HOME' score, often used in the US based studies to capture inputs into the child; while some of the measures are directly linked to the cognitive development of the child (like reading to the child), the other are thought to provide an environment conducive to learning (like regular bed time); see Todd and Wolpin (2007), for further discussion and references.

A range of variables in the MCS record different dimensions of the 'home learning environment' (HLE) and social/routine activities. For the former, these include: how often the child is read to (5 categories from 'never' to 'every day'); how often the child paints or draws at home (5 categories); how often the child is helped with reading (5 categories); how often the child is helped with writing (5 categories); how often the child is helped with maths (5 categories); and how often the child visits the library (3 categories). In addition, fathers are also asked how often they read to their child (5 categories). These represent 6 of the 7 dimensions that Melhuish et al. (2008) utilise in constructing their HLE index for the Effective Pre-school, Primary & Secondary Education (EPPSE) data although here we take a latent variable approach rather than aggregating the scores on each dimension into a single numerical index as in Melhuish et al. (2008).

In addition to the home learning environment, a number of variables reflect parenting 'style', including socialisation, routine and discipline. In MCS1, when the children are 9 months old, we use the mother's response to four questions, designed to capture her attitudes towards child rearing; these include: importance for development of talking to the baby, cuddling the baby, stimulating the baby, and importance of regular sleep and eating time for the baby. For all the four questions mother responds on a five point Likert scale from 'strongly agree' to 'strongly disagree'. As the children get older we use variables that record the different ways that parents regulate their child's behaviour and their relationship with the child. These include: whether the child has a regular bedtime; how much TV the child watches; and whether the parents smack, or shout at the child if they are being naughty (3 categories).

Melhuish et al. (2008) in their analysis find that the home learning environment is more important, relative to the social/routine activities, for the cognitive development of the children. In our paper we do some robustness check where we use only the home learning measures of parental inputs, and drop the social/routine measures; the results (available on request) from this re-defined latent parental investment are almost identical, qualitatively and quantitatively, to the results presented in the paper.

4.3.2 Other characteristics

Variables in the vector X_t^θ which affect the latent cognitive ability are the child's age in months, and our main variable of interest, poverty status. It is important to control carefully for age since the cognitive tests are typically standardised against norms within a three month age range, and hence there may still be variation in cognitive development within these age groups (Connelly, 2013).

In vector X_t^λ we include a range of variables which, in the literature, have been shown to affect the parental inputs. It has been established in the literature that larger families have a negative impact on children's educational outcomes, justification for this comes from the resource (financial and time) constraints hypothesis (Iacovou, 2001; Black et al., 2005). To capture the resource constraints that the family might face we include two variables: number of other siblings in the household; and a dummy for a single parent household. We also include a poverty dummy in vector X_t^λ, as parental investment is one of the pathways via which poverty impacts children's development (Duncan et al. 1998). Finally we include mother's education (= 1 if NVQ 4 or above, corresponding to higher education or equivalent), to capture the fact that educated parents, especially mothers, systematically spend (invest) more time in their children (Guryan et al., 2008).

In vector X_0, which captures the initial conditions (both θ_0 and λ_0) we use: birth weight, a dummy for the first born children (=1 if the child is first born), mother's age at birth, mother's education at birth; and ethnicity of the child (=1 for white children). We include birth weight as it is often used as a proxy both for genetic endowment and for prenatal resource allocations by parents (Del Bono et al., 2012). Birth order has been shown to be significant in long term outcomes for children (Black et al., 2005), with first born children outperforming their younger siblings; to capture this we include a dummy for first born children. Mother's age and education at birth are included to capture any early disadvantage that the child might face, as young and less educated mothers often come from disadvantaged backgrounds which they pass on to their children (Hawkes and Joshi, 2012). Using the MCS data Dearden et al. (2006) have shown there are differences in birth outcomes (especially gestation and birth weight) by ethnicity and these differences remain even after controlling for various confounding factors; to capture these difference we include a dummy for ethnicity in our analysis.

5 Results

In this paper, the final sample for analysis comprises 8,741 children. These are the children for whom we have information across all four sweeps of the MCS; any loss of observations is due to attrition and missing information on relevant covariates. For details of the sample used, see Appendix A. Descriptive statistics (not weighted) for all the covariates and measurement variables are given in Table A2 in Appendix A.

5.1 Episodic and persistent poverty

Table 1 reports the episodic incidence of child poverty in our sample according to the measure described in sub-section 4.1. The incidence of poverty in the sample is about 20% over the four sweeps. This is rather lower than the incidence in the MCS sample when each sweep is examined separately, which is as high as 30%. However the rate of child poverty we find is similar to that reported in other studies using a balanced sample from the MCS (see, for example, Schoon et al., 2012).

Table 2 presents the individual poverty profiles, and the proportion of children who experience each poverty profile. The interpretation is as follows. For $T = 2$, there are 4 different poverty profiles: $PS = 00$ indicates no episodes of poverty while $PS = 01$ indicates that the child was not in poverty in the first sweep but was in poverty in the second sweep etc.. Analogously, for $T = 4$, there are 16 different poverty profiles, and $PS = 1111$ denotes being in poverty in all four sweeps. Finally, PPP is the prevalence of persistent poverty. As can be seen, (100-64.1=) 36% of all children have experienced at least one spell of relative poverty by the time they are aged 7. This is much higher than the 19% of children who are in poverty at age 7 (Table 1).

5.2 Child poverty and cognitive development

The correlations between the eight test scores are shown in Table 3. As can be seen, children's performance on each of the tests is positively correlated with their ranking on other tests. Moreover, the tests would appear to capture different dimensions of cognitive development: for example, the highest correlation in the ranking for BAS-PC(7) is the equivalent test taken two years earlier, BAS-PC(5), rather than with any other test administered at age 7.

Figure 2 shows the average test score ranking according to the poverty status of the household at the time the test was taken. As can be clearly seen, the average test scores for the non-poor children are significantly higher than the average scores for the children in poverty across all tests in all years. This finding is consistent with the previous literature in this area. Figure 3 shows the average scores for the two extreme poverty profiles: children who have never been in poverty and those that have always been in poverty at each sweep. The differences are larger here than in Figure 2 and this is prima facie evidence to suggest that there may be cumulative effects from persistent poverty on cognitive test score outcomes.

