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## A decomposition analysis of the relationship between parental income and multiple child outcomes †

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### Abstract

This paper explores the relationship between family income and six child developmental outcomes in mid-childhood. The outcomes span development in cognitive, emotional, behaviour and health domains. We examine the income gradients in a consistent manner that allows comparison across outcomes and decompose the income gradients into two overlapping sets of pathways. The first operates through observed parental behaviours and their inputs into children that are associated with income. The second captures the influence of other observed family characteristics, such as low parental education, that tend to co-occur with low income. There is also a residual portion of the income gradient that is not associated with observed inputs or measures of parental background and human capital. We find that the extent of the income gradient differs across outcomes. The strongest gradients are associated with cognitive outcomes, the weakest with health outcomes. Some inputs account for part of the explained income gradient across all six child outcomes but it is more common for specific inputs to be strongly associated with a limited number of outcomes. This variation in the role of inputs suggests that the underlying mediators of the social gradients in different domains of child development are not the same.

**Keywords:** Child outcomes; distal and proximal influences; income gradients; path analysis; multiple imputation; bootstrapping.

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# A decomposition analysis of the relationship between parental income and multiple child outcomes<sup>†</sup>

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## 1. Introduction

The income gradient, or the raw correlation between parental income and their child's outcome, is widely used as a summary measure of social inequalities. Raw differences in educational outcomes between poor and rich pupils are commonly used standard statistics produced by governments to monitor educational inequalities (e.g. Cabinet Office, 2009), income gradients in child health have been argued to exist in both privately and publicly funded systems (Case *et al.*, 2002; Currie *et al.*, 2007) and there is a long literature comparing intergenerational mobility across place and time which focuses on the association between earnings or incomes of parents and children (Solon, 1999, 2002; Blanden *et al.* 2007). Theories of human capital development emphasise the long-term consequences of early developmental deficits for adult outcomes (Cunha and Heckman, 2007).

The importance of this topic means research has taken different approaches to understanding this relationship. We discuss this below but note that one hallmark of many studies, particularly those that seek to establish causality, is that they focus on a single domain of child outcomes (for example, educational attainment). This makes comparison of the size of income related inequalities in different child outcomes difficult. It also means that the contribution of different factors that are associated with income inequalities is hard to compare across outcomes. In this paper we address this issue directly. We examine the association between parental income and six different childhood outcomes within a unified statistical framework that allows comparison of the role of correlated parental behaviours across outcomes. The outcomes are educational performance (children's IQ and their school achievement); behaviour (their locus of control, self-esteem and behavioural difficulties) and their physical health (fat mass), all measured between the ages of seven and nine. The motivation for this approach is that child development is multi-dimensional and it is thus important to understand which of the types of inputs that parents buy or have access to are associated with different outcomes and the degree to which those inputs are differentially associated with parental resources.

Conceptually our approach is based on insights from ecological models of child development that distinguish distal and proximal influences on child development (Bronfenbrenner 1979, 1986). Proximal processes, which are posited as the primary drivers of development, describe the immediate environment as it is experienced by the child. Distal factors have no direct effect on children but operate only through observed and unobserved proximal processes. Income is one of number of distal factors which are, by definition,

associated with developmental outcomes via their impact on the proximal environment. We decompose the income gradients into two overlapping pathways that recognises this ordering of influences and provides estimates of the contribution of each factor to the gradient that are consistent with paths implied by theory. The first pathway operates through observed parental behaviours and their inputs into children that vary with income. These include parenting behaviour, maternal psychosocial functioning, school quality, and measures of the quality of the home environment. The second operates through observed distal characteristics of the family that are associated with income and include the education and the labour market status of parents and the neighbourhood in which the family lives. Conditional on these pathways, there remains a residual portion of the gradient is not associated with either observed inputs or observed measures of parental background and human capital.

