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Abstract

This paper examines the impacts of family inputs — i.e., maternal employment, child care and home learning — on the early development of British children. Using rich longitudinal data from the UK Millennium Cohort Study we estimate cognitive and non-cognitive achievement production functions that allow outcomes to depend on the history of family inputs and unobserved child endowments. We find evidence of small effects on early child outcomes of all the family inputs under consideration. Nonetheless, according to some models, family inputs are found to reduce socio-economic status inequalities in early child development quite substantially, while according to other models they are found to magnify them. Attempting to equalize child outcomes through early policy interventions that generically affect family inputs may therefore prove difficult.

JEL Classification: J24, J15, I20
Keywords: Education production functions; early interventions; cognitive and non-cognitive skill formation.

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1 Introduction

A. Motivation

Does maternal employment change the strength of the association between parental socio-economic status (SES) and child outcomes over the first few years of life of a child? How does the home environment in which a child grows affect this relationship? And how do child care decisions influence these processes? The aim of this paper is to provide answers to such questions, which are of fundamental interest to economists and social scientists and of crucial relevance for policy makers.

The level of most nations' investments in children is massive. Government expenditures on all levels of education are enormous. In the late 2000s, among industrialized countries, the expenditures per primary-school pupil were approximately £4,500 a year, while the expenditures per secondary-school student were nearly £6,000, representing a substantial increase of 17 and 13 percent respectively over the same expenditures one decade earlier (Hanushek 2002; OECD 2011).

In addition, considerable public and private resources are spent on housing, feeding, clothing, and transporting children, for providing nonparental care services, and for assuring provision of health care services. Another cost (and perhaps one of the most important and difficult to assess) refers to the implicit value of the time that parents spend monitoring, teaching, and caring for their children. Related to this parental time investment are the employment decisions that parents commit to during their offspring's childhood. Mothers' paid work, in particular, could be seen as a key factor in this process. This is because, on the one hand, it represents a direct reduction of the time that mothers spend with their offspring and, on the other hand, by increasing family income, it potentially expands the resources that are made available to children.

Many studies have documented robust and convincing evidence on the existence of an SES gradient in child outcomes (e.g., Currie and Hyson 1999; Carneiro and Heckman 2002).[1] More recently, the literature has emphasized the presence of the gradient early on in life (Case, Lubotsky, and Paxson 2002; Almond and Currie 2011a and 2011b; Currie 2011). In fact, there is also a good deal of empirical evidence that the differences between children from high-status and low-status households tend to increase as the children become older (Feinstein, 2003; Cunha and Heckman 2007 and 2008; Cunha, Heckman, and

[1] Considering family income as a specific component of SES, a large literature examines whether family income affects child development or not (e.g., Almond and Currie 2011a). The recent evidence is mixed, with some finding positive effects (Løken, Mogstad, and Wiswall 2012; Dahl and Lochner 2012) and others finding none (Blau 1999; Løken 2010). For a review of the earlier literature, see Haveman and Wolfe (1995).

Schennach 2010).[2]

To bolster this evidence and motivate our analysis further, Figure 1 shows SES gradients in cognitive skills and emotional development for British boys and girls drawn from the UK Millennium Cohort Survey.[3] Parental socio-economic status is measured in terms of maternal education.[4] University degrees or higher qualifications define high SES (HSES), all post-secondary qualifications that are short of a university degree are designated medium-high SES (MHSES), while GCSE (or equivalent) qualifications that are attained at age 16 at the completion of secondary (compulsory) education define medium-low SES (MLSES). Lower level qualifications identify low SES (LSES).

The figure reports cognitive and non-cognitive ability gradients relative to LSES at ages 3, 5 and 7. We stress three features of academic and policy relevance. First, there is a strong gradient at age 7, especially for cognitive skills and among boys. For instance, boys with MLSES mothers attain a cognitive skill outcome that is one quarter of a standard deviation higher than boys from LSES households, while the gap between LSES boys and boys from HSES households rises to more than two-thirds of a standard deviation. These inequalities are quantitatively large and broadly confirm already known empirical evidence on parental SES gradient on early child outcomes (e.g., Carneiro and Heckman 2002; Case, Lubotsky, and Paxson 2002; Feinstein 2003; Currie 2011). The cognitive gradient for girls is also large, although the difference between MLSES and LSES seems to be smaller.

Second, the gradient for non-cognitive skills is still large at age 7 but less pronounced than that for cognitive development. The largest gap is between children from LSES households and children from HSES households and is about 0.4 standard deviations. Although statistically significant and economically meaningful, this smaller gap may be indicative of the greater malleability of non-cognitive skills and of the potential for policy intervention (e.g., Heckman and Rubinstein 2001; Heckman, Stixrud, and Urzua 2006; Heckman 2006). Third, the evolution by age suggests that there is indeed some reduction of the non-cognitive gradient for girls, although the reduction for boys is not substantial. We observe instead an increase of the cognitive gradient for both boys and girls (Feinstein

[2] Recent studies, however, raise a number of concerns about the actual occurrence of this widening gap. See for example Jerrim and Vignoles (2012).

[3] The description of the data and of the statistical procedure used to produce the graphs will be postponed to Sections 3 and 5, respectively.

[4] Alternative measures of parental SES are income and occupation. One problem with such measures is that they are typically observed at specific points in time and can only imperfectly reflect the lifetime resources available to children, even without considering measurement error problems. In addition, when the mother has never worked, it is difficult to infer the permanent income conditions of her household. Using father's education (or income or occupation), while not entirely solving some of the previous concerns, raises further issues for single-mother households.

2003). For example, compared to their achievements at age 3, boys in the top HSES increase their verbal scores at age 7 by about one-third with respect to boys from the lowest SES. The life cycle pattern of the gradient is an interesting and important dimension of the issue we study here, but it is not the focus of the current paper and is thus left for future research.

B. Background and Related Literature

Despite these stylized facts and the important contributions mentioned earlier, relatively few studies have examined how maternal work and home environment in conjunction with child care decisions affect early child development (ECD) *and* their marginal impact on the SES gradient on ECD outcomes.[5] Most of our knowledge about such relationships is descriptive and is mainly drawn from epidemiological and developmental research, which usually fails to focus on all the three processes together (e.g., Desai, Chase-Lansdale, and Michael 1989; Baydar and Brooks-Gunn 1991; Belsky and Eggebeen 1991; Blau and Grossberg 1992; McLoyd 1998; Harvey 1999; Han, Brooks-Gunn, and Waldfogel 2001; Brooks-Gunn, Han, and Waldfogel 2002; Love et al. 2003; Brooks-Gunn and Markman 2005; Raikes et al. 2006; Grantham-McGregor et al. 2007; Kelly et al. 2011). From this body of literature the evidence is mixed, with some studies finding advantageous effects of maternal employment or of the home learning environment or of non-maternal child care arrangements on child outcomes, and others finding no impact or detrimental effects.

The same inconclusive evidence emerges from the economics literature, which again has typically concentrated its attention on only one of the three processes of interest in our analysis at a time. In the case of maternal employment, for instance, Baum (2003) and James-Burdumy (2005) find evidence of an adverse impact when maternal employment begins in the first year of the child's life, whereas employment after the first year appears to have less clear-cut effects. Other studies find that the negative effect on cognitive outcomes can be associated with maternal employment over a longer period of the child's life and not just with work during the first year only (e.g., Ruhm 2004; Liu, Mroz, and van der Klaauw 2010; Ermisch and Francesconi 2013).

Reviewing a large body of empirical research, Blau and Currie (2006) conclude that there is little convincing evidence that structural child care inputs (i.e., the technological

[5] An alternative, but related, strand of research investigates the causal effect of maternal education on child outcomes (e.g., Behrman and Rosenzweig (2002); Currie and Moretti (2003); Black, Devereux, and Salvanes (2005); Holmlund, Lindhal, and Plug (2011); Carneiro, Meghir, and Parey (2013). In this paper, instead, we take a different stance, considering mother's education as a proxy for parental permanent income and exploring how family decisions — i.e., our endogenous family inputs — affect inter-household SES inequalities in child outcomes.

characteristics of child care provision, such as the child-staff ratio, group size, teacher education and training, safety, staff turnover and program administration) affect early child outcomes. A number of studies instead provide evidence that process quality of child care (i.e., the characteristics of the interactions between children and their caregivers, their environment, and other children) does have a positive influence on child outcomes. There is also a substantial literature that examines the effects of programs providing universal child care on child outcomes. Again, the findings are mixed: some find positive effects (e.g., Berlinski, Galiani, and Gertler 2009; Havnes and Mogstad 2010 and 2011; Black et al. 2012) and others find negative results (Herbst and Tekin 2010; Magnuson, Ruhm and Waldfogel 2007).

A number of studies consider multiple family inputs jointly. For instance, in an empirical analysis of the sources of racial test score gaps in the United States, Todd and Wolpin (2007), who build on their earlier methodological work (Todd and Wolpin 2003), find that home inputs are substantive determinants of children's cognitive outcomes. In particular, differences in home inputs are found to account for 10–20 percent of the black-white and the Hispanic-white test score gaps, with differences in school inputs and in mother's schooling accounting only for very small portions of the gap.

Gregg et al. (2005) analyze maternal work and non-maternal child care arrangements in England. They find that full-time employment in the first 18 months after a birth by mothers who predominantly use informal substitute care from relatives or friends leads to poorer cognitive outcomes for children. But they find no evidence that part-time working or full-time working with more formal care substitution leads to negative early outcomes, and even for the adversely affected groups the magnitude of the effects is small at around one-tenth of a standard deviation.