There may be a number of possible explanations for the differences observed in the raw data. For example: even though the test scores are age-adjusted (within 3 month age bands), children's cognitive development is extremely rapid in their early years, and the tests are not administered to all children at exactly the same age. Hence the age of the child when tested can impact significantly on the test score outcome. Also, as suggested by the previous literature and the Field (2010) review, the background characteristics of the child, parental investment and parenting style may also influence the test scores. Our estimation method directly addresses these various issues.

5.2.1 Baseline model

The results from the two different SEM specifications, of the baseline model, are reported in Table 4 (for episodic poverty) and Table 5 (for persistent poverty), respectively. What we have reported are the estimated coefficients of the structural model (equations (1) to (3)). The coefficients (factor loadings) from the measurement models (equations (4) and (5)) are available on request. Panel A in both tables reports estimates of equation (1) and Panel B reports the estimated coefficients of equation (2).

Findings consistent across the two specifications are as follows. From Panel A of both Tables 4 and 5, there is evidence of clear persistence with respect to cognitive ability (θ_t) – previous latent cognitive ability is positively and significantly correlated with current latent cognitive ability. Thus a child developing well at age 3 is also likely to be doing well at age 5 and age 7, even after controlling for all other factors. From Table 5, Panel A, a one standard deviation (SD) higher latent cognitive ability at age 3 is associated with a 0.694 SD higher latent cognitive ability at age 5; this is equivalent to 19 percentile ranks; similarly a one SD higher latent ability at age 5 is associated with a 0.894 SD higher latent ability at age 7; equivalent to 25 percentile ranks. The percentile rank changes are calculated by multiplying the observed SD changes in the latent variable by the SD of the underlying measures; all the test scores have SD of around 28 (see Table A2 in Appendix). Also, higher birth weight, higher mothers age at the time of birth, having a mother with higher education (NVQ 4 or above), being first born, and being white are all associated with higher development at 9 months.

Panel A from both Tables 4 and 5, also reveals that lagged latent parental investment (λ_{t-1}) has a positive and significant impact on a child's latent cognitive ability, at all ages. From Table 5, if parental investment at age 3 increases by one SD, then the child's cognitive ability at age 5 would increase by 0.269 SD, equivalent to an increase of 8 percentile ranks. Finally, panel B reveals that mothers with higher education on average provide higher levels of parental investment at all ages while having other siblings in the household significantly reduces the level of parental investment in the child at age 3 and age 5.

Current poverty has a negative and a significant impact on cognitive development, at all ages, in both specifications. The only exception is the insignificant effect of current poverty on development at 9 months in specification 2 reported in Table 5. Poverty at 9 months has a significant effect on parental investment at 9 months (in both specifications) and at 3 years (in specification 2).

To capture fully the impact of persistent poverty on the cognitive ability of the child we now focus on the estimates from specification 2 as presented in Table 5. At age 3, a child who is in poverty can be expected to be 0.263 SD (7 percentile ranks) below the latent cognitive ability score of a child who has no experience of poverty. However, a child who has been persistently in poverty since birth can be expected to be (0.263+0.189=) 0.452 SD (13 percentile ranks) below the latent cognitive ability score of the child who has never been in poverty.

As noted above, one important benefit of the SEM approach is that it allows us to separately identify the direct and the indirect effects of poverty on latent cognitive ability. These are presented in Table 6, for the SEM specification 2 in Table 5. The interpretation of the table is as follows. Reading down the first column, the total effect of $P1$ (poverty at 9 months, or birth) on latent cognitive ability at age 3 is 0.254 SD. The direct effect is 0.189 (the coefficient on the poverty dummy in Table 5). However, there is also an indirect effect through the impact of $P1$ on latent parental investment in the child at 9 months, λ_1, and through past cognitive development, θ_1, which then affects the child's cognitive ability. The indirect via parental investment is just –0.006 SD, and the indirect effect via past development is

–0.059; both are not significant. The total effect of $P1$ on latent cognitive ability is then the sum of the direct and indirect effects.

We can perform similar calculations at each age. For example, at age 7, while the direct effect of poverty at 9 months ($P1$) on latent cognitive development is not statistically significant, the indirect effect of $P1$ is significantly negative. These indirect effects of poverty at 9 months on cognitive development at age 7 are manifested through latent parental investment, with effects from age 3 years being significant, as well as through poorer past cognitive ability, especially at age 3.

The direct effect of being in persistent poverty on cognitive development at age 7, if we just consider the statistically significant effects is: (–0.084–0.098 =) –0.182 SD; 5 percentile ranks lower than the child who has never been in poverty. However the total (direct + indirect) effect of being persistently in poverty is (–0.232 –0.196 –0.149 –0.084 =) –0.661 SD; which translates to almost 19 percentile ranks lower than the child who has never been in poverty. Three-quarters of the impact of being in poverty on children's cognitive development is driven by its indirect effects on parental investment and the persistence in cognitive ability (mainly the latter).

5.2.2 Model with endogenous inputs

The results for the model with endogenous inputs are presented in Tables 7, 8 and 9. In the first stage, we use the following proxies (R_t) for θ_t: number of siblings in the households, single parent household, and whether or not mother works. Justification for these comes from the resource constraint hypothesis mentioned in section 4.3.2 above. (Results for the first stage are available on request.)

Table 7 gives the result for specification 1 but this time taking into account the endogeneity of inputs; these results need to be compared with the results in Table 4. In Panel B, in the model for latent parental investment we now have current latent ability of the child (equation (10)). For all waves the coefficient on current cognitive ability of the child is insignificant. Overall the only difference of taking into account endogeneity of inputs, relative to the baseline model is that coefficient on poverty dummy in latent parental investment equation at age 9 months is now insignificant. Similarly comparing specification 2 from the baseline model (Table 5) to the model with endogeneity of inputs (Table 8) there is no change in results quantitatively or qualitatively; the only exception being that poverty dummy in the equation for latent parental investment at 9 months (panel B, Table 8) is now insignificant.

