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# Persistent poverty and children's cognitive development: evidence from the UK Millennium Cohort Study

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**Summary.** We use data from the four sweeps of the UK Millennium Cohort Study of children born at the turn of the 21st century to document the effect that poverty, and in particular persistent poverty, has on their cognitive development in their early years. Using structural equation modelling, we show that children born into poverty have significantly lower test scores at age 3, age 5 and age 7 years, and that continually living in poverty in their early years has a cumulative negative effect on their cognitive development. For children who are persistently in poverty throughout their early years, their cognitive development test scores at age 7 years 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

'Give me a child until he is seven and I will give you the man' (attributed to St Francis Xavier (1506–1552))

## 1. Introduction

In this paper we investigate the effect 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 19000 children born in the UK around the turn of the 21st 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 effect of living in poverty on their cognitive development. We assess the effect of both *episodic* (period-by-period) poverty and *persistent* poverty, to examine the cumulative effect 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; Gregg and Macmillan, 2009). Specifically, there is a large literature exploring the effect of poverty and low income on the development of children. Brooks-Gunn and Duncan (1997) reviewed evidence from numerous national longitudinal data sets for the US 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 that they described points towards the negative effect of poverty on child development.

The link between early educational attainment and socio-economic status (SES) of families has also been emphasized by policy makers. In March 2010, the UK Child Poverty Act enshrined

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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 recognized, with a target to be 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 that 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 years (‘foundation years’ in the terminology of the review).

The effect of persistent 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 examine systematically and robustly the effect 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 effect on their cognitive development.

The remainder of this paper is organized 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.

The programs that were used to analyse the data can be obtained from

<http://wileyonlinelibrary.com/journal/rss-datasets>

## 2. Background literature

When discussing the effect of poverty on children, the timing and the duration of poverty are 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 influence on their development and ability formation (Knudsen *et al.*, 2006). Thus it is not surprising that the effect of poverty is also found to be greater for poverty experienced in early childhood (usually defined as from birth to 7 years) relative to late childhood or adolescence. Duncan *et al.* (2010) used the US Panel Study of Income Dynamics and found significant and quantitatively large detrimental effects of poverty in the early years (from 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 that was given by Heckman and Masterov (2007), where development in later years is dependent on 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) used 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. Using data from Indonesia, Pakpahan *et al.* (2009) found 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 that are associated with poverty which in themselves have a negative effect 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 or single mother) by itself is associated with poorer outcomes for children (Mayer, 1997). Dahl and Lochner (2012) used an instrumental variable approach to establish causality from family income to child development. Even after controlling for numerous confounding factors they found that family income has an independent causal link to child development: more so for the low income families.

There are several pathways through 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 that is often stressed in the literature is the home environment, which is taken to include everything from the quality and quantity of inputs (learning resources, toys, etc.) that are 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 child, such as government programmes or low income (Becker and Tomes, 1986). Using the data for the USA from the Panel Study of Income Dynamics and the 'Infant health and development program', Brooks-Gunn *et al.* (1993) showed that provision of learning experiences in the home can account for up to half of the effect of poverty on the intelligence quotient scores of 5-year-old children. Similarly, a more recent study by Gelber and Isen (2013) analysing the Head Start programme from the USA found that a significant part of the effect of the programme on child development was via the increased parental investment, as a result of participation in the programme.

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

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 is 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 we measure it with error. Cunha and Heckman (2008) discussed the issue in terms of 'measurement error' whereas Jerrim and Vignoles (2013) focused on the implications in terms of 'regression to the mean'. The basic argument is that the imperfection or 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 achieving a relatively high or low score on a given day is likely to be followed by a less extreme score (i.e. it will be respectively lower or 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, numerous proxies are 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 (Todd and Wolpin, 2007). The source of the problem is that there are inputs that we do not observe but parents do, and that parents may modify their inputs on the basis of 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 influence on children's development and attainment. He 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 some parallels with Feinstein's study in that we are interested in the effect of family background on children's early cognitive development also, although our focus is on poverty and the persistence of poverty rather than differences over time by SES.

Gregg and Macmillan (2009) examined the effect of parental income on children's education and test scores (the youngest children that they had were aged 7 years) by using various UK cohort studies: the National Child Development Study (born in 1958); the 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); the Avon Longitudinal Study of Parents and Children (which is a Bristol-based birth cohort of children born in 1991–1992); the Longitudinal Study of Young People in England (which is a national sample of children born in England in 1989–1990). They consistently found that children born into poorer families have a lifelong disadvantage.

Goodman and Gregg (2010) utilized the second and the third sweeps of the MCS. Their focus was 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 did not take into account the persistence of poverty in documenting or explaining the existence of the gap in ability. Blanden and Machin (2010) also utilized the second and the third sweeps of the MCS. They examined the connection between parental income and children's vocabulary and behaviour. Consistent with the previous literature, their findings also suggest that better child outcomes are associated with higher income.