Another example is the study by Blau (1999), which examines the effects of maternally reported school inputs (e.g., group size, staff-child ratios, and teacher training) as well as of type of care, cost of care, hours per week, and month per year spent in the arrangement on a series of cognitive and non-cognitive and test scores, controlling for measures of the quality of the home environment. Blau finds that the effects of child care quality are generally insignificant, and sometimes wrong-signed, while measures of the home environment are statistically significant and have relatively large effects.[6]

Bernal (2008) estimates jointly employment and child care decisions of women after

[6]It is possible that, in Blau's (1999) work, maternal reports on school inputs are measured with error, and this might bias their estimated effects toward zero. This finding however is confirmed by the estimates reported in Todd and Wolpin (2007). In any case, the differential effects of school inputs are not part of the analysis in the present study. This is left for future research.

childbirth to evaluate the effects of these choices on children's cognitive outcomes. Her results indicate that the effects of both maternal paid work and child care on children's outcomes are negative and sizable: having a mother that works full-time *and* uses child care during one year is associated with a reduction in cognitive test scores of approximately 1.8 percent (or 0.13 standard deviations of the score distribution). Bernal and Keane (2010) extend Bernal's (2008) study on children of married women to examine the effects on children of single mothers. They confirm Bernal's previous results and find that a mother working full-time and placing a child in child care for one full year reduces the child's cognitive ability test score by 2.7 percent on average, or 0.14 standard deviations.

But, as recognized by Del Boca, Flinn, and Wiswall (2012), structural modeling comes with some limitations. In their study, which nonetheless emphasizes the importance of modeling household time decisions and money investments in children jointly with household preferences, such limitations include the treatment of fertility as an exogenous process, the lack of an explicit consideration of the time and money inputs of individuals and institutions outside of the household (e.g., schools), and the absence of self-investment.[7] Our analysis shares some of the same limitations too.

C. Our Contribution

As mentioned already, our approach is related to the work of Todd and Wolpin (2007). Their study, which builds on Todd and Wolpin (2003), estimates a dynamic child quality production function that views child development as a cumulative process, with the final child quality level being determined by heritable endowments and the sequence of family and school inputs supplied during the developmental period. This estimating framework allows for unobserved endowment effects, potentially endogenous input choices, and cumulative effects of child investments at early stages of the development process. Their results indicate that both contemporaneous and lagged inputs matter in the production of current achievement, and that it is important to allow for unobserved child-specific endowment effects and the endogeneity of inputs.

We build on this framework and, besides the home environment, we focus on the effects of maternal work and child care decisions. Considering these other family decisions is important for at least two reasons. First, they interact with standard home inputs affecting their productivity and their impact on child outcomes. Second, they are the target of a wide array of policy interventions in most industrialized countries. Thus,

[7] Although desirable, adding such decisions and inputs raises a host of endogeneity problems, many of which are described in Liu, Mroz, and van der Klaauw (2010).

understanding how they influence child outcomes is of key policy relevance. Moreover, we analyze not only cognitive but also non-cognitive outcomes, which have been shown to be strong predictors of later outcomes and, likewise, to affect them causally (Heckman, Stixrud, and Urzua 2006; Heckman and Kautz 2012).

In addition to the estimation of the technological relationship between maternal work, child care arrangements, home inputs and child outcomes, we also focus on the specific contribution that each of those processes has on the socio-economic status gradient. This is important when we are interested in addressing issues of inequality across households. Finally, and for the first time, we perform our analysis for Britain. This is significant in and of itself, but it is also essential if we try to build up robust scientific evidence for the design of effective policy interventions.

The rest of the paper is organized as follows. Section 2 provides the econometric framework to address the main questions of this study. It presents a number of estimation methods discussing their identifying assumptions. Section 3 describes the data used in estimation. Section 4 shows the production function estimates of the effect of maternal employment, child care decisions, and home inputs on cognitive and non-cognitive outcomes of children. We investigate heterogeneity across estimation methods and, using cross-validation techniques, assess the model that performs best according to an out-of-sample root mean-squared error criterion. We finally show the results of the decomposition of the contribution of each of the three processes under analysis to the SES gradient. Section 5 concludes.

2 Econometric Issues and Methods

We use a simple framework for modeling early child development (ECD) outcomes based on the production function approach suggested by Krueger (1999) and Todd and Wolpin (2003; 2007). Let Y_{it} denote an early outcome for child i at age t.[8] We consider two sets of inputs into the production function of the EDC outcome Y: that is, the vector of observed inputs, X_{it}, which includes both endogenous and exogenous inputs, and the vector of unobserved inputs denoted by u_{it}. Let ϕ_{i0} be the child's endowment at conception (e.g., the child's mental capacity and ability) and ϵ_{it} be a random shock that is not under the parents' control, including measurement error.

[8]Since we do not consider sibling/mother fixed effects models, we formulate our discussion as if we had only one child per household.

A general formulation of ECD production function is then

$$Y_{it} = Y\big(\mathbf{X}_i(t), \mathbf{u}_i(t), \phi_{i0}, \epsilon_{it}\big), \tag{1}$$

where $\mathbf{X}_i(t)$ and $\mathbf{u}_i(t)$ are the histories of the vectors of observed and unobserved inputs up to age t, respectively. A straightforward regression analog of (1) is given by

$$Y_{it} = \sum_{k=1}^{t} X_{i,t+1-k}\beta_k + \sum_{k=1}^{t} u_{i,t+1-k}\theta_k + \alpha_t\phi_{i0} + \epsilon_{it}, \tag{2}$$

where all inputs enter linearly and additively.

Direct estimation of (2) is complicated by the double problem that the inputs u are unobserved and that information on the initial endowment ϕ_0 is generally missing or unreliable. Leaving aside these two problems, another issue with the estimation of (2) is that it imposes strict data restrictions, requiring information on the *full history* of the observed inputs, $\mathbf{X}_i(t)$.

Scientific research has witnessed the implementation of a variety of contributions which, facing different data limitations, have aimed at estimating (2) in different ways. Much of the available evidence is drawn from works that rely exclusively on *contemporaneous* input measures. They thus estimate a relationship as:

$$Y_{it} = X_{it}\beta_1 + \eta_{it}, \tag{3}$$

where, borrowing the notation used in (2), we have

$$\eta_{it} = \sum_{k=2}^{t} X_{i,t+1-k}\beta_k + \sum_{k=1}^{t} u_{i,t+1-k}\theta_k + \alpha_t\phi_{i0} + \epsilon_{it} \tag{4}$$

Many of the early economics studies and of the studies in the epidemiological and medical literatures estimate models like (3).

What are the restrictions imposed by the contemporaneous specification (3) in relation to the general production function given in (2)? Essentially, these boil down to three. First, expression (3) imposes a past input irrelevance assumption, $\beta_t = \beta_{t-1} = ... = \beta_2 = 0$. This means that contemporaneous inputs are sufficient statistics for the entire history of inputs. Second, all the unobserved (omitted) inputs, $\mathbf{u}_i(t)$, must be orthogonal to the included current input measures. Third, contemporaneous inputs must be unrelated to the child's unobserved endowment, $\text{Cov}(X_{it}, \phi_{i0}) = 0$.

Another popular variant of (2) is a *value added* (VA) specification, which relates the

ECD outcome Y_{it} to contemporaneous input measures, X_{it}, and the lagged (baseline) outcome, $Y_{i,t-1}$, as in

$$Y_{it} = X_{it}\beta_1 + \lambda Y_{i,t-1} + \nu_{it}, \tag{5}$$

where the new residual is given by:

$$\begin{aligned}\nu_{it} &= \sum_{k=1}^{t-1} X_{i,t-k}(\beta_{k+1} - \lambda\beta_k) + (\alpha_t - \lambda\alpha_{t-1})\phi_{i0} + u_{it}\theta_1 \\ &+ \sum_{k=1}^{t-1} u_{i,t-k}(\theta_{k+1} - \lambda\theta_k) + (\epsilon_{it} - \lambda\epsilon_{i,t-1}).\end{aligned} \tag{6}$$

As with the contemporaneous input specification, also the VA model imposes a set of restrictions on the ECD production function (2) (Todd and Wolpin 2003). First, it requires an age equivalence impact of all observed inputs X, according to which $\beta_k = \lambda\beta_{k-1}$, for all ages $k = 1, t-1$. Second, it imposes $\theta_k = \lambda\theta_{k-1}$, for all ages $k = 1, t-1$, i.e., an age equivalence impact of all unobserved inputs u. Third, $\alpha_t = \lambda\alpha_{t-1}$, which amounts to an age equivalence impact of the unobserved child endowment ϕ_0. Finally, by imposing $\mathrm{Cov}(u_{it}, X_{it}) = \mathrm{Cov}(u_{it}, Y_{i,t-1}) = 0$, the VA specification requires that the contemporaneous omitted inputs be uncorrelated with the included inputs and lagged outcome.[9]

There are two additional models based on the VA specification that, in different ways, try to account for the fact that $\mathrm{Cov}(Y_{i,t-1}, \nu_{it})$ might not be zero. The first, called a *value added – fixed effects* (VA–FE) model, which imposes $\alpha_t - \lambda\alpha_{t-1} = \alpha'$, can be written as

$$Y_{it} = X_{it}\beta_1 + \lambda Y_{i,t-1} + \alpha'\phi_{i0} + \nu'_{it} \tag{7}$$

where ν'_{it} is an appropriate re-definition of ν_{it} in (6).[10] The second variant, which can be seen as a *value added – instrumental variables* (VA–IV) model, relies on past outcomes, $Y_{i,t-2}$), as instruments for the baseline outcome, $Y_{i,t-1}$. Instrumentation here could help address the issue of measurement error in the outcome variable (Andrabi et al. 2011).[11]

[9] Another frequently estimated VA specification is $Y_{it} - Y_{i,t-1} = X_{it}\beta_1 + \nu_{it}$, which is more restrictive than (5), as it sets $\lambda = 1$.

[10] Due to space limitations, in our empirical analysis below, we shall not present the estimates obtained from this model specification.

[11] The study by Andrabi et al. (2011) applies a value-added approach to estimate education production functions using data from Pakistani public and private schools. This work emphasizes the importance of persistence in interpreting value-added models of learning and accounts for imperfect persistence, unobserved heterogeneity, and measurement error. The main finding of this study is that only a small fraction of learning persists between grades. Instead, models that assume perfect persistence would yield biased estimates of input variables, while ignoring unobserved heterogeneity or measurement error would bias the estimation of the learning persistence process. We shall use some of the insights of this study in

In fact, it is well know that, in the context of the strict VA specification (5) and (6), measurement error attenuates the coefficient on lagged achievement and can bias input effect estimates.