We use a cohort data source from the UK that allows us to consider an unusually rich set of factors that potentially influence developmental outcomes and are correlated with household income. The richness of our data means that we are able to control for many influences that are unobserved in other studies, such as child diet and school fixed effects. In addition, we address as an integral component of our estimation the issue of missing data that inevitably arises when using rich observational data that tracks individuals over a number of years. It is particularly important to deal with these appropriately in our type of application because differing sample sizes will confuse comparison of gradients across outcomes, which is the key focus of the analysis. We use a multiple imputation method combined with bootstrapping to derive estimates of the coefficients of interest and their distributions. However, as in all observational studies, there is the possibility that the estimated relationships partially capture correlated unmeasured influences and we do not claim to show causal relationships.

We find that the magnitude of the income gradient and the proportion that can be accounted for by observed parental behaviours differs across outcomes. Whilst some behaviours are predictive of gradients in all domains, there are clear differences in the relative importance of a number of pathways. Differences in the home learning environment between low- and high-income children, and paternal learning activities in particular, are associated with greater income disparities in cognitive outcomes than other outcomes. Income gradients in children's self-esteem and behaviour problems are much more strongly linked to maternal psychosocial functioning (which includes measures of depression, chaotic life events and social support) than are gradients in cognitive or health outcomes. Measures of children's diet at age 3 account for a larger proportion of the gradient in fat mass than in

other outcomes. Our analysis also uncovers evidence that there are some aspects of poor children's environments that serve as protective factors that offset other higher risk factors of poor children for obesity.

The paper is structured as follows. Section 2 presents our approach in detail and discusses it with reference to related literatures, including those that have sought to establish causality. In Section 3 we describe our data and the treatment of missing values. Section 4 presents the unconditional income gradients and alternative decompositions of these gradients. Section 5 provides a summary of key findings and a discussion of their implications.

## **2. Modelling framework**

We begin by outlining the approach we take and defining distal and proximal influences on child development. We then present formally our statistical model and discuss the interpretation of the estimates we derive. The final part of this section compares the pathway approach adopted here to other related literatures which seek to understand the role of income on child development, highlighting both points of similarity and the unique contribution of the pathway approach.

### **2.1 *Distal and proximal influences on child outcomes***

Our conceptual and methodological approach requires that each variable in our data be classified into one of two sets. These are first, proximal factors that influence child development directly and second, distal factors that have only an indirect influence in that they operate only via some proximal mechanism. The classification of a variable is not something that can be established statistically, but comes from previous research into the determinants of child development and depends on the application in hand (Feinstein *et al.*, 2008).

In our context we make this partition in the following way. Income is a distal influence on children's development: it impacts on children only to the extent that it affects their material circumstances and lived environments. Income is only one of a number of distal influences on children. Other distal factors, such as parental education and family structure, will also be important in shaping the overall proximal environment. The distal factors considered in this study include demographic characteristics such as family structure, maternal age and ethnicity; parental labour market characteristics; educational qualifications of the child's parents and grandparents; and aspects of the local environment captured by

deprivation indices and exposure to social housing. We focus on the raw income gradient because of its widespread use as a measure of social inequalities but the decomposition method we employ could equally be applied to the gradient defined by any distal factor, for example to the analysis of black-white gaps that have been the focus of much of the US literature (Fryer and Levitt, 2006). In this case ethnicity becomes the key stratifying variable and income would be simply one of the set of correlated distal factors that enter the decomposition. The income gradient we estimate here is a broader concept than the causal effect of income. The causal or ‘treatment effect’ of an increase in family income forms one component of the pathways decomposition and is what is referred to here as the direct contribution of income. This causal effect has been the subject of a great deal of research (see Section 2.4) and in that approach, distal factors other than income (such as parental education) can be thought of simply as confounders. However, the direct contribution of income is not the only component of the raw income gradient that is of interest. This raw gradient reflects all the influences in poorer children’s lives that influence their development and thus includes the correlation between income and other distal factors. Understanding the contributions of other characteristics that co-occur with low income is important for a rounded picture of the sources of the gradient.