None of the studies cited above examine the effect of persistent poverty. In contrast, Schoon *et al.* (2010) used the MCS data to look at the effect 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 years. Their findings suggest that persistent financial hardship has a large and negative effect on children's cognitive development, whereas the effect 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) examined the effect 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 Schoon *et al.* (2012) confirmed 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 used the MCS data and investigated the effect of persistent poverty, maternal depression and 'family status' (defined as mothers' relationship status) on the cognitive and behavioural development of children, at age 3 years. Their findings also suggest that poverty has a negative effect 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) looked at the effect of parenting and persistent poverty on cognitive development of children at age 5 years. Their findings echo those of Schoon *et al.* (2012): the negative effect 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 some 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 years. This gives us an important advantage in modelling the persistence in cognitive development, and it 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) examined the effect of persistent poverty on young children in Scotland. They noted that poverty is multi-dimensional and that many, if not most, of its effects can be captured through correlated characteristics such as low parental education and poor health. Indeed, low income is not statistically significantly correlated with child outcomes (such as being overweight, poor language, social and emotional development) 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 effect is indirect, through its effect on other factors which are correlated with outcomes. In our analysis, we can capture and distinguish between both the direct and the indirect effect 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), whereby a child's current cognitive ability depends on their previous ability and the past inputs (parental investments). Further, as in Cunha and Heckman (2008) we assume that 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 is 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 structural equation model has two components—a structural model and a measurement model.

#### 3.1. Structural model

Let  $\theta_t$  be the stock of latent cognitive ability of the child at time  $t$ . A child's ability at time  $t$ ,  $\theta_t$ , depends on past ability stock  $\theta_{t-1}$  and past parental investment  $\lambda_{t-1}$ ; it depends also on some exogenous covariates  $X_t^\theta$ , 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  $t = 1, \dots, T$  represent the different time periods of childhood, with  $t = 0$  representing the initial endowments that a child is born with,  $\gamma_{1t}$ ,  $\gamma_{2t}$  and  $\gamma_{3t}$  are time varying parameters to be estimated, and  $\eta_t$  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  $X_t^\lambda$  (including poverty),

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

where  $\gamma_{4t}$  is a vector of time varying parameters to be estimated, and  $\nu_t$  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 identify separately the initial endowments  $\theta_0$  and initial parental investment in the child,  $\lambda_0$ , 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  $j \in \{1, \dots, m_t^k\}$ ) are the measures that are available for the latent ability and latent parental investment at time  $t$ .  $m_t^k$  are the number of measures that are 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 ( $\theta_t$  and  $\lambda_t$ ).  $\varepsilon_{j,t}^k$  are the measurement errors, which capture the difference between the observed measures and the unobserved latent variables.  $\mu_{j,t}^k$  can depend on regressors as long as they are independent of the latent variables  $\theta_t$  and  $\lambda_t$  and the error term  $\varepsilon_{j,t}^k$ .

### 3.3. Identification

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

To be able to identify all the parameters of interest in equations (1)–(5) we need the following assumptions.

*Assumption 1.*  $\varepsilon_{j,t}^k$  is mean 0 and independent across agents and over time for  $t \in \{1, \dots, T\}$ ,  $j \in \{1, \dots, m_t^k\}$  and  $k \in \{\theta, \lambda\}$ .

*Assumption 2.*  $\varepsilon_{j,t}^k$  is mean 0 and independent of  $(\theta_t, \lambda_t)$  for  $t \in \{1, \dots, T\}$ ,  $j \in \{1, \dots, m_t^k\}$  and  $k \in \{\theta, \lambda\}$ .

*Assumption 3.*  $\varepsilon_{j,t}^k$  is mean 0 and independent from  $\varepsilon_{i,t}^l$  for  $t \in \{1, \dots, T\}$ ,  $j \in \{1, \dots, m_t^k\}$  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  $\eta_t$  are normally distributed, although this is not needed for identification. The assumptions that we make here are the same assumptions as made by Cunha and Heckman (2008), page 747 and appendix A2.

3.3.1. *Identification of the factor loadings*

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

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

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

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

$\alpha_{2,t-1}^\theta$  can be identified by taking the ratio of equation (7) to equation (6), and  $\alpha_{2,t}^\theta$  can be identified by taking the 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 obtain the error-corrected estimates of the latent variables. For example, consider  $\theta_t$ : we can use the estimated factor loadings to construct

$$\hat{\theta}_t = \sum_{j=1}^{m_t^\theta} \omega_{j,t} Y_{j,t}^\theta \quad \omega_{j,t} = \frac{(\hat{\alpha}_{j,t}^\theta)^2}{\sum_{j=1}^{m_t^\theta} (\hat{\alpha}_{j,t}^\theta)^2} \tag{9}$$

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

3.4. *Endogeneity*

If we assume that  $\eta_t$  is independent of  $\lambda_t$ , then the assumptions in Section 3.3 fully identify the model. We call this 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 the child's current ability which has an effect on their investment in the child, so that  $\theta_t$  can be expected to impact  $\lambda_t$ . In equation (1) using lagged parental investment,  $\lambda_{t-1}$ , to explain child's current ability,  $\theta_t$ , should solve the issue of reverse causation. However, we have a dynamic model where  $\theta_{t-1}$  impacts  $\theta_t$  and, if the inputs are endogenous, then  $\theta_{t-1}$  can also impact  $\lambda_{t-1}$ . This will then violate the assumption that  $\eta_t$  is independent of  $\lambda_t$ .

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):

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

where  $\zeta_t$  is the normal error term that is orthogonal to  $(\theta_t, X_t^\lambda, R_t)$ ; and we assume that there is at least one such variable  $R_t$  that impacts parental investment but not the ability of the child. One possible way that  $R_t$  can be interpreted is that it reflects the family resources or constraints that limit the ability of the parents to invest in their children but do not have a direct influence on a child's ability, although we recognize that it may be difficult to find a variable which satisfies this exclusion restriction. Cunha *et al.* (2010) discussed in detail the justification of the investment function given by equation (10); they further suggested that to estimate equation (10) we can use two-stage least squares where the past values of  $R_t$  are used as proxies for  $\theta_t$ .