Another prominent class of estimators used to account for the permanent unobserved factors in (2) makes use of variation across observations within which the unobserved factors are assumed to be fixed. One such fixed effect estimator uses variation that occurs within children, at different ages.[12] This is the *cumulative specification*, which modifies the general ECD production function (2) in

$$Y_{it} = \sum_{k=1}^{t} X_{i,t+1-k}\beta_k + \varepsilon_{it}, \tag{8}$$

where, making use of (2), the residual is given by

$$\sum_{k=1}^{t} u_{i,t+1-k}\theta_k + \alpha_t\phi_{i0} + \epsilon_{it}. \tag{9}$$

If expression (8) is first differenced, so that we obtain

$$\begin{aligned} Y_{it} - Y_{i,t-1} &= \sum_{k=1}^{t-1}(X_{i,t+1-k} - X_{i,t+1-k+1})\beta_k + X_{i1}\beta_t \\ &\quad +(\alpha_t - \alpha_{t-1})\phi_{i0} + (\varepsilon_{it} - \varepsilon_{i,t-1}), \end{aligned} \tag{10}$$

it is straightforward to see from (10) that parameter identification can be achieved if: (a) the effect of child endowment on outcomes is independent of age (i.e., $\alpha_t = \alpha_{t-1}$); and (b) later input choices are invariant to the realization of earlier outcomes.

Assumption (b), i.e., the assumption that input choices do not respond to prior outcome realizations, is arguably strong on theoretical grounds. For instance, it is reasonable to expect that parents choose inputs at a given point in time (e.g., spend time reading to the child) on the basis of past observed outcomes (e.g., the child's reading proficiency). One way of relaxing this assumption is then to combine the cumulative specification with the value added model in what we call *cumulative value added* (CVA) specification, i.e.,

$$Y_{it} = \sum_{k=1}^{t} X_{i,t+1-k}\beta_k + \lambda Y_{i,t-1} + v_{it}, \tag{11}$$

our analysis, especially in relation to learning persistence, even though our focus is not on school inputs.

[12] A second important fixed effect estimator uses variation that occurs within families, i.e., across siblings. This is not described here since we do not apply it in our empirical analysis. See Todd and Wolpin (2003).

whereby the residual in (11) is given by:

$$v_{it} = (\alpha_t - \lambda\alpha_{t-1})\phi_{i0} + u_{it}\theta_1 + \sum_{k=1}^{t-1} u_{i,t-k}(\theta_{k+1} - \lambda\theta_k) + (\epsilon_{it} - \lambda\epsilon_{i,t-1}). \tag{12}$$

Here, the introduction of $Y_{i,t-1}$, which is assumed to be a sufficient statistics for the missing (unobserved) historical inputs, explicitly recognizes the relationship between observed input choices (including past choices) with earlier realizations of achievement. Identification of the observed input impacts in (11) requires the same assumptions as those imposed by the VA model (5), except that the age equivalence impact of all observed inputs is no longer needed. As in the VA specification, measurement error could be an issue. We thus instrument $Y_{i,t-1}$ in (11) either with its earlier realization, $Y_{i,t-2}$, or with alternate outcomes. This is what we call *cumulative value added – instrumental variable* (CVA–IV) specification.

A further class of estimators focuses on the importance of individual specific heterogeneity in learning. The insight here is that lagged achievement, as in the VA specification (5) or the CVA specification (11), only captures individual heterogeneity if it enters through a one-time process, but talented children are likely to learn faster than less talented children. As in Andrabi et al. (2011), then, we assume that the unobserved child endowment effect in (2) is independent of age, i.e., $\alpha_t = \alpha$. Then, first differencing the specification of the VA model (5) yields

$$Y_{it} - Y_{i,t-1} = (X_{it} - X_{i,t-1})\beta_1 + \lambda(Y_{i,t-1} - Y_{i,t-2}) + (\nu_{it} - \nu_{i,t-1}), \tag{13}$$

where the differenced residual takes the form

$$\begin{aligned} \nu_{it} - \nu_{i,t-1} \quad = \quad & X_{i,t-1}(\beta_2 - \lambda\beta_1) + u_{i,t-1}(\theta_2 - \lambda\theta_1) \\ & +\theta_1(u_{it} - u_{i,t-1}) + (\epsilon_{it} - \lambda\epsilon_{i,t-1}) - (\epsilon_{i,t-1} - \lambda\epsilon_{i,t-2}). \end{aligned} \tag{14}$$

As in the case of the cumulative specification, identification of (13) relies on the assumption that later input choices do not vary with the realization of earlier outcomes and on the additional assumption that the output response to later input choices is independent of early choices. We estimate (13) using a generalized method of moments (GMM) after having instrumented for $Y_{i,t-1}$–$Y_{i,t-2}$ using specific contemporaneous exogenous inputs and lagged outcomes, $Y_{i,t-2}$ (Arellano and Bond 1991). Strict exogeneity of inputs rules out feedback effects, according to which a child or a mother who experience a positive or negative shock will not adjust inputs (e.g., change labor supply or child care arrangements) in response. This assumption allows us to use changes in time-varying characteristics — i.e., changes in maternal work, child care utilization and home learning environment — as exogenous controls in (13). This is however a strong assumption. It is likely that a mother changes her labor supply if her child overperforms or underperforms at school. Feedback effects instead can be accounted for by the other estimating method that relies on predetermined inputs, according to which inputs are uncorrelated with present and future disturbances but are potentially correlated with past disturbances. With this approach we estimate (13) using lagged inputs and lagged outcomes as instruments.

In our empirical analysis we shall estimate all the models described in this section. For each of them, we will provide a specific assessment of the effect of maternal employment, home investments and child care arrangements. We will also try and determine which of the models performs best from a statistical standpoint. Before turning to the estimation results, the next section describes our data source, outcome measures and input variables.

3 Data

Our analysis is based on the UK Millennium Cohort Study (MCS), a longitudinal study of a sample of children born between September 2000 and August 2001 in England and Wales, and between November 2000 and January 2002 in Scotland and Northern Ireland. The study has repeated measurements of children cognitive and non-cognitive outcomes and contains rich information about parental socio-economic background, employment status, child care arrangements, and specific parental inputs at various points in time. This makes this study particularly well-suited to estimate the models described in the previous section.

The MCS sampling frame is based on the UK electoral wards' geography. The sample is clustered geographically and disproportionately stratified to over-represent (i) the three smaller countries of the UK (Wales, Scotland and Northern Ireland), (ii) areas in England with higher minority ethnic populations in 1991 (where at least 30 percent of the population were Black or Asian); and (iii) disadvantaged areas (drawn from the poorest 25 percent of wards based on the Child Poverty Index). A list of all nine month old children living in the sampled wards was derived from Child Benefit records provided by the Department of Work and Pensions. Child Benefit claims cover virtually all of the child population except those ineligible due to recent or temporary immigrant status.

The first wave of data collection took place when infants were around 9 months old and includes data on 18,818 babies in 18,552 families. Subsequent information was collected when children were about 3, 5, and 7 years old. During each sweep of interviews, interviewers administered physical and cognitive assessments, while the mother (usually the main respondent) was asked to report about the socio-economic circumstances of the family as well as the child's health and emotional development.

Our sample includes all singleton children interviewed at 9 months with at least one cognitive or non-cognitive measure of development at ages 3, 5, or 7 and valid information on a set of family background variables and maternal inputs (14,793 children). We further select only cases where the main respondent was the natural mother. This leaves us with 14,263 children. As we observe very little about the school environment, we keep only children attending state-funded schools at ages 5 and 7 (about 93.2 percent of the sample). Our final sample thus consists of 13,297 children and 34,389 children-year observations.

The MCS records a number of standard tests of cognitive development. These are mainly taken from the British Ability Scales (BAS). The BAS are a set of standard age-adjusted tests of cognitive abilities and educational achievements suitable for use with young children (Elliott, Smith, and McCulloch 1996 and 1997). Our measure of *cognitive development* is derived from three assessments: the BAS Naming Vocabulary test at ages 3 and 5 and the BAS Word Reading at age 7. The Naming Vocabulary Test is a test where children are shown pictures of objects and are asked to identify them. In the Word Reading Test the child reads aloud a series of words presented on a card. Although the tests are not exactly the same, here we assume they measure child cognitive outcomes (verbal ability) over time. In each case the tests were administered via Computer Assisted Personal Interviewing (CAPI) by interviewers who were specifically trained, but did not have a psychology background. All tests were adjusted for age and difficulty of the question with a reference to a set of standard tables, and expressed as T-scores which have mean 50 and standard deviation 10. For ease of interpretation, we transform them into z-scores, with mean 0 and standard deviation 1 in a representative population.

The Strengths and Difficulties Questionnaire (SDQ) is a brief behavioral screening questionnaire designed to measure psychological adjustment in children aged 3 to 16 (Goodman 1997 and 2001). In the MCS, parents were asked to answer a battery of 25 questions which identify five different components: (i) hyperactivity/inattention, (ii) conduct problems, (iii) emotional symptoms, (iv) peer problems, and (v) pro-social behavior. The respondent indicates whether each item is (a) "not true", (b) "somewhat true", or (c) "certainly true" of the child in question. The responses are then scored so that higher scores indicate more problematic behavior. Responses to the first four sub-scales (i.e., excluding pro-social behavior) are then summed up to obtain the Total Difficulty Score, which varies between 0 and 40 and is taken here as a measure of the child *emotional development*. For ease of interpretation, the score is reverse-coded and expressed as a z-score using the mean and the standard deviation observed in a representative sample of the UK population.[13] The SDQs were administered at ages 3, 5, and 7, so that we can construct consistent measures of the child's psychosocial development over time.