The proximal pathways through which income and these other distal factors influence children are potentially very numerous. Two broad types of mechanism have been proposed in the literature and our rich data set allows us to include measures which attempt to examine both mechanisms. The first is the financial capital or investment model, which posits that poverty affects child development because it hampers parents’ ability to purchase the materials, experiences and services that are conducive to successful development (Bradley and Corwyn, 2002; Becker and Tomes, 1986). This mechanism is operationalised here with measures of the physical home environment (such as whether it is clean and safe); measures of cognitively stimulating materials in the home environment (such as books and CDs) and of stimulating parental behaviours (such as the frequency the child is read to and taken to museums); and measures of childcare mode and intensity. The second is the family process perspective, which argues that income impacts on non-material parental resources, such as the way parents monitor their children and respond to their needs (Elder and Caspi, 1988; Conger *et al.* 1992; McLoyd, 1990). Key factors emphasized by this perspective are perceived financial strain, parental psychological well-being and the warmth and sensitivity of parent-child interactions.

Finally, whilst in our data we observe an unusually rich variety of potential proximal factors substantial unobserved influences are likely to remain. The effect of these unobserved proximals will be partially picked up by the included variables, to the extent they are correlated, but the importance of orthogonal unobserved factors is quantified by the portion of the income gradient that remains unexplained by the total set of proximal variables.

## 2.2 Statistical method

Our decomposition of the income gradient builds on path analysis methods that have a long history in the social sciences (Bollen, 1989). The method allows the researcher to express the overall income gradient as the sum of a number of ‘pathways’, which are built up from a set of underlying regressions specifying the nature of the relationships between income, other distal factors, proximal factors, and developmental outcomes. The approach has clear parallels with graphical chain modelling and, in common with that approach, can be viewed as a form of structural equation modelling (SEM) in which simplifying assumptions are made about the structural equations in order to avoid the computational problems that arise when fitting a single complex model to very high-dimensional data (Berrington *et al.*, 2008) provides further discussion in a graphical chain modelling framework). A number of studies have used more restricted versions of the method presented here (Blanden *et al.*, 2007; Goodman *et al.*, 2011; Waldfogel and Washbrook, 2011). The current analysis extends the methods used in those papers by distinguishing analytically between distal and proximal variables, constructing estimates of the standard errors for the path coefficients, dealing with missing data in a consistent and sophisticated way and allowing comparison across multiple domains of child development.

We define the unconditional income gradient in the  $Y^{\text{th}}$  developmental outcome of the  $i^{\text{th}}$  child,  $Y_i$  ( $i = 1, \dots, N$ ), as  $\delta$  from the regression of  $Y_i$  on the log of family income ( $X_i$ ):

$$Y_i = \delta X_i + e_i \quad (1)$$

where  $e_i$  is a residual error term uncorrelated with log income. In what follows we set out the underlying structural equations and show how they combine to give a disaggregated expression for  $\delta$ .

[---FIGURE 1 HERE---

The underlying path model is expressed diagrammatically in Figure 1, where arrows are used to denote the dependent and independent variables in each equation and are not

intended to imply a causal relationship. The path coefficients are defined according to the following set of equations:

$$Y_i = \boldsymbol{\gamma}\mathbf{P}_i + \boldsymbol{\theta}\mathbf{D}_i + \pi X_i + \mu_i \quad (2)$$

$$\mathbf{P}_i = \boldsymbol{\beta}\mathbf{D}_i + \boldsymbol{\lambda}X_i + \boldsymbol{\eta}_i \quad (3)$$