### 3.5. Direct versus indirect effects

The SEM approach allows us to identify both the direct and the indirect effects of poverty on cognitive development. The direct effects are simply how poverty affects cognitive development, whereas the indirect effects capture how poverty affects parental investment, which in turn impact on cognitive development. Equation (1) gives us the direct effect of the exogenous variables (including poverty) on cognitive ability whereas equation (2) gives us the direct effect 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 effect 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:

- (a) the direct effect of parenting inputs on children's ability,
- (b) the direct effect of poverty on children's ability and
- (c) the indirect effect of poverty on children's ability, via its effect on parenting inputs.

### 3.6. Episodic versus persistent poverty

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

To capture the effect 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.  $X_t^\theta$  now includes  $P_t, P_{t-1}, P_{t-2}$ , etc. This allows us to identify the direct effect 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’ effect of poverty in the literature. The indirect effect of previous episodes of poverty via lagged cognitive development and lagged parental investment still exists. Similarly we allow parental investment to be influenced by persistent poverty;  $X_t^\lambda$  now includes  $P_t, P_{t-1}, P_{t-2}$ , etc.

A diagrammatic representation of the estimated structural and measurement model is given in Fig. 1. Estimation is performed by using MPLUS version 7 (Muthen and Muthen, 2010).

Fig. 1 illustrates the dynamics of the structural and the measurement models for the baseline specification (i.e. the specification without endogenous inputs), which is outlined in Section 3, with two time periods; we have four time periods and initial conditions. The unobservable (latent) variables are in ellipses and the observable variables in rectangles. The large rectangle gives us the structural relationship (given by equations (1) and (2)) and the broken rectangles represent the measurement models (given by equations (4) and (5)). The single-headed arrows illustrate the theorized unidirectional causal relationships between variables. For the structural model, ability at time  $t, \theta_t$ , is determined by past ability,  $\theta_{t-1}$ , past parental investment,  $\lambda_{t-1}$ , and covariates  $X^\theta$ ; parental investment is in turn influenced by covariates  $X^\lambda$ . 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  $\theta_1$ . Each unobservable latent variable  $\theta$  and  $\lambda$  is measured by a series of observable variables  $Y^\theta$  and  $Y^\lambda$  respectively; this measurement model will vary over time.

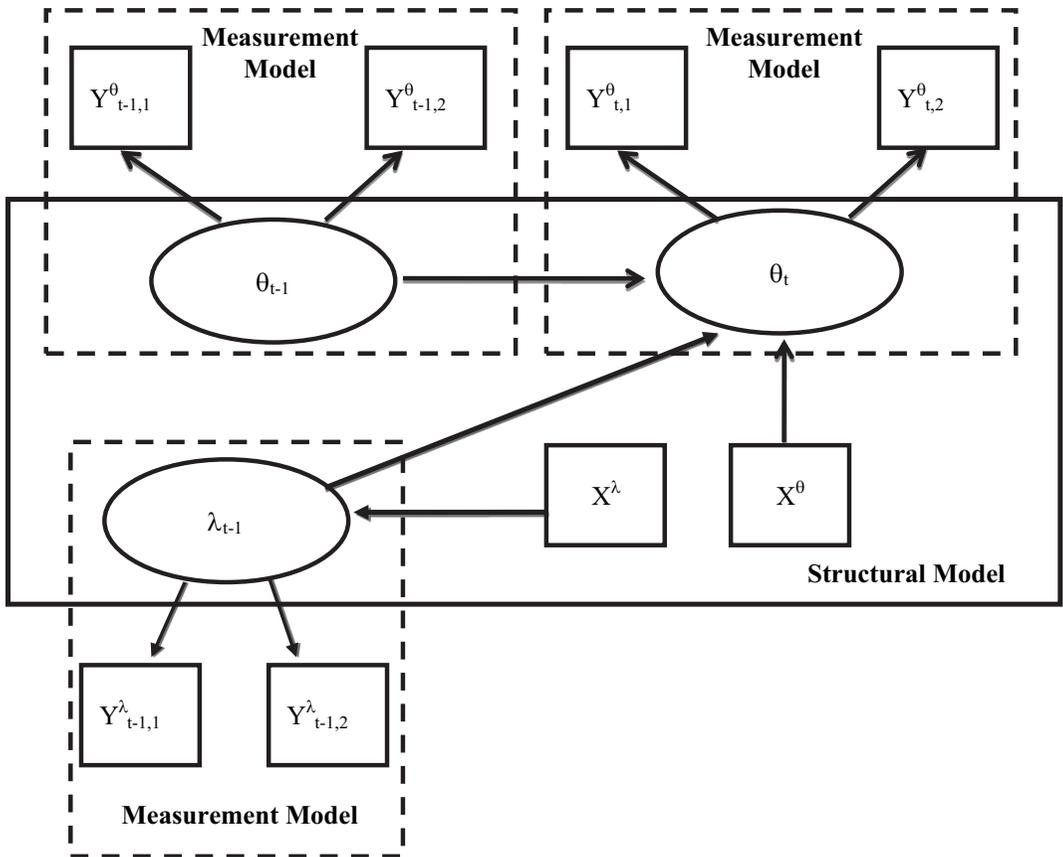


Fig. 1. Structural and measurement model

#### 4. Data and measurement

The UK MCS is following a large sample of around 19000 babies born in 2000–2001. The first sweep MCS1 took place in 2001–2002 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, whereas the third sweep MCS3 was administered when the children had reached age 5 years and had started school. Finally, the fourth sweep MCS4 was undertaken in 2008 when the children were 7 years old. The age 11 years 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 socio-economic 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 have been used throughout the analysis—see Hansen (2012) for details.