Figures 2 and 3 show the frequency distributions by child's age and sex of the cognitive and non-cognitive skill measures, respectively, while Table 1 reports the corresponding means and standard deviations.[14] The distributions are very similar by sex. As children age, we observe a slightly increased dispersion in outcomes, especially in the case of verbal scores (Figure 2). Both outcomes, but the Total Difficulty scores in particular, are skewed to the left, especially as children grow older.

We focus on three sets of inputs. The first is *maternal employment*, which is available for all waves. Although the survey offers precise information on hours worked, here we focus on the distinction between non-working mothers (reference category), mothers in part-time employment, and mothers in full-time employment. The distinction between part-time and full-time work is based on the number of hours worked in a typical week, with a cutoff at 30. Table 1 shows that the percentage of working mothers increases as children grow older. When the child is 3 years old, more than 48 percent of all mothers in our sample work either full time or part time (almost 16 and 33 percent, respectively). By the time the child is aged 7, the proportion of working mothers increases to 61 percent, with two-thirds of them being in part-time jobs and the other one-third being in full-time jobs.

The second input of interest is *child care*. The MCS collects detailed information about child care arrangements at every wave, including the type of regular child care used (the respondent can specify more than one option), the number of hours, the exact period of the day in which the arrangement was in place and, for those who used formal or paid child care, the amount paid per hour, week, or session. We restrict our attention to the main regular arrangement, as defined by the respondent and do not consider the number of hours or the amount paid. Where the mother is not working we assume that she is the main carer, so that child care arrangements are defined only for working mothers. We consider two different types of arrangements: informal and formal (or paid) child care. Informal care includes care provided by the partner, grandparents, other relatives or friends. Formal care includes care provided by nurseries, child minders, nannies, or

[13] For more details, see http://www.sdqinfo.com/norms/UKNorm3.pdf.

[14] Means and standard deviations differ from their notional standards (0 and 1, respectively), partly reflecting selection as well as noise.

others.[15] In the UK all children aged 5 attend primary schools, so that for ages 5 and 7 child care arrangements are those which are in place outside normal school hours. These include the use of breakfast and after-school clubs, which are included in the formal care category.

Table 1 indicates that working mothers mainly use informal child care arrangements, which account for 20, 31, and 29 percent of care arrangements at ages 3, 5, and 7, respectively. Use of formal arrangement is lower at ages 3 and 5 (16 and 15 percent, respectively), but increases to 25 percent at age 7, possibly because of the greater availability of before- and after-school arrangements for school aged children. The proportion of children with no child care arrangement (or, alternatively, whose mothers are not in paid employment) decline from 52 percent at age 3 to 39 percent at age 7.[16]

Finally, we focus on the *home learning environment*. This is a measure of the time the mother devotes to the child in a range of activities, including (i) reading, (ii) telling stories, (iii) playing music or teaching songs, (iv) drawing, (v) playing sports/games outdoors, (vi) playing games indoors, (vii) going to the park. In the Parenting Activities module administered at ages 5 and 7, mothers were asked to indicate how frequently they carried out these activities with their children on a 6- or 8-point scale, ranging from "every day" to "none at all". At age 3, instead, mothers were asked question on a more limited range of activities (i.e., reading, playing music or teaching songs, drawing, and teaching a sport or other physical activity), and the questions were formulated so to include also the time that other carers spent in these activities with the child. Thus, although in most cases these activities refer to the mother's time spent with the child, our indicator should be more broadly seen as a measure of the general home learning environment.

The indicator is constructed by combining the mother's answers to the relevant questions using principal component analysis. Using the Kaiser criterion, which suggests to retain only those factors with eigenvalues greater or equal to one, we find evidence of a single common factor. This explains about 37 percent of the total variance at each age 3, 5, and 7. All items load positively onto the single factor at each age of the child. At age 7, for example, after rotation the factor loadings are 0.514 (reading), 0.546 (story telling), 0.549 (teaching songs), 0.704 (drawing), 0.684 (outdoor activities), 0.724 (indoor activities), and 0.492 (going to the park). Our measure of home learning environment is strongly correlated over time — with correlation coefficients of 0.582 between ages 5

[15] Separating out nurseries from other forms of paid child care does not change any of our main results.

[16] It is worth noticing that we have a non-negligible fraction of the sample with missing information. This could be due to the complex structure of the child care module which contains more than 50 questions. In the analysis, therefore, we shall consider this as a separate category.

and 7, and of 0.384 between ages 3 and 5 — as well as to maternal education — with correlation coefficients of 0.21 at age 3, 0.143 at age 5, and 0.091 at age 7. Figure 4 shows the frequency distributions of the home learning environment measure by child age and sex. The distributions are similar by sex. As children grow older, the distributions tend to be less skewed to the left and become more symmetric. Our empirical analysis also includes other individual and family characteristics. Some are time invariant, such as parity, mother's age at birth, ethnicity, and region of birth (not shown for brevity in Table 1). Other characteristics included in the analysis are time varying. These comprise child's age (in days) at the time of the interview (and its square), a dichotomous indicator for single parent households, and number of siblings. Just over two-fifths of children are firstborn, almost 90 percent of them are whites, and their mothers were on average 29 years old at their birth. As children age, the family size (number of siblings) increases, and about one in five children has lived in a single-parent household. Because we perform our analysis separately on girls and boys, Table 1 reports the summary statistics for all variables by sex.

4 Results

As described in Section 2, the estimation of general education production functions, which account for the presence of unobserved endowments, input choices that are selected in response to such endowments, and learning heterogeneity, is challenging. Longitudinal data like the MCS presented in the previous section enable us to perform this estimation accommodating most of its challenges. Here we present the estimates from the specifications discussed in Section 2, which impose different set of restrictions on the general model (2).

A. Main Estimates

Tables 2a and 2b report the estimated production function coefficients for cognitive outcomes for boys and girls, respectively. The corresponding estimates for non-cognitive outcomes are in Tables 3a and 3b. We present estimates only on the three sets of inputs of interest, i.e., maternal employment, child care use, and the home learning environment. In all tables, each column shows coefficient estimates for a different model specification.

We begin with Tables 2a and 2b. From the contemporaneous specification in column (i), we find that maternal work, whether part time or full time, increases cognitive achievement significantly by about 0.2 of a standard deviation regardless of child's sex. Formal child care arrangements do not affect cognitive development, while a better home learning environment improves cognitive skills by 0.07 of a standard deviation. As discussed in Section 2, however, the contemporaneous specification places strong restrictions on the production technology even though it is less demanding than other specifications in terms of data requirements.

When historical data on inputs are available, a simple test of the contemporaneous model is to include lagged input measures in the analysis and check whether their associated coefficients are significantly different from zero. Column (ii) shows the estimates from the cumulative model, which augments the contemporaneous specification by including lagged data on inputs. The F-test rejects the contemporaneous specification against the cumulative model for both boys and girls. In the case of boys, the estimated effects of current inputs decline considerably when lagged inputs are included, suggesting that omitting historical measures leads to an overstatement of the impact of contemporaneous inputs. In the case of girls, instead, we cannot detect any significant difference in the effects of maternal work and child care arrangements, but we again find that the contemporaneous specification overstates the impact of the current home learning environment. The cumulative effect of home learning, however, is positive as it is that of maternal employment irrespective of child's sex, whereas the cumulative effect of formal child care is positive only for girls but not for boys.

Column (iii) of Tables 2a and 2b shows the results from the VA–IV specification. The input estimates from the strict value-added specification as given in (5), which includes a one-period-lagged outcome along with contemporaneous inputs, are essentially identical to those of the VA–IV model. The only exception is the persistence parameter on the lagged dependent variable, λ, that in the standard VA specification is significantly lower at about 0.4 for both boys and girls. One striking feature of the value-added results is that, as compared to the contemporaneous and cumulative specifications, the input effect estimates are much weaker in the case of boys' cognitive achievement. For girls' instead the VA–IV effects are similar to those found with the two previous specifications, except for mother's full time employment which, albeit still significant, drops to less than 0.1 of a standard deviation. As mentioned in Section 2, the instrumentation of the VA–IV model helps us address the potential measurement error problem of the VA specification. Correcting for measurement error increases λ from 0.4 to about 0.72 for boys and 0.62 for girls, consistent with sizeable measurement error attenuation (Andrabi et al. 2011).

The fourth column presents the CVA estimates of (11), which adds to the strict value-added model the one-period-lagged input variables without instrumentation. As in the case of the simple VA model the persistence estimate is around 0.4 for both boys and girls.

But the pattern of estimated effects for the main inputs is different by sex. For boys, the current input effects are no longer statistically significant, while lagged maternal work increases cognitive achievement by 0.09 of a standard deviation and lagged home learning environment by just 0.02 of a standard deviation. For girls instead, contemporaneous maternal employment leads to a statistically significant increase of 0.12–0.14 of a standard deviation, while lagged employment does not have any impact. As in the cumulative model, lagged formal child care continues to be a significant determinant of girls' cognitive achievement, but not of boys'.

Some of the features of the results from the CVA specification persist when we analyze the estimate a CVA–IV specification, which accounts for the endogeneity of prior achievement, $Y_{i,t-1}$ in (11), by instrumenting it with its earlier realization, $Y_{i,t-2}$ (column (v)).[17] In particular, none of the contemporaneous inputs has an effect for boys, while maternal part- and full-time employment increase girls' cognitive skills by 0.16 and 0.12 of a standard deviation. Boys' cognitive development instead is positively affected only by lagged maternal work.

Column (vi) presents results obtained using the GMM–predetermined estimator. As in Andrabi et al. (2011), the estimate of the persistence parameter λ is statistically different from models that correct for measurement error only, such as the VA–IV specification in column (iii), for both boys and girls. This means that there is substantial omitted heterogeneity in learning which biases standard estimates upward. Differently from the earlier results, the effect estimates of contemporaneous maternal full-time work on boys' cognitive skills is negative and large, over 0.4 of a standard deviation, while the effect of part-time work, which is also negative, is statistically less well measured.[18] According to this specification, boys' cognitive development is strongly affected by current home learning environment. We find a similar positive effect estimate of about 0.19 of a standard deviation in the case of girls. But differently from boys', the GMM–predetermined estimates of maternal employment on girls' cognitive development are positive, although not statistically significant at conventional levels. Reassuringly, the Hansen's J test cannot reject the overidentifying restrictions implied by the model, suggesting that instrumenting the difference $Y_{i,t-1} - Y_{i,t-2}$ in (13) using previous year outcomes works well. We find the same result when the difference is instrumented using alternate outcomes. We take this as an indication that, regardless of the instrumentation, the effect estimates of the inputs

[17]The same results as those shown here were found when we used alternate prior subjects as instruments. Those estimates therefore are not presented.