Our finding is not at odds with the finding in the literature. Cunha and

Heckman (2008) estimate a linear technology function as we do here and find that allowing for endogeneity in inputs does not change their estimates from the baseline model. Similarly Cunha et al. (2010) estimate a non-linear technology function and find that allowing for endogeneity in inputs does not change their estimates from the baseline model.

6 Concluding discussion

There is a consensus in the literature that family background, parental inputs, and income poverty can all have significant effects on children's early cognitive development. Much has been written about the importance of education and cognitive skills in early years for future life trajectories. Given the high degree of persistence in ability formation, differences in early year's ability are one of the main sources of variation in socioeconomic outcomes across individuals.

This paper documents the impact of both episodic poverty and persistent poverty on the cognitive development of children in the UK. Controlling for parental investments and family circumstances, we find evidence of a direct negative impact of income poverty on the cognitive development of children, consistent with the recent evidence of Dahl and Lochner (2012) for the US. Moreover, as in Schoon et al (2012), we find that persistent poverty has a larger cumulative negative impact on children's cognitive development than episodic poverty.

As a robustness check, we experimented with using the log of household equivalised income instead of the poverty dummy in our model. The estimated coefficient on log income was positive indicating a non-linear relationship between ability formation and income. This finding of diminishing returns to income is also consistent with Dahl and Lochner (2012) who found that the link between ability and income is stronger at lower levels of income. Including log income instead of poverty status had no qualitative or quantitative impact on the other estimated coefficients in our model (results available on request).

Taking into account both the direct effects and the indirect effects of poverty on parental investment, the cognitive development test scores for children who are persistently in poverty throughout their early years are almost 20 percentile ranks lower at age 7 than for children who have never experienced poverty. This result is robust to the parental investment and family background of the child. Given the evidence of strong persistence in cognitive development, any detrimental impact of poverty on children's cognitive development in their early years is likely to have a lasting legacy effect well beyond the particular episodes of poverty. Poverty at birth and/or age 3 can therefore seriously impact on children's development by the time they start school and thereafter well into their adult lives. This suggests that policy targeted at poverty alleviation should be directed at these very early years.

As in Schoon et al. (2012) and Kiernan and Menash (2011), we also find that positive parenting can mitigate the impact of poverty to some extent. Those who would argue that the quality of parenting skills and investment are important for children's development may therefore draw some encouragement from our results. It is clear that, controlling for income, parental investments do indeed impact significantly on children's cognitive ability. However, we find evidence that poverty also adversely affects parental investments, especially in the very early years, and this subsequently has a negative impact upon children's cognitive development. Thus poverty not only has a direct negative impact on children's cognitive development, but also has an indirect effect through its adverse impact on parental inputs. However, this result weakens when the endogeneity of inputs is taken into account.

While we have focussed solely on cognitive skills, it has been established in the literature that non-cognitive development is also important. For their US data, Cunha et al. (2010) find that including non-cognitive ability lowers the estimates of self-productivity i.e. the estimated coefficient on lagged cognitive ability. The impact of neglecting non-cognitive skills in our model is therefore an empirical question for future work in this area.

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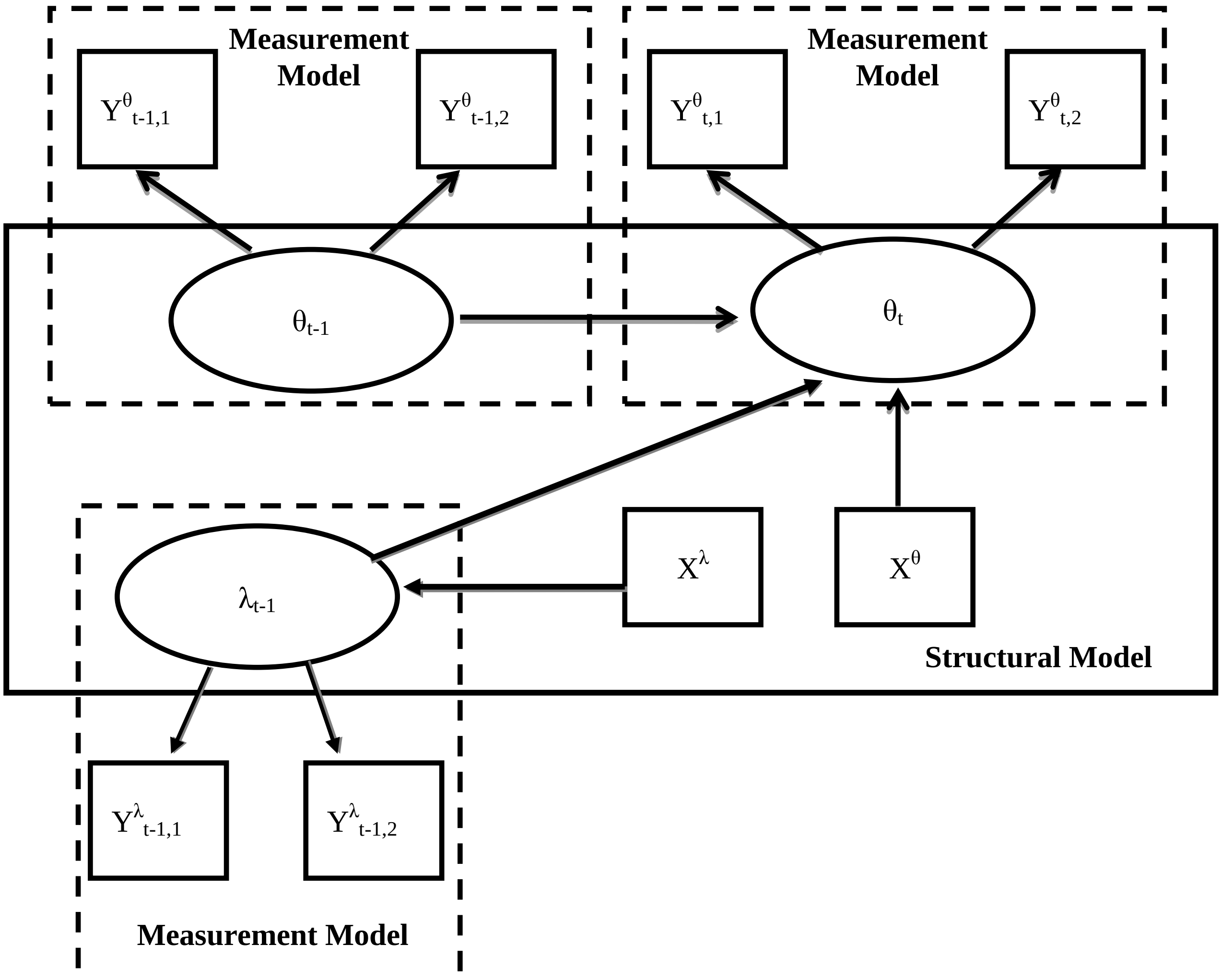
Figure 1: Structural and measurement model