##### 4.1. *Measuring child poverty*

Although several criteria are currently in use for measuring child poverty, a commonly utilized measure is relative income poverty. This is the measure of poverty that is reported in the official households below average income statistics on poverty (Department for Work and Pensions, 2010) and is defined as living in a household with net equivalent income less than 60% of the median UK household income. Equivalization takes into account family size and composition by rescaling income by the number of 'equivalent adults'. As with the households below average income statistics, the MCS uses the modified Organisation for Economic Co-operation and Development household equivalence scale (Organisation for Economic Co-operation and Development, 2009) which weights the first adult as 0.67, the second adult and each child over 14 years old as 0.33 and each child under 14 years old as 0.20. The MCS equivalized income is then compared with the official poverty thresholds from the households below average income statistics, for the appropriate year of the MCS sweep. Children living in households below the households below average income threshold for that year are defined as being in poverty for that sweep. Thus the measure of child poverty utilized in our analysis is identical to the commonly employed definition for the UK (as used in the Child Poverty Act 2010 for example).

##### 4.2. *Cognitive test scores*

It is difficult to capture the latent cognitive ability of a child at age 9 months (sweep 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 that are given by the main respondent. The version of the test which is used in MCS assesses children in three areas: fine motor function, gross motor function and communicative gesture (Dezateux *et al.*, 2004). A child is classified as having a delay in a particular item if she or he cannot perform a task that 90% of the children of their age can do.

The MCS records several standard tests of cognitive development at ages 3 (sweep MCS2), 5 (sweep MCS3) and 7 (sweep MCS4) years. In each case, these are age appropriate tests

administered to the children themselves. We focus on the children's performance across all 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 whereas Connelly (2013) and Hansen (2012) provide full details of the implementation of these tests in the MCS.

The British ability scales (BASs) are a set of standard age appropriate individually administered tests of cognitive ability and educational achievements that are suitable for use with young children (Elliott *et al.*, 1996, 1997). Six different BAS tests have been administered across the MCS sweeps. The BAS naming vocabulary test assesses expressive verbal ability and vocabulary, as well as language development. This test was administered in sweeps MCS2 and MCS3. The BAS pattern construction test assesses spatial problem solving, dexterity and co-ordination. This test was administered in sweep MCS3 and again in sweep MCS4. The BAS picture similarity test was administered in sweep MCS3; this test assesses non-verbal reasoning or problem solving. Finally, the BAS word reading test, which was administered in sweep MCS4 (age 7 years), assesses the child's educational knowledge of reading.

In addition to the six BAS-based tests, two further tests were administered. First, in sweep MCS2, the Bracken school readiness assessment is used to assess the 'readiness' of young children for formal education by testing their knowledge and understanding of a range of basic concepts (Bracken, 2002). Second, in sweep MCS4, children's numerical and analytical skills are assessed by using a variant of the National Foundation for Educational Research standard progress in mathematics test.

For each of the tests, we use the age-standardized 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 0–100 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% 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 that are 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. 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

Melhuish *et al.* (2008) discussed different home learning variables (such as reading to the child), and the factors that capture social or routine activities (like regular bedtimes) which comprise the home environment. The measures that are used here are similar to those in the 'HOME'-score which is often used in US-based studies to capture parental inputs. Whereas some of the measures are directly linked to the cognitive development of the child, others are considered to provide an environment that is conducive to learning (see Todd and Wolpin (2007) for further discussion).

A range of variables in the MCS record different dimensions of the 'home learning environment' and social or routine activities. For the former, these include mothers' responses to how

often the child is read to (five categories from ‘never’ to ‘every day’), how often the child paints or draws at home (five categories), how often the child is helped with reading (five categories), how often the child is helped with writing (five categories), how often the child is helped with mathematics (five categories) and how often the child visits the library (three categories). In addition, fathers are also asked how often they read to their child (five categories).

In addition to the home learning environment, a number of variables reflect parenting ‘style’, including socialization, routine and discipline. In sweep MCS1, when the children are 9 months old, we use the mother’s responses to four questions, designed to capture her attitudes towards child rearing, 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 the mother responds on a five-point Likert scale from ‘strongly agree’ to ‘strongly disagree’. As the children grow 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 television the child watches and whether the parents smack or shout at the child if they are being naughty (three categories).

#### 4.3.2. Other characteristics

Variables in the vector  $X_t^0$  which affect the latent cognitive ability are 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 standardized against norms within a 3-month age range, and hence there may still be variation in cognitive development within these age groups (Connelly, 2013).