[18]This finding echoes the results found by James-Burdumy (2005) and Ermisch Francesconi (2013) who use within-family (mother) fixed effects models.

of interest are well identified.[19]

We also performed our analysis using a standard within-child fixed-effects model, which takes advantage of the panel structure of the MCS. For convenience the results from this specification are not reported. The broad pattern of results from this specification is similar to that found with the GMM-predetermined model in column (vi), although the input effects are generally less precisely measured.

Tables 3a and 3b show the results for the non-cognitive outcome obtained from the same set of specifications. As in the case of cognitive achievement, we typically find a decline in the absolute value of input effects as we move from the more restrictive contemporaneous specification to the other models, especially value-added models. For instance, for boys, the CVA–IV (column (v)) effects of current maternal part-time and full-time work of 0.09 standard deviations are approximately half the size of the corresponding effects found in the contemporaneous and cumulative specifications (columns (i) and (ii), respectively). The other inputs, instead, seem to play more marginal roles, except that — according to the GMM-predetermined specification in column (vi) — formal day care increases emotional skills by 0.11 standard deviations and home learning environment by 0.06 standard deviations. Interestingly, in the case of girls, apart from the contemporaneous and cumulative models and once measurement error problems of the VA specification are accounted for, none of the inputs of interest affects the formation of non-cognitive skills. Moreover, for both boys and girls, past outcomes, the persistence parameter λ is close to zero in the GMM-predetermined model that account for endogenous input responses to past outcome realizations.

B. Goodness of Fit and Model Selection

An important issue in our analysis is how to select among all the competing model specifications we have estimated. As in Todd and Wolpin (2007), we address this issue by using a cross-validation method, whose goal is to find the model that performs best according to an out-of-sample root mean-squared error (RMSE) criterion (Hastie, Tibshirani, and Friedman 2001). Cross-validation is useful in situations like ours, in which the models that are compared are non-nested and when it is not clear which is the preferred null hypothesis model.[20]

[19] We also estimated the GMM specification under the assumption of strict exogeneity of inputs. For the sake of brevity we do not show these results. The λ estimates are similar to those reported in column (vi) of Table 2. But, irrespective of child's sex, the effect estimates on the other inputs are generally weaker and statistically less well determined than those found with the GMM–predetermined specification.

[20] Stone (1976) shows that, for models estimated using maximum likelihood methods, the cross-validation method with random hold-out samples is asymptotically equivalent to the Akaike information

Cross-validation requires us to partition our sex-specific samples into a number of complementary subsets. In particular, we divide each sample into five roughly equal-sized subsamples.[21] Each model is then estimated on one of the five subsamples separately and used to construct the RMSE for the other four left-out subsamples. This procedure is repeated alternating the subset of data that is left out. The RMSE values are then averaged over the five rounds to obtain the mean RMSE for that model specification.

Table 4 shows the mean RMSE for each of the production function specifications presented in Tables 2a-2b and 3a-3b, except for the contemporaneous and the VA–IV models. The reason for these exceptions is simple and based on conventional specification tests reported in the two tables. The contemporaneous specification is always strongly rejected against the cumulative specification as revealed by the F test results. Similarly, the VA–IV model is generally rejected against the cumulative value-added specifications (columns (iv) or (v) in Tables 2a-2b and 3a-3b), although this is not the case when the comparison is the CVA–IV model for girls' emotional skills.

As seen in Table 4, the GMM–predetermined model is the specification that exhibits the lowest RMSE in the case of cognitive achievement for both boys and girls. For the non-cognitive outcome, instead, the specification that statistically performs best is given by the CVA–IV model, irrespective of the sex of the child.

Taking stock of these results, it is useful to refer back to the input effect estimates presented in the previous subsection and summarize our key substantive findings. For boys, a mother working full-time reduces the child's cognitive development by 0.44 standard deviations. The effect of part-time employment is again negative and large (0.2 of a standard deviation) but less statistically significant. For girls, instead, maternal work is positively associated with cognitive achievement but, irrespective of how intensely the mother is attached to the labor market, this effect is not statistically significant. The more time the mother devotes to improve the home learning environment the higher the child's cognitive outcome, with a one unit increase in the home learning environment measure leading to a 0.18–0.19 standard deviations increase in cognitive skills for both boys and girls. Irrespective of child's sex, we can never detect a significant relationship between cognitive skills and formal day care arrangements.

In the case of emotional development, current maternal part- and full-time work have now positive effects, of about 0.09 standard deviations, on boys' achievement. No other input, whether current or lagged, has an impact on the boys' outcome. Likewise, none of

criterion.

[21] The same qualitative results emerge when we partition the original samples into three or four subsets. The results from these alternative exercise are therefore not shown for convenience.

the three sets of inputs affects girls' non-cognitive skill formation.

C. Input Contributions to the SES gradient

Using the production function estimates in Tables 2a-2b and 3a-3b, we examine the extent to which differences in inputs can account for socio-economic status (SES) disparities in outcomes. Our results are summarized in Figure 5. As mentioned in the Introduction while presenting Figure 1, parental SES is proxied by mother's education. Mothers with university degrees or higher qualifications define high SES (HSES) households. Households in which women have post-secondary qualifications that are short of a university degree are called medium-high SES (MHSES) households, while mothers with GCSE (or equivalent) qualifications that are attained at age 16 at the completion of secondary (compulsory) education define medium-low SES (MLSES) households. Lower level qualifications identify low SES (LSES) families.

Figure 5 reports gradients at age 7 relative to LSES obtained from a baseline model (shown also in Figure 1) — which includes child's parity, age and age squared, region of birth, mother's age at birth and its square, ethnicity, number of siblings, and an indicator for single parent families as a basic set of inputs — the contemporaneous specification, the CVA–IV model, and the GMM–predetermined specification. The contemporaneous model was chosen because it can be seen as a standard benchmark, even it has been statistically rejected against other specifications. The last two models, instead, were the preferred models according to the cross-validation criterion. The baseline model does not include our three inputs of interest, i.e., maternal work, child care arrangements, and home learning environment. It therefore serves as a natural comparison model against which we can examine how the three inputs jointly reduce or magnify the SES gradient on outcomes.[22] From each of the estimated specifications, we compute model-specific idiosyncratic residuals, which are then regressed on the four SES indicators. The implied estimated coefficients from such regressions are shown in Figure 5. To ease the estimates' interpretation, we complement Figure 5 with Table 5, which reports the differences (in levels and percentages) between HSES coefficients from each of the competing models and the corresponding HSES coefficient from the baseline specification.[23]

According to the contemporaneous model, the overall impact of parental inputs on the

[22]As stressed in the Introduction, the age pattern of the SES gradient is not a focus of this study. One of the reasons is that most of the model specifications of interest cannot be estimated at age 5 or earlier due to our limited possibility (or impossibility) of coherently measuring lagged outcomes and inputs at earlier ages.

[23]The results obtained for the other levels of parental SES are very similar to those reported in Table 5 and thus are not shown for convenience.

SES gradient in cognitive achievement is quite circumscribed, in spite of the role played by maternal employment and home learning time. Approximately only 7 percent of the gap in cognitive skills between the HSES and LSES groups (or about 0.04–0.05 of a standard deviation) would be closed jointly by the three parental inputs of interest. A slightly greater (but still limited) proportion, between 12 and 17 percent, of the SES gradient in emotional skills could be reduced by the inputs under scrutiny.

The evidence emerging from the CVA–IV model is substantially different. In the case of cognitive skill production, all three family inputs together contribute to over 50 percent of the reduction in the parental SES gradient for both boys and girls. This reduction is only partially due to the role of the family inputs and primarily picks up the role played by the lagged outcome. In the case of non-cognitive development (for which the CVA–IV specification shows the best statistical performance), they go even further and eliminate the gradient entirely.

Finally, the estimates from the GMM–predetermined specification (which the cross-validation method identifies as the preferred model for cognitive skill production) indicate that the three family inputs jointly lead to a reduction of 19 percent (0.11 of a standard deviation) in the gradient for girls' cognitive skill development. For boys, instead, they magnify the gradient on the cognitive outcome by approximately 25 percent at all SES levels. This is likely to be driven by the large negative effect of maternal employment detected by the GMM–predetermined model (see Table 2). The same magnification effect is observed also for non-cognitive skill development, with an increase of the gradient at the HSES level of approximately 67 percent (0.26 standard deviations) and 23 percent (0.09 standard deviations) for boys and girls respectively.

5 Conclusions

This study estimated early cognitive and non-cognitive skill production functions, acknowledging the possibility that early child development is a cumulative process that is likely to depend on the entire history of relevant inputs, parental ability, and unobserved endowments. We focused on a specific set of family inputs that comprise maternal employment, child care arrangements, and home learning environment. One of our distinctive goals was to examine how those three family inputs affect the parental socio-economic status on early child development outcomes.

Using rich longitudinal data from the UK, we estimated several alternative specifications of the ECD production function, which impose different restrictions on the data.

We do not have a one-size-fits-all interpretation of the input effects across all model specifications. In general, across almost all the specifications considered, formal child care arrangements seem to play no role in shaping early child outcomes. Maternal work instead has small positive impacts on cognitive development according to some of the more restrictive specifications, and zero or even negative effects according to specifications that account for lagged input effects or heterogeneous learning dynamics. The evidence on the effect of home learning environment is also mixed, ranging from small and positive in some cases to small and negative in others. Much of the same conclusions can be made for non-cognitive skill formation, with the exception that none of the three family inputs has a substantial impact on girls' emotional development.