Notes: The figure illustrates the dynamics of the structural and the measurement models for the baseline specification (i.e. the specification without endogenous inputs), outlined in section 3 of the paper, with two time periods; in the paper we have four time periods and initial conditions. The unobservable (latent) variables are in ellipses and the observable variables in rectangles. The solid rectangle gives us the structural relationship (given by equations (1) and (2) in the paper) and the dotted rectangles represent the measurement models (given by equations (4) and (5) in the paper). The single headed arrows illustrate the theorised unidirectional causal relationships between variables. For the structural model: ability at time t (θ_t) is determined by past ability (θ_{t-1}), past parental investment (λ_{t-1}), and covariates (X^{θ}); parental investment is in turn influenced by covariates X^{λ}. If we take the first two time periods (i.e. t = 2) then there will be initial conditions represented by X_0, which will influence θ_1. Each unobservable latent variable (θ and λ) is measured by a series of observable variables (Y^{θ} and Y^{λ}, respectively); this measurement model will vary over time.

Figure 2: Average test rank scores by poverty state: period-by-period

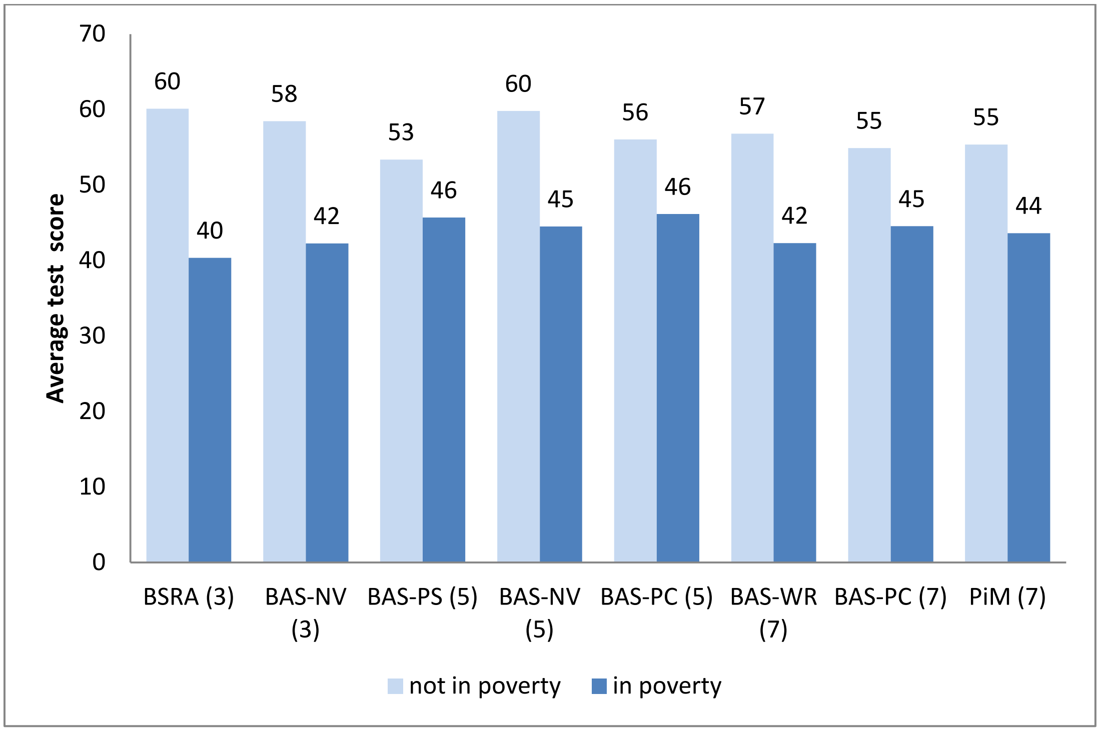


Figure 3: Average test rank scores by poverty state: never *vs* always in poverty