In vector  $X_t^\lambda$  we include a range of variables which have been shown to affect the parental inputs. It has been established in the literature that larger families have a negative influence on children’s educational outcomes. Justification for this comes from the resource (financial and time) constraints hypothesis (Black *et al.*, 2005). To capture the resource constraints that the family might face we include two variables: the number of other siblings in the household and a dummy for a single-parent household. We also include a poverty dummy in vector  $X_t^\lambda$ , as parental investment is one of the pathways via which poverty impacts children’s development. Finally we include mother’s education (equal to 1 if National Qualifications Framework 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  $\theta_0$  and  $\lambda_0$ ) we use birth weight, a dummy for the first-born children (equal to 1 if the child is the first born), mother’s age at birth, mother’s education at birth and ethnicity of the child (equal to 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. 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 (Hawkes and Joshi, 2012). Using the MCS data Dearden *et al.* (2006) have shown that 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 also include a dummy for ethnicity in our analysis.

## 5. Results

In this paper, the final sample for analysis comprises 8741 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 the on-line appendix A. Descriptive statistics 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 that was described in Section 4.1. The incidence of poverty in the sample is about 20% over the four sweeps, which 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 four different poverty profiles: PS = 00 indicates no episodes of poverty whereas 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 that they are aged 7 years. This is much higher than the 19% of children who are in poverty at age 7 years (Table 1).

5.2. Child poverty and cognitive development

Fig. 2 shows the average test score ranking according to the poverty status of the household at the time that 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. Fig. 3 shows the average scores for the two extreme poverty profiles: children who have never been in poverty and those who have always been in poverty at each sweep. The differences are larger here than in Fig. 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 several possible explanations for the differences that are observed in the raw data. For example, as suggested by the previous literature, 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.

Table 1. Poverty incidence†

<i>Results for the following sweeps:</i>				
	<i>MCS1, 2001–2002</i>	<i>MCS2, 2004–2005</i>	<i>MCS3, 2006</i>	<i>MCS4, 2008</i>
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	8741	8741	8741	8741

†The poverty rate is based on the poverty indicators provided by the MCS (see the text for further information). The threshold is household equivalized income less than 60% of the median household income where income is equivalized according to the Organisation for Economic Co-operation and Development equivalence scale. In all reported statistics, the MCS weights which take into account the survey design have been used.

**Table 2.** Prevalence of persistent poverty†

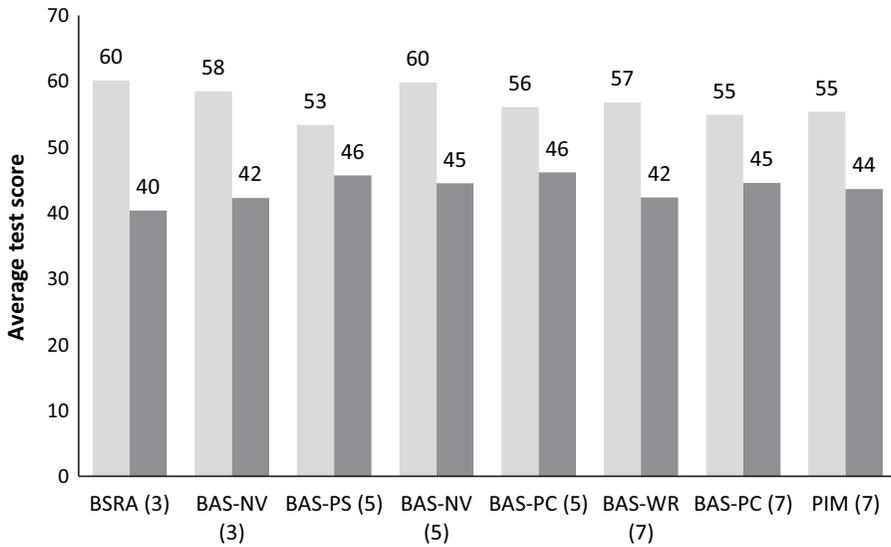
Row	Results for the following time horizons:					
	T = 2		T = 3		T = 4	
	PS	PPP (%)	PS	PPP (%)	PS	PPP (%)
1	00	72.1	000	67.0	0000	64.1
2	01	7.7	001	5.1	0001	2.9
3	10	6.7	010	4.1	0010	3.5
4	11	13.5	100	4.4	0100	3.4
5			101	2.3	1000	3.8
6			011	3.6	0101	0.7
7			110	2.9	1001	0.6
8			111	10.5	1010	1.1
9					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
Total		100.0		100.0		100.0

†PS is the poverty profile or status. The digits describe the poverty status in each sweep, so, for example, 001 represents individuals who were not in poverty in sweep MCS1 nor in sweep MCS2 but are in poverty in sweep MCS3—see the text for details. PPP is prevalence of persistent poverty (i.e. the proportion of the sample in each poverty state) calculated by using the poverty rate measure reported in Table 1. In all reported statistics, the MCS weights which take into account the survey design have been used.