Our main substantive conclusion therefore is that the three family inputs under analysis — maternal employment, child care arrangements and home learning environment — have only modest impacts on early child outcomes. Despite this, their effect on how outcomes differ by parental socio-economic status is not negligible, especially when this effect works through past outcome realizations. According to some of the model specifications that include lagged input and outcome effects, differences in family inputs can jointly account for up to 50 percent of the SES gradient in the cognitive outcome and could entirely eliminate the outcome gap between children in low SES households and children in high SES households. However, according to other specifications that are better suited to capture heterogeneity in learning, differences in family inputs are likely to increase, rather than attenuate, cognitive and non-cognitive outcome inequalities.

The SES results from the former class of models are encouraging as they are indicative of some malleability in the production of all skills, especially non-cognitive abilities (Heckman, Stixrud, and Urzua 2006), and open the possibility for effective early policy interventions (Heckman 2006; Heckman and Masterov 2007). The results from the latter class of models, instead, raise caution about the salience of using either maternal employment or parental time investment in home learning activities as tools to help equalize outcomes across different SES groups.

Although this study represents the first attempt to estimate early production functions structurally for Britain, there are a few desirable extensions to consider in future work. First, the muted effect of family inputs on outcomes measured at ages 3–7 does not exclude the possibility of large effects at earlier ages. This is something that cannot be assessed with MCS data, but could be addressed with datasets in other countries and should be of interest for future data collection exercises, such as the new UK birth cohort (Life Study). Second, an analysis that examines child outcomes over different ages would provide a useful picture of the dynamic evolution of skill formation for British children. This is likely to become easier as more sweeps of the MCS are collected. Third, greater attention could be devoted to issues related to the quality of parental time with the child and the quality of non-maternal child care services (Sammons et al. 2004) as well as to the role of fathers. Fourth, it might be important to consider other inputs which have been excluded in our study, especially school inputs, such as in Todd and Wolpin (2007) and Andrabi et al. (2012). This can be a potentially fruitful avenue of research when analysts can merge children in the MCS to administrative school records. Finally, more direct policy implications would require us to gain greater knowledge not only of the input choices made by parents (and schools) but also of parental preferences. This may need the formulation and estimation of a fully structural model of family and school input decisions that would allow us to account for the possibility that changes in one input (or its price) affect decisions about other inputs.

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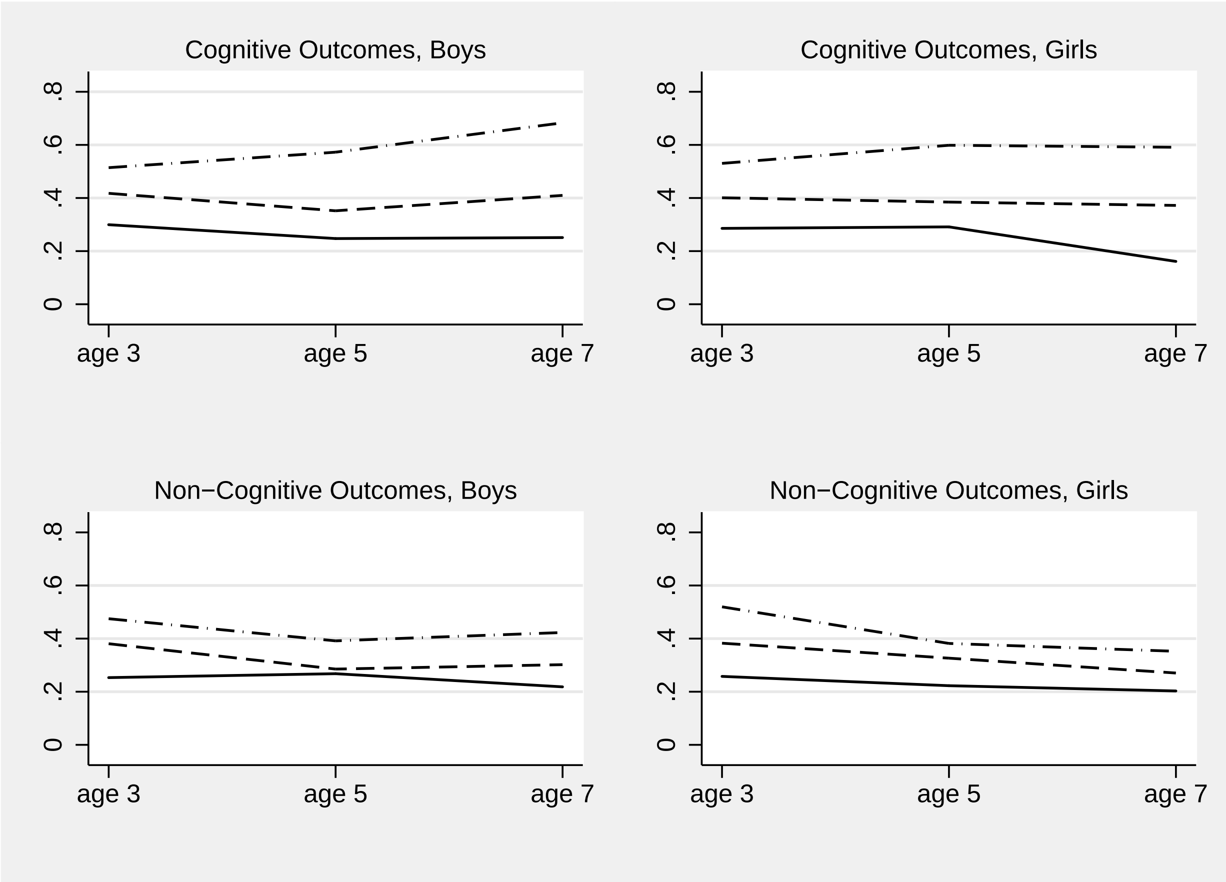
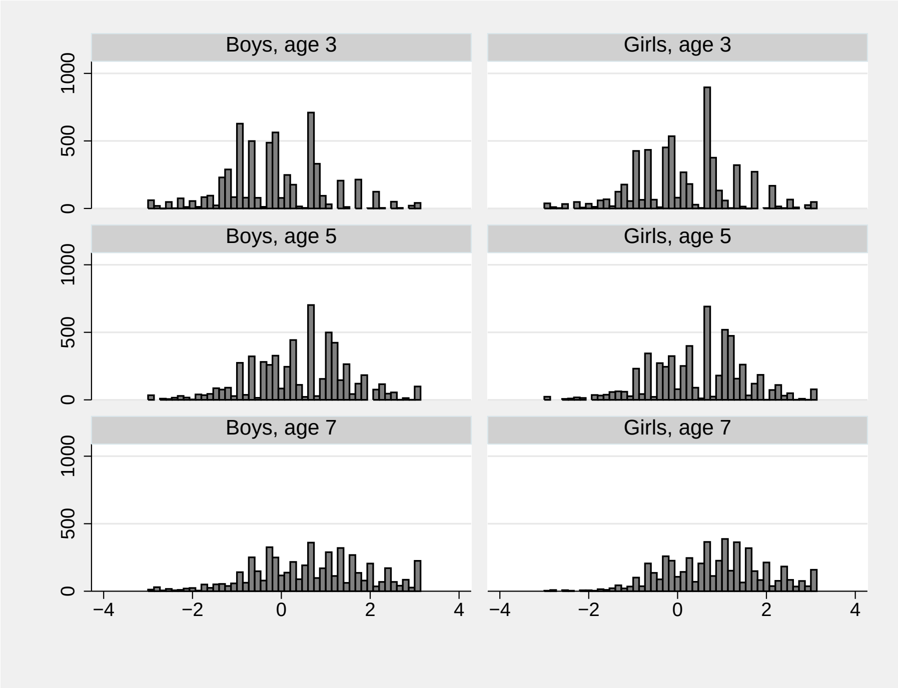
Figure 1: SES Gradient in Cognitive and Emotional Ability by Child's Sex and Age



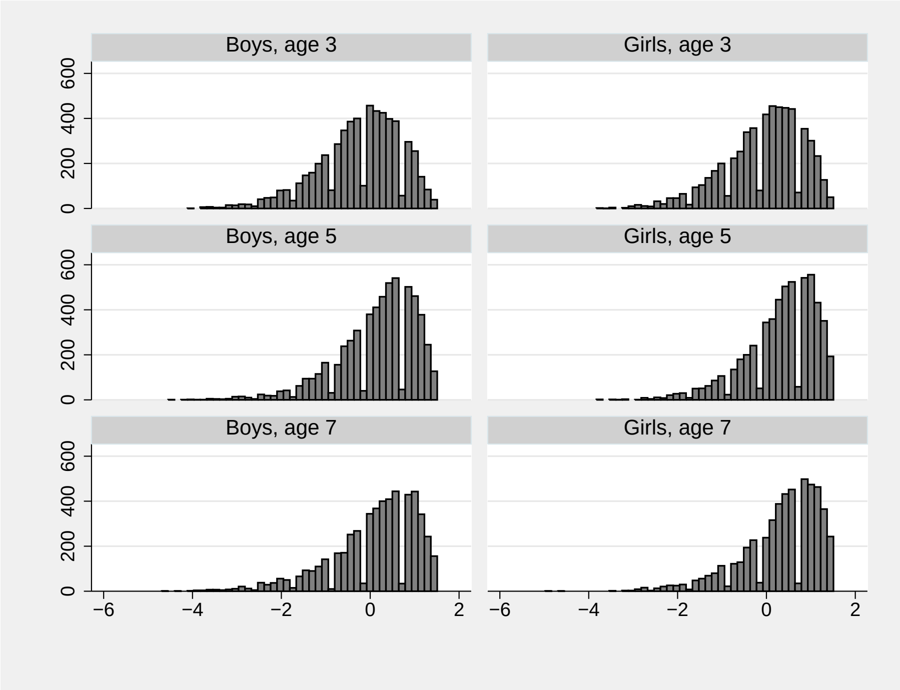
Source: UK Millennium Cohort Study (MCS).
Notes: Figures are relative to children whose mothers have less than GCSE (or equivalent) qualifications. Solid line represents children whose mothers have GCSE (or equivalent) qualifications (MLSES); dashed line represents children with mothers with qualification levels above GCSE (or equivalent) qualifications but short of university degrees (MHSES); dash-dotted line represents children whose mothers have qualification levels equivalent to university degree or above (HSES). Figures are the coefficients of the four SES indicators regressed on the idiosyncratic residuals obtained from a model that includes child's parity, age and age squared, ethnicity, number of siblings and an indicator for experience of life in a single parent household. Cognitive outcomes are measured by BAS naming vocabulary scores at ages 3 and 5 and by BAS word reading scores at age 7. Non-cognitive outcomes are measured by the Total Difficulty scores derived from the Strengths and Difficulties Questionnaires at all ages.