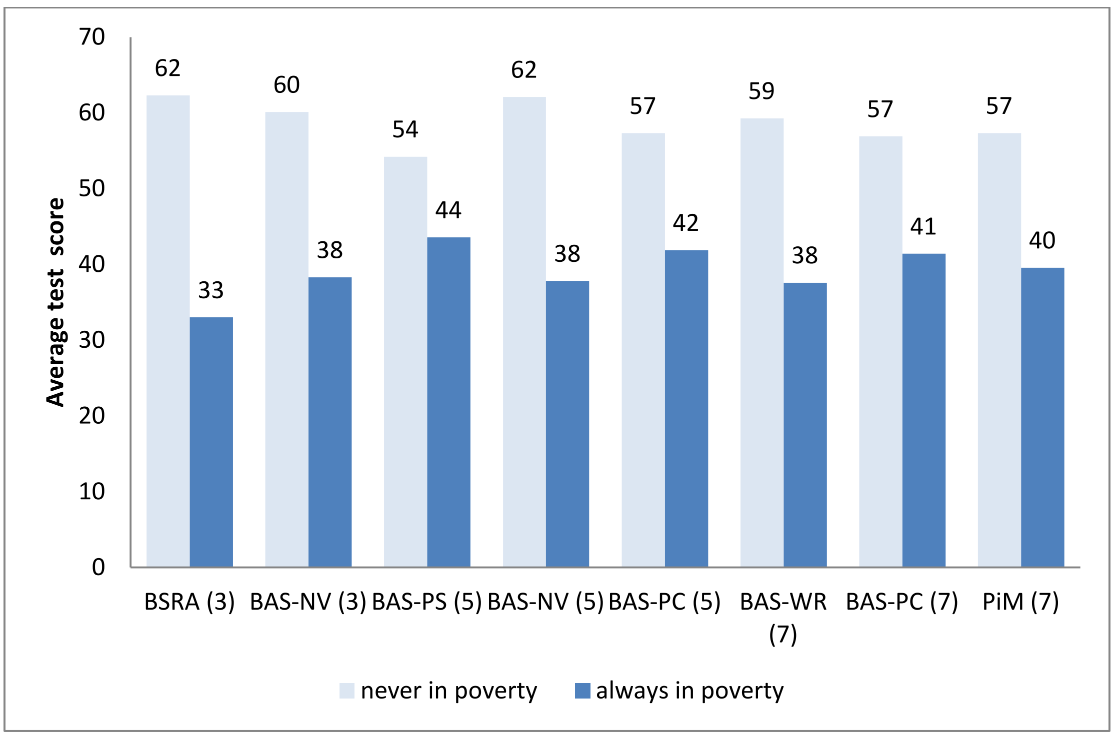


Table 1: Poverty incidence

Sweep	MCS1 2001-2	MCS2 2004-5	MCS3 2006	MCS4 2008
Average age of the child	9 months	3 years	5 years	7 years
Poverty rate	20.2	21.2	21.5	18.7
Sample size	*8,741*	*8,741*	*8,741*	*8,741*

Notes to Table 1:

1. Poverty rate is based on the poverty indicators provided by the MCS (see text for further inforamtion). The threshold is household equivalised income less than 60% of median household income where income is equivalised according to the OECD equivalence scale.
2. In all reported statistics, the MCS weights which take into account the survey design, non-response bias and attrition over time have been taken into account.

Table 2: The prevalence of persistent poverty

	Time horizon $T=2$		Time horizon $T=3$		Time horizon $T=4$	
Row	PS	PPP	PS	PPP	PS	PPP
1	00	72.1	000	67.0	0000	64.1
2	01	7.7	001	5.1	0001	2.9
3	10	6.7	010	4.1	0010	3.5
4	11	13.5	100	4.4	0100	3.4
5			101	2.3	1000	3.8
6			011	3.6	0101	0.7
7			110	2.9	1001	0.6
8			111	10.5	1010	1.1
9					0011	1.6
10					0110	1.4
11					1100	1.8
12					1011	1.2
13					1101	1.2
14					0111	2.2
15					1110	2.4
16					1111	8.2
		100.0%		100.0%		100.0%

Notes to Table 2:

1. PS is the poverty profile or status. The digits describe the poverty status in each sweep, so that, for example, 001 represents individuals who were not in poverty in MCS1 nor in MCS2 but are in poverty in MCS3 – see text for details.
2. PPP is prevalence of persistent poverty (i.e. the proportion of the sample in each poverty state) calculated using the poverty rate measure reported in Table 1.
3. In all reported statistics, the MCS weights which take into account the survey design, non-response bias and attrition over time have been taken into account.

Table 3: Cognitive assessment scores

		MCS2: age 3		MCS3: age 5			MCS4: age 7		
		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
	Test	BSRA(3)	BAS-NV(3)	BAS-PS(5)	BAS-NV(5)	BAS-PC(5)	BAS-WR(7)	BAS-PC(7)	PiM(7)
1	BSRA(3)	1.000							
2	BAS-NV(3)	0.557	1.000						
3	BAS-PS(5)	0.270	0.206	1.000					
4	BAS-NV(5)	0.489	0.493	0.295	1.000				
5	BAS-PC(5)	0.328	0.245	0.319	0.317	1.000			
6	BAS-WR(7)	0.435	0.298	0.230	0.359	0.324	1.000		
7	BAS-PC(7)	0.325	0.247	0.300	0.290	0.552	0.317	1.000	
8	PiM(7)	0.370	0.262	0.307	0.365	0.383	0.490	0.468	1.000

Notes to Table 3:

1. The tests scores are:
   BSRA(3) – percentile rank Bracken School Readiness Assessment, age 3
   BAS-NV(3) – percentile rank BAS naming vocabulary, age 3
   BAS-PS(5) – percentile rank BAS picture similarity, age 5
   BAS-NV(5) – percentile rank BAS naming vocabulary, age 5
   BAS-PC(5) – percentile rank BAS pattern construction, age 5
   BAS-WR(7) – percentile rank BAS word reading, age 7
   BAS-PC(7) – percentile rank BAS pattern construction, age 7
   PiM(7) – percentile rank Progress in Maths, age 7
2. Correlations are (weighted) pairwise Pearsonian correlations between the percentile ranking on each test.
3. All correlations are statistically significantly different from zero at the $p = 0.01$ level.
4. In all reported statistics, the MCS weights which take into account the survey design, non-response bias and attrition over time have been taken into account.