$$\mathbf{D}_i = \boldsymbol{\alpha}X_i + \mathbf{v}_i \quad (4)$$

where  $\mathbf{P}_i$  is an  $m \times 1$  vector of proximal variables;  $\mathbf{D}_i$  is an  $n \times 1$  vector of distal variables other than income;  $\boldsymbol{\gamma}$ ,  $\boldsymbol{\theta}$ ,  $\boldsymbol{\beta}$ ,  $\boldsymbol{\lambda}$  and  $\boldsymbol{\alpha}$  are  $1 \times m$ ,  $1 \times n$ ,  $m \times n$ ,  $m \times 1$  and  $n \times 1$  matrices of coefficients respectively;  $\pi$  is a scalar coefficient;  $\boldsymbol{\eta}_i$  and  $\mathbf{v}_i$  are vectors of residual error terms and  $\mu_i$  is a scalar residual error. The path analysis approach requires that the errors in each of the  $(m + n + 1)$  structural equations be conditionally independent of the explanatory variables (Bollen, 1989). If this assumption is valid then the coefficients can be consistently estimated by ordinary least squares regression. We use a non-parametric bootstrap to conduct statistical inference on these OLS point estimates, which means no restrictions are placed on the marginal or joint distributions of any of the error terms.

Equation 2 specifies the child outcome as a function of all the variables in the model. Our assumption is that income, and other distal factors, are associated with the outcome solely via their association with proximal processes.  $\mathbf{D}_i$  and  $X_i$ , therefore, are included in equation 2, not as direct determinants of the child outcome, but rather as proxies for unobservable proximal factors that may be correlated with the observed factors  $\mathbf{P}_i$ . The inclusion of  $\mathbf{D}_i$  and  $X_i$  is to mitigate omitted variable bias in the estimates of  $\boldsymbol{\gamma}$ , given that the  $\boldsymbol{\gamma}$  are identified from differences in observed proximal factors between children from equivalent family backgrounds. Large and significant estimates of  $\boldsymbol{\theta}$  and  $\pi$  imply that there are systematic differences in the unobserved proximal influences on the outcome between children from different social backgrounds. Note the effect of a given proximal variable on the outcome is estimated conditional on all other observed proximal variables.

There are several key threats to consistency of the estimates in equation 2. One is that, even conditional on the distal variables, unmeasured proximal processes are correlated with the included proximal measures. If this is the case then the pathway attributed to a particular proximal variable will partially pick up the contribution of the correlated unmeasured factor. This form of bias is minimised by the fact that we can include many proximal variables due to the rich nature of our data. A second source of bias is reverse causation, by which the child outcome itself influences parental behaviour. We reduce the risk of this problem by the

timing of our measured variables, as we use explanatory variables that are measured in the preschool period only, which is at least two years (and often more) before the outcome is observed. There still remains the possibility that the endowments with which the child is born (often referred to as innate ability in the cognitive setting) are correlated with the proximal variables. This could arise, for example, if parents observe the child's endowment and adapt their behaviour accordingly. Our focus on descriptive decompositions that can be compared across outcomes precludes the use of techniques to address this problem directly, which are discussed briefly in Section 2.4. Hence the role of parental response to inherited characteristics should be borne in mind when interpreting our results.

Equation 3 embodies the assumption that the environment that parents are able to provide for their children reflects the constraints imposed by their socio-economic resources, of which income is only a part. The matrix of parameters  $\beta$  in equation 3 captures the net association of each distal variable other than income with each proximal factor, while the parameter vector on income,  $\lambda$ , captures the conditional association of income and the proximal factors, controlling fully for other distal variables. Again, correlation between the unmeasured determinants of each proximal factor and the included distal predictors will invalidate the conditional independence of the error terms. Perhaps the key characteristic of concern here is parental cognitive ability which is not measured in our data and so cannot be included as an observed distal factor. We expect that the influence of this factor will load heavily onto the estimated parental education coefficients, so these should not be interpreted as a causal effect of qualifications.