Figure 2: Frequency Distribution of Cognitive Outcomes by Child's Sex and Age



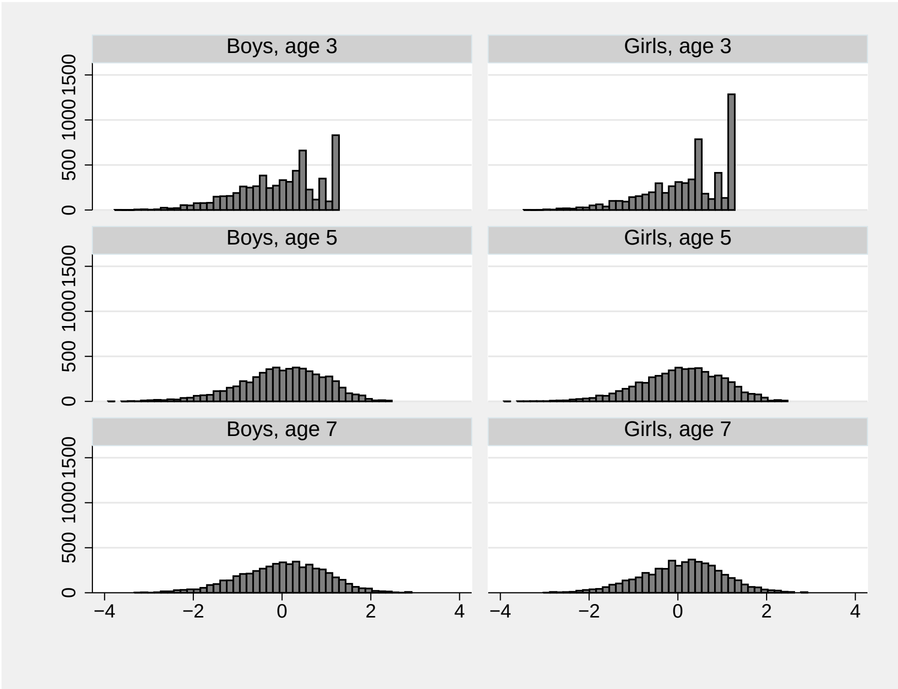
Source: UK Millennium Cohort Study (MCS).
Note: Cognitive outcomes are measured by BAS naming vocabulary scores at ages 3 and 5 and by BAS word reading scores at age 7.

Figure 3: Frequency Distribution of Non-Cognitive Outcomes by Child's Sex and Age



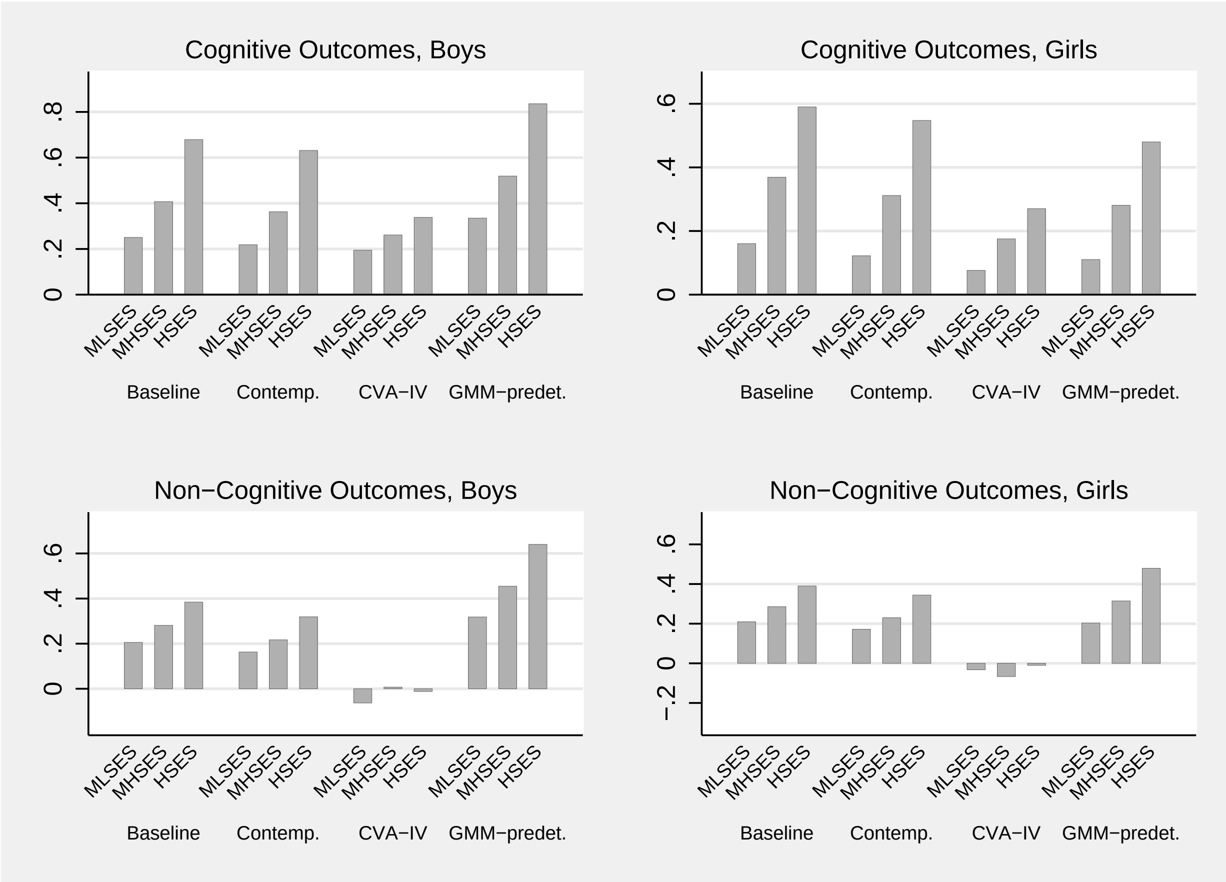
Source: UK Millennium Cohort Study (MCS).
Note: Non-cognitive outcomes are measured by the Total Difficulty scores derived from the Strengths and Difficulties Questionnaires at all ages.

Figure 4: Frequency Distribution of Home Learning Environment Scores by Child's Sex and Age



Source: UK Millennium Cohort Study (MCS).
Note: For a detailed explanation of how this measure has been constructed see the text in Section 3.

Figure 5: Input Contribution to the SES Gradient at Age 7



Source: UK Millennium Cohort Study.
Notes: The figure shows the SES gradient (relative to LSES) in child's cognitive and non-cognitive outcomes at age 7. Each bar is the average value of the model-specific idiosyncratic residuals. For further details of the baseline model, see the note to Figure 1.

Table 1: Summary Statistics by Child's Sex and Age

	Boys at age (years):			Girls by age (years):		
	3	5	7	3	5	7
Outcomes						
Cognitive outcome	-0.14	0.42	0.067	0.13	0.47	0.84
(Verbal score)	(1.10)	(1.11)	(1.26)	(1.09)	(1.05)	(1.10)
Number of observations	5,801	5,903	5,242	5,645	5,693	5,139
Non-cognitive outcome	-0.24	0.16	0.11	-0.06	0.34	0.34
(Total Difficulty score)	(0.93)	(0.89)	(0.98)	(0.89)	(0.81)	(0.88)
Number of observations	5,860	5,854	5,418	5,639	5,621	5,163
Inputs						
Maternal employment						
Not working	0.52	0.45	0.40	0.51	0.46	0.39
Working full time	0.16	0.18	0.22	0.15	0.18	0.22
Working part time	0.33	0.37	0.38	0.36	0.36	0.39
Child care arrangement						
None	0.51	0.45	0.41	0.52	0.46	0.40
Informal	0.21	0.32	0.29	0.20	0.31	0.28
Formal	0.16	0.15	0.24	0.16	0.14	0.25
Missing	0.12	0.09	0.06	0.12	0.09	0.07
Home learning environment	0.06	0.01	0.02	0.19	0.07	0.09
	(0.94)	(0.96)	(0.97)	(0.90)	(0.93)	(0.92)
Time varying exogenous inputs						
Child age at interview (in days)	1145	1907	2640	1146	1905	2638
	(73.65)	(89.74)	(88.97)	(74.23)	(89.70)	(88.46)
Single parent household (=1)	0.17	0.19	0.20	0.17	0.19	0.21
Number of siblings	0.74	0.83	0.87	0.75	0.84	0.87
	(0.44)	(0.37)	(0.34)	(0.44)	(0.37)	(0.34)
Time invariant exogenous inputs						
Firstborn (=1)	0.43	0.43	0.43	0.41	0.42	0.42
Mother's age	29.00	28.94	29.05	29.08	29.01	29.14
	(5.83)	(5.84)	(5.81)	(5.85)	(5.84)	(5.82)
White (=1)	0.87	0.87	0.87	0.87	0.87	0.87
N	6,111	5,991	5,418	6,111	5,991	5,260

Notes: Figures are means (standard deviations for the continuous variables are in parentheses). *N* is the total number of observations.