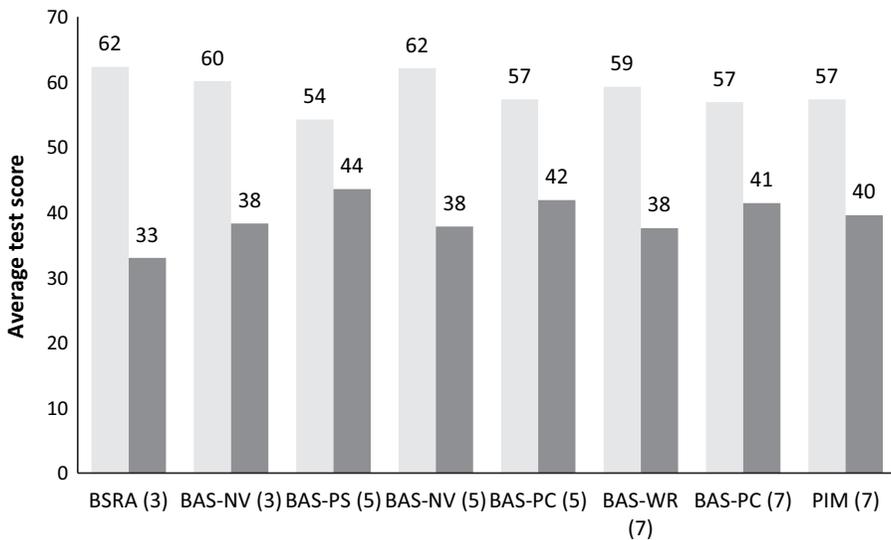
### 5.2.1. Baseline model

The results from the two different SEM specifications, of the baseline model, are reported in Tables 3 and 4 (for episodic poverty) and Tables 5 and 6 (for persistent poverty). We have reported the estimated coefficients of the structural model (equations (1)–(3)). The coefficients (factor loadings) from the measurement models (equations (4) and (5)) are available on request. Tables 3 and 5 report estimates of equation (1) and Tables 4 and 6 report the estimated coefficients of equation (2).

Findings that are consistent across the two specifications are as follows. From Tables 3 and 5, there is evidence of clear persistence with respect to cognitive ability,  $\theta_t$ —previous latent cognitive ability is positively and significantly correlated with current latent cognitive ability. Thus a child developing well at age 3 years is also likely to be doing well at age 5 and age 7 years, even after controlling for all other factors. From Table 5, a 1-standard-deviation (SD) higher latent cognitive ability at age 3 years is associated with a 0.694-SD higher latent cognitive ability at age 5 years; this is equivalent to 19 percentile ranks; similarly a 1-SD higher latent ability at age 5 years is associated with a 0.894-SD higher latent ability at age 7 years; 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 an SD of around 28 (see Table A2 in the on-line appendix). Also, higher birth weight, higher mother's age at the time of birth, having a mother with higher education (National



**Fig. 2.** Average test rank scores by poverty state, period by period (BSRA, Bracken school readiness assessment; NV, naming vocabulary test; PS, picture similarity test; PC, pattern construction test; WR, word reading test; PIM, progress in mathematics test): ■, not in poverty; ■, in poverty



**Fig. 3.** Average test rank scores by poverty state, never (■) versus always (■) in poverty (BSRA, Bracken school readiness assessment; NV, naming vocabulary test; PS, picture similarity test; PC, pattern construction test; WR, word reading test; PIM, progress in mathematics test)

Framework Qualifications 4 or above), being first born and being white are all associated with higher development at 9 months.

Tables 3 and 5 also reveal that lagged latent parental investment,  $\lambda_{t-1}$ , has a positive and significant effect on a child's latent cognitive ability, at all ages. From Table 5, if parental investment at age 3 years increases by 1 SD, then the child's cognitive ability at age 5 years would increase by 0.269 SDs, which is equivalent to an increase of eight percentile ranks. Finally,

**Table 3.** Specification 1—latent cognitive development and the incidence of poverty†

Parameter	Latent cognitive development $\theta_t$							
	MCS1, age 9 months, $\theta_1$		MCS2, age 3 years, $\theta_2$		MCS3, age 5 years, $\theta_3$		MCS4, age 7 years, $\theta_4$	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
$\theta_{t-1}$	—	—	0.504	0.000	0.700	0.000	0.908	0.000
$\lambda_{t-1}$	—	—	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
<i>Initial conditions</i>								
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	—	—	—	—	—	—

†The table gives the estimates of the structural parameters in equation (1) in the paper, where latent ability at time  $t$ ,  $\theta_t$ , is determined by past latent ability,  $\theta_{t-1}$ , past latent parental investment,  $\lambda_{t-1}$ , 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. All the reported coefficients are standardized. For the continuous independent variables, the coefficient represents the change in the dependent variable associated with a 1-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. In all reported statistics, the MCS weights which take into account the survey design have been used. Sample size 8741; comparative fit index CFI = 0.714; root-mean-square error RMSE = 0.029.

**Table 4.** Specification 1—latent cognitive development and the incidence of poverty†

Parameter	Latent parental investment $\lambda_t$					
	MCS1, age 9 months, $\lambda_1$		MCS2, age 3 years, $\lambda_2$		MCS3, age 5 years, $\lambda_3$	
	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

†The table gives the estimates of the structural parameters in equation (2) in the paper, where parental investment at time  $t$ ,  $\lambda_t$ , is determined by a set of control variables including poverty at time,  $t$ ,  $P_t$ . Refer to the footnotes to Table 3.

Tables 4 and 6 reveal that mothers with higher education on average provide higher levels of parental investment at all ages whereas having other siblings in the household significantly reduces the level of parental investment in the child at age 3 and age 5 years.

Current poverty has a negative and a significant effect 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

**Table 5.** Specification 2—latent cognitive development and the persistence of poverty†

Parameter	Latent cognitive development $\theta_t$							
	MCS1, age 9 months, $\theta_1$		MCS2, age 3 years, $\theta_2$		MCS3, age 5 years, $\theta_3$		MCS4, age 7 years, $\theta_4$	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
$\theta_{t-1}$	—	—	0.449	0.000	0.694	0.000	0.894	0.000
$\lambda_{t-1}$	—	—	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
<i>Initial conditions</i>								
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	—	—	—	—	—	—

†Refer to the footnotes to Table 3. Sample size 8741; comparative fit index CFI = 0.713; root-mean-square error RMSE = 0.029.