Equation 4 closes the system (see also Figure 1) as it captures the unconditional relationship between each distal factor (other than income) and income. Differences in proximal factors associated with particular distal characteristics can only contribute to the income gradient if those distal characteristics are not randomly distributed with respect to income. The parameter vector  $\alpha$  captures the degree to which each distal factor other than income is associated with income. It is not intended to imply a causal relationship running from income to the other distal factor:  $\alpha$  is simply a raw correlation, scaled appropriately.

Substitution of equations 3 and 4 into equation 2 allows us to write the decomposition:

$$\begin{aligned}
Y_i &= (\boldsymbol{\gamma}\boldsymbol{\beta}\boldsymbol{\alpha} + \boldsymbol{\gamma}\boldsymbol{\lambda} + \boldsymbol{\theta}\boldsymbol{\alpha} + \pi)X_i + (\boldsymbol{\gamma}\boldsymbol{\eta}_i + \boldsymbol{\theta}\boldsymbol{v}_i + \mu_i) \\
&\equiv \delta X_i + e_i \\
\therefore \delta &\equiv \boldsymbol{\gamma}\boldsymbol{\beta}\boldsymbol{\alpha} + \boldsymbol{\gamma}\boldsymbol{\lambda} + \boldsymbol{\theta}\boldsymbol{\alpha} + \pi
\end{aligned} \tag{5}$$

The unconditional income gradient,  $\delta$ , can be written as the sum of four types of ‘path’ coefficient, each of which represents a different pathway from income to an outcome,  $Y$ , in Figure 1. As equation (5) makes clear, a path coefficient is the product of the partial effects of one variable on another. These path coefficients can be combined in different ways to give alternative decompositions of the income gradient.

The  $(m + n + 1)$  variables entering the structural equations 2 to 4 are a mixture of binary, categorical and continuous variables. Linear regression (or probability) models are used to estimate all the equations in order to preserve the adding up property shown in equation 5. For categorical variables a reference category is omitted entirely from the model and the remaining categorical indicators are treated as binary. Point estimates of the parameters in equations 2 to 4 are estimated using equation-by-equation OLS and the estimates are stacked into matrices and combined according to equation 5. Standard errors for the combined path coefficients are estimated by a non-parametric bootstrap with 200 repetitions, which removes the need to make any assumptions about the joint distribution of the residual errors. Each repetition re-samples (with replacement) from the original dataset, estimates the  $m + n + 1$  ordinary linear regressions given in equations 2 to 4, and calculates the nonlinear combinations of the coefficients. This method produces 200 estimates of each path coefficient which together give the sampling distribution of the population parameter. We take the mean as the point estimate of the coefficient and the standard deviation as its standard error. The entire decomposition process is repeated separately for each of the six child outcome variables. Item non-response is addressed through multiple imputation. This is discussed more fully in Section 3.3, but briefly the process described above is repeated 10 times, each on a different imputed dataset, and the 10 sets of estimates are then combined using Rubin’s rules.

For tractability our decomposition approach relies on the identifying assumptions that the effects of different factors on the outcome are linear and additively separable. We tested the sensitivity of our findings to the linearity assumption by recoding continuous variables into sets of discrete categorical variables and re-running the analysis. The results were

virtually unchanged. However, if there are non-trivial interaction effects between multiple factors this will be missed by our model.

### ***2.3 Interpreting the estimates from the model***

Income is associated with the observed proximal factors that influence the outcome in two ways. From the equations and Figure 1, income affects the observed proximal variables (the path  $\boldsymbol{\gamma}\boldsymbol{\lambda}$ ). It is also correlated with distal variables that independently influence the proximal variables (the path  $\boldsymbol{\gamma}\boldsymbol{\beta}\boldsymbol{\alpha}$ ). Summing these two terms together, the component  $\boldsymbol{\gamma}(\boldsymbol{\beta}\boldsymbol{\alpha} + \boldsymbol{\lambda})$  gives the part of the income gradient that can be attributed to differences in observed proximals in total. The remaining portion of the income gradient ( $\boldsymbol{\theta}\boldsymbol{\alpha} + \boldsymbol{\pi}$ ) is the part that reflects the association of income with unobserved proximals. This residual portion can be broken into two terms: the first is the path  $\boldsymbol{\theta}\boldsymbol{\alpha}$ , which measures the correlation of income with other distal factors that operate via unobserved proximals. The second term,  $\boldsymbol{\pi}$ , is the pathway by which income itself operates via unobserved proximal influences.