Table 2a: Effect of Maternal Employment, Child Care Arrangement, and Home Learning Environment on Cognitive Development — Boys

	Contemp. (i)	Cumulat. (ii)	VA–IV (iii)	CVA (iv)	CVA–IV (v)	GMM–predet. (vi)
Mother works full time	0.186**	0.076+	0.107+	0.012	0.011	-0.433*
	(0.031)	(0.041)	(0.057)	(0.039)	(0.069)	(0.179)
Mother works part time	0.196**	0.110**	0.024	0.028	-0.076	-0.201+
	(0.025)	(0.031)	(0.048)	(0.029)	(0.052)	(0.103)
In formal child care	0.004	-0.018	-0.057	-0.026	-0.054	0.093
	(0.027)	(0.033)	(0.048)	(0.031)	(0.051)	(0.122)
Home learning environment score	0.065**	-0.018	-0.038+	-0.016	-0.028	0.178**
	(0.010)	(0.014)	(0.020)	(0.013)	(0.024)	(0.056)
Mother worked full time (t-1)		0.140**		0.091*	0.157*	
		(0.043)		(0.041)	(0.070)	
Mother worked part time (t-1)		0.142**		0.094**	0.207**	
		(0.033)		(0.031)	(0.050)	
In formal child care (t-1)		0.061+		0.049	-0.011	
		(0.036)		(0.034)	(0.060)	
Home learning environment score (t-1)		0.078**		0.023+	-0.016	
		(0.013)		(0.013)	(0.024)	
Lagged cognitive outcome (t-1)			0.717**	0.401**	0.712**	0.348**
			(0.040)	(0.010)	(0.041)	(0.043)
F-test on lagged inputs		14.29		4.47	20.02	
(p-value)		(0.000)		(0.001)	(0.000)	
Hansen J test						1.36
(p-value)						(0.929)
Observations	16,946	10,323	4,360	10,057	4,360	4,360

Notes: Each model also controls for child's age (and age square), number of siblings, mother's age at birth, and indicator variables for having experience of life with a single parent, being a firstborn child, being of white ethnicity, and region of residence.
+ significant at 10% level; * significant at 5% level; ** significant at 1% level.

Table 2b: Effect of Maternal Employment, Child Care Arrangement, and Home Learning Environment on Cognitive Development — Girls

	Contemp. (i)	Cumulat. (ii)	VA–IV (iii)	CVA (iv)	CVA–IV (v)	GMM–predet. (vi)
Mother works full time	0.180**	0.167**	0.096*	0.115**	0.116*	0.221
	(0.029)	(0.038)	(0.048)	(0.036)	(0.058)	(0.156)
Mother works part time	0.208**	0.183**	0.155**	0.141**	0.162**	0.182+
	(0.024)	(0.029)	(0.041)	(0.027)	(0.046)	(0.09 7)
In formal child care	-0.000	0.000	-0.013	-0.010	-0.011	0.032
	(0.025)	(0.031)	(0.040)	(0.028)	(0.043)	(0.104)
Home learning	0.074**	-0.034**	-0.066**	-0.020+	-0.097**	0.188**
environment score	(0.010)	(0.013)	(0.017)	(0.012)	(0.021)	(0.055)
Mother worked		0.019		-0.024	-0.039	
full time (t-1)		(0.039)		(0.037)	(0.059)	
Mother worked		0.069*		0.004	-0.018	
part time (t-1)		(0.030)		(0.028)	(0.044)	
In formal		0.090**		0.090**	0.003	
child care (t-1)		(0.033)		(0.031)	(0.050)	
Home learning		0.100**		0.029*	0.054*	
environment score (t-1)		(0.013)		(0.012)	(0.022)	
Lagged cognitive			0.615**	0.405**	0.611**	0.388**
outcome (t-1)			(0.037)	(0.010)	(0.037)	(0.038)
F-test on lagged inputs		16.07		3.35	7.04	
(p-value)		0.0000		0.0051	0.218	
Hansen J test						7.59
(p-value)						0.18
Observations	16,477	10,047	4,359	9,851	4,359	4,359

Note: See notes to Table 2a.

+ significant at 10% level; * significant at 5% level; ** significant at 1% level.

Table 3a: Effect of Maternal Employment, Child Care Arrangement, and Home Learning Environment on Non-Cognitive Development — Boys

	Contemp. (i)	Cumulat. (ii)	VA–IV (iii)	CVA (iv)	CVA–IV (v)	GMM–predet. (vi)
Mother works full time	0.218**	0.188**	0.102**	0.082**	0.092*	-0.160*
	(0.026)	(0.032)	(0.032)	(0.025)	(0.039)	(0.081)
Mother works part time	0.176**	0.166**	0.099**	0.077**	0.093**	-0.102*
	(0.021)	(0.025)	(0.027)	(0.020)	(0.031)	(0.049)
In formal child care	0.056*	-0.006	-0.060*	-0.020	-0.047+	0.105**
	(0.022)	(0.026)	(0.026)	(0.020)	(0.028)	(0.053)
Home learning environment score	0.106**	0.043**	0.000	0.018*	0.020	0.059*
	(0.009)	(0.012)	(0.012)	(0.009)	(0.015)	(0.028)
Mother worked full time (t-1)		0.080*		0.037	0.024	
		(0.032)		(0.026)	(0.039)	
Mother worked part time (t-1)		0.081**		0.054**	0.017	
		(0.025)		(0.020)	(0.029)	
In formal child care (t-1)		0.051+		-0.024	-0.047	
		(0.026)		(0.021)	(0.032)	
Home learning environment score (t-1)		0.085**		0.016+	-0.038*	
		(0.010)		(0.009)	(0.015)	
Lagged non-cognitive outcome (t-1)			0.961**	0.657**	0.966**	0.027
			(0.024)	(0.010)	(0.024)	(0.032)
F-test on lagged inputs		18.72		2.15	8.91	
(p-value)		0.0000		0.0572	0.1127	
Hansen J test						2.12
(p-value)						0.833
Observations	17,045	10,355	4,436	10,087	4,436	4,436

Note: See notes to Table 2a.

+ significant at 10% level; * significant at 5% level; ** significant at 1% level.

Table 3b: Effect of Maternal Employment, Child Care Arrangement, and Home Learning Environment on Non-Cognitive Development — Girls

	Contemp. (i)	Cumulat. (ii)	VA–IV (iii)	CVA (iv)	CVA–IV (v)	GMM–predet. (vi)
Mother works full time	0.187**	0.134**	-0.035	0.054*	-0.007	0.058
	(0.024)	(0.029)	(0.030)	(0.024)	(0.037)	(0.076)
Mother works part time	0.192**	0.166**	0.011	0.103**	0.031	0.049
	(0.020)	(0.022)	(0.026)	(0.018)	(0.028)	(0.045)
In formal child care	0.005	-0.021	0.015	-0.007	0.022	0.039
	(0.020)	(0.023)	(0.024)	(0.018)	(0.026)	(0.049)
Home learning	0.127**	0.076**	0.001	0.032**	0.011	0.042
environment score	(0.009)	(0.011)	(0.012)	(0.008)	(0.014)	(0.027)
Mother worked		0.082**		-0.004	-0.038	
full time (t-1)		(0.029)		(0.024)	(0.039)	
Mother worked		0.099**		0.005	-0.037	
part time (t-1)		(0.022)		(0.018)	(0.027)	
In formal		0.001		-0.017	-0.029	
child care (t-1)		(0.024)		(0.020)	(0.031)	
Home learning		0.071**		0.001	-0.020	
environment score (t-1)		(0.010)		(0.008)	(0.014)	
Lagged non-cognitive			0.970**	0.620**	0.976**	0.023
outcome (t-1)			(0.025)	(0.010)	(0.026)	(0.029)
F-test on lagged inputs		14.73		0.38	5.87	
(p-value)		0.0000		0.865	0.3192	
Hansen J test						4.26
(p-value)						0.513
Observations	16,423	10,003	4,367	9,765	4,367	4,367

Note: See notes to Table 2a.
$^{+}$ significant at 10% level; * significant at 5% level; ** significant at 1% level.

Table 4: Cross-Validation RMSE for Selected Alternative Specifications

	Cognitive outcome		Non-cognitive outcome	
	Boys	Girls	Boys	Girls
Cumulative	1.132	1.018	0.902	0.800
CVA	1.409	1.004	0.843	0.763
CVA–IV	1.428	1.003	0.839*	0.761*
GMM–predetermined	1.111*	0.965*	0.920	0.809

Notes: Figures are based on five roughly equally sized random holdout samples. Each model is estimated on one of the five samples separately and used to compute the RMSE for the other four left-out samples. This procedure is repeated alternating the subset of data that is left out. The number in each cell is the average RMSE over the five rounds.
* denotes the model specification with the smallest RMSE value.

Table 5: SES Gradient Closed by Family Inputs

	SES Gradient at baseline	Contemp.	CVA–IV	GMM–predet.
		Boys		
Cognitive outcome				
HSES vs LSES	0.679	0.631	0.338	0.836
		[7.1%]	[50.2%]	[123.1%]
Non-cognitive outcome				
HSES vs LSES	0.384	0.319	–0.012	0.640
		[17.0%]	[–3.1%]	[166.6%]
		Girls		
Cognitive outcome				
HSES vs LSES	0.590	0.548	0.270	0.480
		[7.2%]	[54.2%]	[18.6%]
Non-cognitive outcome				
HSES vs LSES	0.390	0.344	–0.010	0.480
		[11.7%]	[–2.6%]	[122.9%]

Notes: The first column reports the HSES vs LSES gradient estimated from a baseline model which, besides mother's education, includes child's age and age squared, mother's age at birth and its square, child's parity, number of siblings, and indicators for region of birth, ethnicity, and having experienced life in a single parent household. The baseline model specification includes neither family inputs nor lagged outcomes. Each of the numbers in the other columns is the SES (HSES vs LSES) gradient. Numbers in square brackets are the percentage of the gradient closed (or magnified) by family inputs and, in the case of CVA–IV and GMM–predetermined specifications, also by lagged outcomes. A number below 100 in square brackets indicates a reduction of the SES gradient, while a number greater than 100 indicates an increase. Negative numbers indicate a full elimination of the gradient.