Table 4: Specification 1 – Latent cognitive development and the incidence of poverty

Panel A

	Latent cognitive development θ_t							
	MCS1: age 9 months		MCS2: age 3 years		MCS3: age 5 years		MCS4: age 7 years	
	θ_1		θ_2		θ_3		θ_4	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
θ_{t-1}	-	-	0.504	0.000	0.700	0.000	0.908	0.000
λ_{t-1}	-	-	0.072	0.001	0.267	0.000	0.076	0.000
P_t	-0.468	0.000	-0.249	0.000	-0.132	0.005	-0.087	0.070
Age (months)	0.017	0.450	0.024	0.123	-0.055	0.032	0.076	0.003
Initial conditions								
Birth weight	0.287	0.000	-	-	-	-	-	-
First born	0.195	0.009	-	-	-	-	-	-
Mother's age (years)	0.197	0.000	-	-	-	-	-	-
Mother's education	0.391	0.001	-	-	-	-	-	-
Ethnicity: white	0.463	0.000	-	-	-	-	-	-

Panel B

	Latent parental investment λ_t					
	MCS1: age 9 months		MCS2: age 3 years		MCS3: age 5 years	
	λ_1		λ_2		λ_3	
	effect	p-value	effect	p-value	effect	p-value
P_t	-0.095	0.071	-0.016	0.722	-0.025	0.597
Mother's education	0.148	0.107	0.244	0.006	0.160	0.025
Other siblings	0.008	0.853	-0.108	0.013	-0.169	0.000
Single parent household	0.041	0.549	0.012	0.875	-0.102	0.089

Notes to Table 4:

1. Panel A gives the estimates of the structural parameters in equation (1) in the paper, where latent ability at time t (θ_t) is determined by past latent ability (θ_{t-1}), past latent parental investment (λ_{t-1}), and a set of control variables including poverty at time t (P_t). For the first period, t=1, we have a set of covariates which capture the initial conditions (X_0); equation (3) in the paper. Panel B gives the estimates of the structural parameters in equation (2) in the paper, where parental investment at time t (λ_t) is determined by a set of control variables including poverty at time t (P_t).
2. All the reported coefficients are standardized. For the continuous independent variables, the coefficient represents the change in the dependent variable associated with a one standard deviation (SD) change in the independent variable. For the binary independent variables the coefficient represents the change associated with a shift in the variable from 0 to 1.
3. In all reported statistics, the MCS weights which take into account the survey design, non-response bias and attrition over time have been taken into account.
4. Sample size: 8,741; CFI = 0.714; RMSE = 0.029.

Table 5: Specification 2 – Latent cognitive development and the persistence of poverty

Panel A

	Latent cognitive development θ_t							
	MCS1: age 9 months		MCS2: age 3 years		MCS3: age 5 years		MCS4: age 7 years	
	θ_1		θ_2		θ_3		θ_4	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
θ_{t-1}	-	-	0.449	0.000	0.694	0.000	0.894	0.000
λ_{t-1}	-	-	0.072	0.001	0.269	0.000	0.076	0.000
P_t	-0.131	0.174	-0.263	0.000	-0.099	0.056	-0.084	0.077
P_{t-1}	-	-	-0.189	0.004	0.076	0.148	-0.058	0.209
P_{t-2}	-	-	-	-	-0.058	0.216	-0.098	0.030
P_{t-3}	-	-	-	-	-	-	-0.001	0.985
Age	0.015	0.515	0.024	0.115	-0.055	0.032	0.076	0.004
Initial conditions								
Birth weight	0.311	0.000	-	-	-	-	-	-
First born	0.208	0.008	-	-	-	-	-	-
Mother's age	0.192	0.000	-	-	-	-	-	-
Mother's education	0.402	0.001	-	-	-	-	-	-
Ethnicity: white	0.457	0.000	-	-	-	-	-	-

Panel B

	Latent parental investment λ_t					
	MCS1: age 9 months		MCS2: age 3 years		MCS3: age 5 years	
	λ_1		λ_2		λ_3	
	effect	p-value	effect	p-value	effect	p-value
P_t	-0.087	0.099	-0.021	0.659	-0.024	0.619
P_{t-1}	-	-	-0.084	0.082	0.026	0.563
P_{t-2}	-	-	-	-	-0.013	0.776
Mother's education	0.150	0.101	0.250	0.005	0.161	0.025
Other siblings	0.008	0.852	-0.108	0.013	-0.169	0.000
Single parent household	0.041	0.549	0.012	0.872	-0.102	0.091

Notes to Table 5:

1. Refer to notes to Table 4.
2. Sample size: 8,741; CFI = 0.713; RMSE = 0.029.

Table 6: Identifying direct and indirect effects of *persistent* poverty on cognitive development

	Latent cognitive development θ_t					
	MCS2: age 3		MCS3: age 5		MCS4: age 7	
	θ_2 effect	p-value	θ_3 effect	p-value	θ_4 effect	p-value
Effects from P1:						
Total effect on θ_t	-0.254	0.000	-0.257	0.000	-0.232	0.000
Direct effect on θ_t	-0.189	0.004	-0.058	0.216	-0.001	0.985
Indirect effect on θ_t	-0.065	0.131	-0.199	0.000	-0.231	0.000
Indirect via λ_1	-0.006	0.148	-0.004	0.145	-0.004	0.147
Indirect via λ_2			-0.023	0.088	-0.020	0.088
Indirect via λ_3					-0.001	0.776
Indirect via θ_1	-0.059	0.173	-0.041	0.177	-0.037	0.176
Indirect via θ_2			-0.131	0.004	-0.117	0.004
Indirect via θ_3					-0.052	0.217
Effects from P2:						
Total effect on θ_t	-0.263	0.000	-0.112	0.028	-0.196	0.000
Direct effect on θ_t	-0.263	0.000	0.076	0.148	-0.098	0.030
Indirect effect on θ_t			-0.188	0.000	-0.098	0.032
Indirect via λ_2			-0.006	0.659	-0.005	0.659
Indirect via λ_3					0.002	0.569
Indirect via θ_2			-0.182	0.000	-0.163	0.000
Indirect via θ_3					0.068	0.147
Effects from P3:						
Total effect on θ_t			-0.099	0.056	-0.149	0.003
Direct effect on θ_t			-0.099	0.056	-0.058	0.209
Indirect effect on θ_t					-0.090	0.056
Indirect via λ_3					-0.002	0.623
Indirect via θ_3					-0.088	0.057
Effects from P4:						
Total effect on θ_t					-0.084	0.077
Direct effect on θ_t					-0.084	0.077

Notes to Table 6:

1. Refer to notes to Table 4.
2. P1 – poverty status at 9 months
   P2 – poverty status at 3 years
   P3 – poverty status at 5 years
   P4 – poverty status at 7 years