**Table 6.** Specification 2—latent cognitive development and the persistence of poverty†

Parameter	Latent parental investment $\lambda_t$					
	MCS1, age 9 months, $\lambda_1$		MCS2, age 3 years, $\lambda_2$		MCS3, age 5 years, $\lambda_3$	
	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

†Refer to the footnotes to Table 4. Sample size 8741; comparative fit index CFI = 0.713; root-mean-square error RMSE = 0.029.

significant effect on parental investment at 9 months (in both specifications) and at 3 years (in specification 2).

To capture fully the effect of persistent poverty on the cognitive ability of the child we now focus on the estimates from specification 2 as presented in Tables 5 and 6. At age 3 years, a child who is in poverty can be expected to be 0.263 SDs (seven 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 SDs

**Table 7.** Identifying direct and indirect effects of *persistent* poverty on cognitive development†

Effect	Latent cognitive development $\theta_t$					
	MCS2, age 3 years, $\theta_2$		MCS3, age 5 years, $\theta_3$		MCS4, age 7 years, $\theta_4$	
	Effect	p-value	Effect	p-value	Effect	p-value
<i>Effects from P1</i>						
Total effect on $\theta_t$	-0.254	0.000	-0.257	0.000	-0.232	0.000
Direct effect on $\theta_t$	-0.189	0.004	-0.058	0.216	-0.001	0.985
Indirect effect on $\theta_t$	-0.065	0.131	-0.199	0.000	-0.231	0.000
Indirect via $\lambda_1$	-0.006	0.148	-0.004	0.145	-0.004	0.147
Indirect via $\lambda_2$			-0.023	0.088	-0.020	0.088
Indirect via $\lambda_3$					-0.001	0.776
Indirect via $\theta_1$	-0.059	0.173	-0.041	0.177	-0.037	0.176
Indirect via $\theta_2$			-0.131	0.004	-0.117	0.004
Indirect via $\theta_3$					-0.052	0.217
<i>Effects from P2</i>						
Total effect on $\theta_t$	-0.263	0.000	-0.112	0.028	-0.196	0.000
Direct effect on $\theta_t$	-0.263	0.000	0.076	0.148	-0.098	0.030
Indirect effect on $\theta_t$			-0.188	0.000	-0.098	0.032
Indirect via $\lambda_2$			-0.006	0.659	-0.005	0.659
Indirect via $\lambda_3$					0.002	0.569
Indirect via $\theta_2$			-0.182	0.000	-0.163	0.000
Indirect via $\theta_3$					0.068	0.147
<i>Effects from P3</i>						
Total effect on $\theta_t$			-0.099	0.056	-0.149	0.003
Direct effect on $\theta_t$			-0.099	0.056	-0.058	0.209
Indirect effect on $\theta_t$					-0.090	0.056
Indirect via $\lambda_t$					-0.002	0.623
Indirect via $\theta_3$					-0.088	0.057
<i>Effects from P4</i>						
Total effect on $\theta_t$					-0.084	0.077
Direct effect on $\theta_t$					-0.084	0.077

†Refer to the footnotes to Table 3. P1, poverty status at 9 months; P2, poverty status at 3 years; P3, poverty status at 5 years; P4, poverty status at 7 years.

(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 identify the direct and the indirect effects of poverty on latent cognitive ability separately. These are presented in Table 7, for the SEM specification 2 in Tables 5 and 6. The interpretation of Table 7 is as follows. Reading down the second column, the total effect of P1 (poverty at 9 months, or birth) on latent cognitive ability at age 3 years is 0.254 SDs. The direct effect is 0.189 (the coefficient on the poverty dummy in Table 5). However, there is also an indirect effect through the effect of P1 on latent parental investment in the child at 9 months,  $\lambda_1$ , and through past cognitive development,  $\theta_1$ , which then affects the child’s cognitive ability. The indirect effect via parental investment is just -0.006 SDs, 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 years, whereas 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 years 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 years.

The direct effect of being in persistent poverty on cognitive development at age 7 years, if we just consider the statistically significant effects, is  $(-0.084 - 0.098) = -0.182$  SDs; five percentile ranks lower than the child who has never been in poverty. However, the total (direct plus indirect) effect of being persistently in poverty is  $(-0.232 - 0.196 - 0.149 - 0.084) = -0.661$  SDs, which translates to almost 19 percentile ranks lower than the child who has never been in poverty. Three-quarters of the effect 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 8–11. In the first stage (the results are available on request), we use the following proxies  $R_t$  for  $\theta_t$ : the number of siblings in the household, single-parent household and whether or not the mother works. Justification for these comes from the resource constraint hypothesis as discussed in Section 4.3.2. We recognize that it is difficult to find variables which satisfy the necessary exclusion restriction. Family formation (the number of children and single parenthood) and mother's decision to work are potentially endogenous decisions which may be related to other unobserved parental or family characteristics which might impact both parental investment and the child's development; it is also possible that parents could attempt to reinforce or compensate for their child's ability such that, for example, parents who are faced with limited resources decide to invest more in a child who is already well endowed (Currie and Almond, 2011).