The terms in the overall decomposition can be disaggregated in different ways to study specific paths accounting for the raw income gradient. Define  $\gamma_j$  as the coefficient on the  $j$ th proximal variable and  $\theta_k$  as the coefficient on the  $k$ th distal variable in the outcome equation 2;  $\beta_{jk}$  as the coefficient on the  $k$ th distal variable and  $\lambda_j$  as the coefficient on income from the  $j$ th proximal equation 3;  $\boldsymbol{\beta}_j$  as the  $(n \times 1)$  vector  $(\beta_{j1} \dots \beta_{jn})'$ ;  $\boldsymbol{\beta}_k$  as the  $(m \times 1)$  vector  $(\beta_{1k} \dots \beta_{mk})$ ; and  $\alpha_k$  as the coefficient on income from the  $k$ th distal equation 4. Then the term  $\gamma_j(\boldsymbol{\beta}_j\boldsymbol{\alpha} + \lambda_j)$  is the part of the income gradient attributed to the  $j$ th proximal variable. It quantifies, for example, the gradient predicted only by differences in the home learning environment between low- and higher-income families or, put another way, the predicted decrease in the overall gradient if the association between income and the home learning environment were eliminated, holding all else equal.

The term  $(\boldsymbol{\gamma}\boldsymbol{\beta}_k + \theta_k)\alpha_k$  is the part of the gradient due to the correlation of income with the  $k$ th distal variable and captures the degree to which the raw gradient is due to the confounding of income with a particular distal factor such as parental education. This is the part that is normally treated as a nuisance in studies aiming to isolate the effect of income on outcomes. But this component can be used to provide answers to the question that if it is not financial resources that generates the better outcomes of higher-income children, what is it? The term can be further split into two parts: an observed and an unobserved term.  $\boldsymbol{\gamma}\boldsymbol{\beta}_k\alpha_k$  is the sum of all the observed proximal pathways through which the  $k$ th distal factor influences

the outcome and  $\theta_k \alpha_k$  is its influence via unexplained pathways (such as the residual effect of parental education on child IQ conditional on all other variables).

The terms  $\gamma_j \beta_{jk} \alpha_k$  and  $\gamma_j \lambda_j$  give the finest level of decomposition. The first estimates the extent to which the contribution of the  $j$ th proximal factor is associated with differences in the  $k$ th distal factor (for example the pathway from parental education to the home learning environment to child IQ) weighted by the association of parental education with income. The second reflects the conditional influence of income itself on the  $j$ th proximal variable (e.g. the pathway from income to the home learning environment to the outcome). Appendix B presents a worked numerical example for a very simple hypothetical model.