Table 7: Specification 1 – Latent cognitive development and the incidence of poverty (Endogenous inputs)

Panel A

	Latent cognitive development θ_t							
	MCS1: age 9 months		MCS2: age 3 years		MCS3: age 5 years		MCS4: age 7 years	
	θ_1		θ_2		θ_3		θ_4	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
θ_{t-1}	-	-	0.557	0.000	0.693	0.000	0.905	0.000
λ_{t-1}	-	-	0.072	0.001	0.266	0.000	0.076	0.000
P_t	-0.462	0.000	-0.246	0.000	-0.131	0.006	-0.086	0.072
Age	0.018	0.412	0.025	0.106	-0.055	0.033	0.076	0.004
Initial conditions								
Birth weight	0.264	0.000	-	-	-	-	-	-
First born	0.184	0.009	-	-	-	-	-	-
Mother's age	0.201	0.000	-	-	-	-	-	-
Mother's education	0.373	0.001	-	-	-	-	-	-
Ethnicity: white	0.471	0.000	-	-	-	-	-	-

Panel B

	Latent parental investment λ_t					
	MCS1: age 9 months		MCS2: age 3 years		MCS3: age 5 years	
	λ_1		λ_2		λ_3	
	effect	p-value	effect	p-value	effect	p-value
P_t	-0.079	0.135	-0.029	0.527	-0.033	0.494
θ_t	-	-	-0.161	0.138	-0.032	0.673
Mother's education	0.142	0.123	0.254	0.004	0.161	0.025
Other siblings	0.025	0.656	-0.108	0.018	-0.171	0.000
Single parent household	0.054	0.638	-0.095	0.394	-0.098	0.102

Notes to Table 7:

1. Panel A gives the estimates of the structural parameters in equation (1) in the paper, where latent ability at time t (θ_t) is determined by past latent ability (θ_{t-1}), past latent parental investment (λ_{t-1}), and a set of control variables including poverty at time t (P_t). For the first period, t=1, we have a set of covariates which capture the initial conditions (X_0); equation (3) in the paper. Panel B gives the estimates of the structural parameters in equation (10) in the paper, where parental investment at time t (λ_t) is determined by ability at time t (θ_t) and a set of control variables including poverty at time t (P_t).
2. All the reported coefficients are standardized. For the continuous independent variables, the coefficient represents the change in the dependent variable associated with a one standard deviation (SD) change in the independent variable. For the binary independent variables the coefficient represents the change associated with a shift in the variable from 0 to 1.
3. Sample size: 8,741; CFI = 0.717; RMSE = 0.028.
4. In all reported statistics, the MCS weights which take into account the survey design, non-response bias and attrition over time have been taken into account.

Table 8: Specification 2 – Latent cognitive development and the persistence of poverty (Endogenous inputs)

Panel A

	Latent cognitive development θ_t							
	MCS1: age 9 months		MCS2: age 3 years		MCS3: age 5 years		MCS4: age 7 years	
	θ_1		θ_2		θ_3		θ_4	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
θ_{t-1}	-	-	0.449	0.000	0.698	0.000	0.894	0.000
λ_{t-1}	-	-	0.072	0.001	0.268	0.000	0.075	0.000
P_t	-0.094	0.361	-0.263	0.000	-0.097	0.064	-0.086	0.072
P_{t-1}	-	-	-0.215	0.002	0.083	0.123	-0.062	0.184
P_{t-2}	-	-	-	-	-0.047	0.342	-0.101	0.026
P_{t-3}	-	-	-	-	-	-	-0.011	0.809
Age	0.016	0.500	0.025	0.113	-0.055	0.033	0.076	0.004
Initial conditions								
Birth weight	0.312	0.000	-	-	-	-	-	-
First born	0.206	0.008	-	-	-	-	-	-
Mother's age	0.192	0.000	-	-	-	-	-	-
Mother's education	0.400	0.001	-	-	-	-	-	-
Ethnicity: white	0.459	0.000	-	-	-	-	-	-

Panel B

	Latent parental investment λ_t					
	MCS1: age 9 months		MCS2: age 3 years		MCS3: age 5 years	
	λ_1		λ_2		λ_3	
	effect	p-value	effect	p-value	effect	p-value
P_t	-0.073	0.170	-0.035	0.475	-0.031	0.517
P_{t-1}	-	-	-0.116	0.019	0.021	0.636
P_{t-2}	-	-	-	-	-0.027	0.563
θ_t			-0.161	0.138	-0.032	0.673
Mother's education	0.146	0.112	0.264	0.003	0.162	0.025
Other siblings	0.026	0.651	-0.108	0.018	-0.171	0.000
Single parent household	0.054	0.638	-0.095	0.391	-0.098	0.102

Notes to Table 8:

1. Refer to notes to Table 7.
2. Sample size: 8,741; CFI = 0.716; RMSE = 0.028.

Table 9: Identifying direct and indirect effects of *persistent* poverty on cognitive development (Endogenous inputs)

	Latent cognitive development θ_t					
	MCS2: age 3		MCS3: age 5		MCS4: age 7	
	θ_2 effect	p-value	θ_3 effect	p-value	θ_4 effect	p-value
Effects from P1:						
Total effect on θ_t	-0.262	0.000	-0.261	0.000	-0.246	0.000
Direct effect on θ_t	-0.215	0.002	-0.047	0.342	-0.011	0.809
Indirect effect on θ_t	-0.047	0.032	-0.214	0.000	-0.235	0.000
Indirect via λ_1	-0.005	0.210	-0.004	0.212	-0.003	0.211
Indirect via λ_2			-0.031	0.022	-0.028	0.022
Indirect via λ_3					-0.002	0.566
Indirect via θ_1	-0.042	0.036	-0.029	0.362	-0.026	0.360
Indirect via θ_2			-0.150	0.002	-0.134	0.002
Indirect via θ_3					-0.042	0.342
Effects from P2:						
Total effect on θ_t	-0.263	0.000	-0.109	0.035	-0.197	0.000
Direct effect on θ_t	-0.263	0.000	0.083	0.123	-0.101	0.026
Indirect effect on θ_t			-0.192	0.000	-0.096	0.039
Indirect via λ_2			-0.009	0.477	-0.008	0.476
Indirect via λ_3					0.002	0.640
Indirect via θ_2			-0.183	0.000	-0.164	0.000
Indirect via θ_3					0.074	0.125
Effects from P3:						
Total effect on θ_t			-0.097	0.064	-0.152	0.003
Direct effect on θ_t			-0.097	0.064	-0.062	0.184
Indirect effect on θ_t					-0.089	0.064
Indirect via λ_3					-0.002	0.524
Indirect via θ_3					-0.087	0.067
Effects from P4:						
Total effect on θ_t					-0.086	0.072
Direct effect on θ_t					-0.086	0.072