Tables 8 and 9 give 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 Tables 3 and 4. In Table 9 in the model for latent parental investment we now have the 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 the endogeneity of inputs, relative to the baseline model, is that the coefficient on the poverty dummy in the latent parental investment equation at age 9 months is now insignificant. Similarly comparing specification 2 from the baseline model (Tables 5 and 6) with the model with endogeneity of inputs (Tables 10 and 11) there is no change in results quantitatively or qualitatively, the only exception being that the poverty dummy in the equation for latent parental investment at 9 months (Table 11) is now insignificant.

Our finding is not at odds with the literature. Cunha and Heckman (2008) estimated a linear technology function as we do here and found that allowing for endogeneity in inputs did not change their estimates from the baseline model. Similarly Cunha *et al.* (2010) estimated a non-linear technology function and found that allowing for endogeneity in inputs does not change their estimates from the baseline model.

### 5.3. Robustness checks

In their analysis, Melhuish *et al.* (2008) found that the home learning environment is relatively more important for children's cognitive development than social and routine activities. We

**Table 8.** Specification 1—latent cognitive development and the incidence of poverty (endogenous inputs)<sup>†</sup>

Parameter	Latent cognitive development $\theta_t$							
	MCS1, age 9 months, $\theta_1$		MCS2, age 3 years, $\theta_2$		MCS3, age 5 years, $\theta_3$		MCS4, age 7 years, $\theta_4$	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
$\theta_{t-1}$	—	—	0.557	0.000	0.693	0.000	0.905	0.000
$\lambda_{t-1}$	—	—	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
<i>Initial conditions</i>								
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	—	—	—	—	—	—

<sup>†</sup>The table gives the estimates of the structural parameters in equation (1) in the paper, where latent ability at time  $t$ ,  $\theta_t$ , is determined by past latent ability,  $\theta_{t-1}$ , past latent parental investment,  $\lambda_{t-1}$ , 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. All the reported coefficients are standardized. For the continuous independent variables, the coefficient represents the change in the dependent variable associated with a 1-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. Sample size 8741; comparative fit index CFI = 0.717; root-mean-square error RMSE = 0.028. In all reported statistics, the MCS weights which take into account the survey design have been used.

**Table 9.** Specification 1—latent cognitive development and the incidence of poverty (endogenous inputs)<sup>†</sup>

Parameter	Latent parental investment $\lambda_t$					
	MCS1, age 9 months, $\lambda_1$		MCS2, age 3 years, $\lambda_2$		MCS3, age 5 years, $\lambda_3$	
	Effect	p-value	Effect	p-value	Effect	p-value
$P_t$	-0.079	0.135	-0.029	0.527	-0.033	0.494
$\theta_t$	—	—	-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

<sup>†</sup>The table gives the estimates of the structural parameters in equation (10) in the paper, where parental investment at time  $t$ ,  $\lambda_t$ , is determined by ability at time  $t$ ,  $\theta_t$ , and a set of control variables including poverty at time  $t$ ,  $P_t$ . Refer to the footnotes to Table 8.

investigate this by including only the home learning measures in our latent parental investment equations. The results (which are available on request) are almost identical, both qualitatively and quantitatively, to the results that are presented in the paper, consistent with the findings of Melhuish *et al.* (2008).

As a further robustness check, we also experimented with using the logarithm of household

**Table 10.** Specification 2—latent cognitive development and the persistence of poverty (endogenous inputs)†

Parameter	Latent cognitive development $\theta_t$							
	MCS1, age 9 months, $\theta_1$		MCS2, age 3 years, $\theta_2$		MCS3, age 5 years, $\theta_3$		MCS4, age 7 years, $\theta_4$	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
$\theta_{t-1}$	—	—	0.449	0.000	0.698	0.000	0.894	0.000
$\lambda_{t-1}$	—	—	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
<i>Initial conditions</i>								
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	—	—	—	—	—	—

†Refer to the footnotes to Table 8. Sample size 8741; comparative fit index CFI = 0.716; root-mean-square error RMSE = 0.028.

**Table 11.** Specification 2—latent cognitive development and the persistence of poverty (endogenous inputs)†

Parameter	Latent parental investment $\lambda_t$					
	MCS1, age 9 months, $\lambda_1$		MCS2, age 3 years, $\lambda_2$		MCS3, age 5 years, $\lambda_3$	
	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
$\theta_t$	—	—	-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

†Refer to the footnotes to Table 9. Sample size 8741; comparative fit index CFI = 0.716; root-mean-square error RMSE = 0.028.

equivalized 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 effect on the other estimated coefficients in our model (the results are available on request).

## 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 years' ability are one of the main sources of variation in socio-economic outcomes across individuals.

This paper documents the effect 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 effect of income poverty on the cognitive development of children, consistent with the recent evidence of Dahl and Lochner (2012) for the USA. Moreover, as in Schoon *et al.* (2012), we find that persistent poverty has a larger cumulative negative influence on children's cognitive development than episodic poverty.

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 years 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 effect 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 years can therefore seriously impact on children's development by the time that they start school and thereafter well into their adult lives. This suggests that policy that is 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 effect 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 effect on children's cognitive development. Thus poverty not only has a direct negative effect on children's cognitive development, but it also has an indirect effect through its adverse effect on parental inputs. However, this result weakens when the endogeneity of inputs is taken into account.

Although we have focused 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) found that including non-cognitive ability lowers the estimates of self-productivity, i.e. the estimated coefficient on lagged cognitive ability. The effect of extending our model to include non-cognitive skills is an empirical question for future work in this area.

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#### Supporting information

Additional 'supporting information' may be found in the on-line version of this article:

'Appendix A: Sample construction'.