Notes to Table 9:

1. Refer to notes to Table 7.
2. P1 – poverty status at 9 months
   P2 – poverty status at 3 years
   P3 – poverty status at 5 years
   P4 – poverty status at 7 years

Appendix A: Sample construction

Table A1: Productive Interviews

MCS Sweep	Number of Households	Number of Children
1	18,552	18,818
2	15,590	15,808
3	15,246	15,459
4	13,857	14,043

MCS surveyed 18,552 households (with 18,818 children, including twins and triplets) for the first sweep, which were then to be followed over time. In the second sweep they added 692 additional households (referred to as the ‘new families’) which should have been eligible for the first sweep but were missed. The productive households (i.e. the households that completed the survey) at each sweep are shown in the table above. Of the 18,552 families which were productive at sweep 1, only 11,721 (61%) were productive in all four sweeps. Refusing to participate was the biggest reason for attrition (other reasons being: emigration, failure to contact, death, etc.); though there are families which have declined to be interviewed in one sweep but then participated in subsequent sweeps. The refusal rates are higher for the ‘disadvantaged’ and ‘ethnic minority’ families, relative to the ‘advantaged’ families, across all the four countries of the UK. For further details on the response rates in the MCS, see Ketende (2010). Once a family has participated in the survey, non-response on specific questions is low, with the exception of questions relating to ‘family income’; and this non-response is not random. Analysis by Hawkes and Lewis (2008) shows that self-employed and families with low income are more likely to ‘refuse to’ answer the questions related with income in MCS.

For our analysis we need information on children from all four sweeps, so our starting sample is the 11,721 families which were productive in all four sweeps of MCS. By definition this will exclude the ‘new families’ which were added in the second sweep. Further in our analysis we use only one child per family (of the twins and triplets, we keep only one child). Any further loss of observations is because of non-response on the relevant covariates used in our analysis. The final sample we work with is 8,741 children, from 8,741 families.

Table A2: Unweighted descriptive statistics for the variables used in the analysis

	MCS1: 9 months		MCS2: 3 years		MCS3: 5 years		MCS4: 7 years	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Measures for cognitive ability:								
Gross motor function delay [1] (1 = delay)	0.121	-						
Fine motor function delay [1] (1 = delay)	0.134	-						
Communicative gestures delay [1] (1 = delay)	0.399	-						
BSR composite score			53.5	28.3				
BAS Naming Vocabulary			53.3	28.1	53.5	28.0		
BAS Picture Similarity					51.3	28.4		
BAS Pattern Construction					52.2	28.6	51.8	28.6
BAS Word Reading							51.6	28.5
Progress in Maths							51.7	28.3
Measures for Parental Investment and Style:								
Importance of stimulating the baby [2]	1.373	0.586						
Importance of talking to baby [2]	1.166	0.401						
Importance of cuddling baby [2]	1.167	0.423						
Importance of regular sleeping/eating for baby [2]	1.573	0.714						
Mother reads to the child [3]			3.336	0.987	3.276	0.915		
Father reads to the child [3]			2.060	1.397	1.990	1.328		
Child paints/draws at home [3]			3.168	0.926	1.980	0.980		
Child helped with alphabet/reading [3]			2.147	1.383	3.388	0.906		
Child helped with writing [3]					2.692	1.190		
Child taken to the library [4]			0.495	0.747	0.446	0.651		
Child helped with counting/maths [3]			3.184	1.029	2.819	1.136		
Regular bedtime [5]			2.159	0.893	2.502	0.775		
Watching TV [6]			1.924	0.649	1.913	0.637		
Shout at the child [7]			1.628	0.541	1.712	0.506		
Smack the child [7]			0.821	0.668	0.681	0.671		
Other covariates:								
Age of the child in months	9.18	0.50	37.49	2.26	62.62	2.92	86.81	2.99

	MCS1: 9 months		MCS2: 3 years		MCS3: 5 years		MCS4: 7 years	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Mother's education[1] (1= NVQ 4 and higher)	0.367	-	0.367	-	0.403	-		
Number of other siblings in the house	0.862	0.979	1.128	0.996	1.315	0.996		
Single parent household[1] (1 = yes)	0.128	-	0.149	-	0.169	-		
Mother works[1] (1 = yes)	0.555	-	0.581	-	0.630	-		
Initial Conditions:								
Ethnicity[1] (1 = white; 0 = otherwise)	0.894	-						
Birth weight (kgs)	3.382	0.581						
Mother's age at birth of the cohort child (years)	29.05	5.704						
First born1 (1 = if the cohort child is first born)	0.431	-						

Notes to Table A2:

1. dummy variable
2. coded as: 1 = strongly agree, 2 = agree, 3 = neither agree nor disagree, 4 = disagree, 5 = strongly disagree
3. coded as: 0 = not at all, 1 = once/twice/less a month, 2 = once/twice a week, 3 = several times a week, 4 = every day
4. coded as: 0 = never/special occasions, 1 = at least once a month, 2 = once a week or more
5. coded as: 0 = never or almost never, 1 = sometimes, 2 = usually, 3 = always
6. coded as: 0 = none, 1 = up to one hour a day, 2 = between 1 and 3 hours a day, 3 = more than three hours a day
7. coded as: 0 = never, 1 = rarely, 2 = more than once a month