#### ***2.4 Relationship of the pathway modelling approach to other methodologies***

We now turn to a discussion of the advantages and disadvantages of the pathways approach relative to others which examine the impact of income on child development. Early work in economics focused on estimation of the ‘reduced form’ effect of income i.e. the association between income and outcomes when other confounding characteristics are controlled (Duncan and Brooks-Gunn, 1997; Klebanov *et al.*, 1998; Dearing *et al.*, 2001). These estimates correspond to the composite ( $\gamma \lambda + \pi$ ) in the pathways approach, which we label the direct contribution of income. Concern that conditional reduced form estimates did not accurately reflect the causal effect of income has led to a focus on adjusting for unobserved heterogeneity. One approach is to exploit variation induced by an experimental intervention or a policy shift. But such studies normally only consider a limited range of outcomes (often a measure of cognitive or educational attainment). In addition, experimental studies rarely involve only changes in incomes as they usually also involve a desired behavioural response. For example, the Minnesota Family Income programme and the Canadian Self-Sufficiency Programme sought an increase in employment of lone mothers (Grogger and Karoly, 2005, provide an extensive discussion of welfare reform experimentation in North America). Cash programmes in many developing countries where the payment is linked to child school attendance or child immunisation (e.g. Baez and Camacho, 2011; Skoufias *et al.*, 2001). Quasi-experimental interventions involve a policy shift by governments which result in income gains for a particular group and the effects on child outcomes can be compared to a non- or less treated group (see for example Dahl and Lochner, 2012; Milligan and Stabile, 2011; Gregg *et al.*, 2009). These studies tend to involve relatively modest income changes for a limited portion of childhood and for select groups. The strength of these studies is to

estimate a causal (but local treatment) effect of income. But they do not generally explore the channels through which the observed effects occur.

These channels have, however, received attention in mediation studies in the developmental psychology literature. Studies such as Guo and Harris (2000), Yeung *et al.*, (2002) and Schoon *et al.*, (2010) use structural equation models to test theories of the way in which income is mediated. These studies exploit the kind of rich observational data we use here. Typically their focus has been on understanding the processes that explain the conditional effect of income only, so their findings correspond to the part of our decomposition that breaks the direct contribution of income into various explained ( $\sum_j \gamma_j \lambda_j$ ) and unexplained ( $\pi$ ) components.

An approach from the economics literature that seeks to get inside the ‘black box’ of the family background-child outcome association is the estimation of human capital production functions, for example, Todd and Wolpin (2003, 2007), Ermisch (2008), Cunha *et al.*, (2010). This approach views child development as a production process and aims to estimate the technology by which inputs are transformed into outputs. In common with the ecological approach employed here it posits that certain factors are the direct determinants of human development, and in that sense inputs are conceptually equivalent to proximal processes. Equation 2, which expresses the outcome as a function of all distal and proximal processes, can be viewed as a simple ‘hybrid’ production function in which distal factors are included to proxy for unobserved inputs (Todd and Wolpin, 2007). A key insight from this approach is that child attainment (often more narrowly described as cognitive ability) reflects the dynamic interaction between the child’s innate ability and the cumulative effect of a series of investments made over the life of the child. Our simple production function is a static approximation to these more complex structural models that attempt to estimate the entire dynamic relationship between inputs and the outcome as it evolves over the child’s life cycle (Cunha *et al.*, 2010).

A key criticism of static, cross-sectional estimates of the production function is that they overstate the importance of contemporaneous input measures because of their correlation with omitted historical inputs. To try to overcome this in the present study, our proximal measures are not only measured prior to the outcomes but are, in many cases, composite measures from multiple waves of data spanning all the preschool years (see Section 3 and Appendix Table A1). They can be viewed, therefore, as summary measures of the whole history of inputs during that period. We also do not employ a value-added

specification, in which lagged outcome measures are included as controls, so the associations we measure in equation 2 capture any effects of the proximal processes that are transmitted via their impact on intermediate outcomes. However, the approach we use here does not model the full dynamic process of child development. Rather the focus is on describing the different income gradients across outcomes as they stand in mid-childhood, and their association with observed and unobserved behaviours and endowments of parents up to this stage of child development. Our production function (equation 2) is just one component of the relationships we seek to measure, alongside the relationships represented in equations 3 and 4.

### **3. Data**

We use a rich cohort data set which contains measures that are frequently collected in surveys of childhood experiences such as cognitive stimulation in the home, maternal depression and discipline style, but also includes measures that are less frequently observed, for example, the child's diet and school identifiers, and is also matched to administrative data.

#### ***3.1 The Avon Longitudinal Study of Parents and Children (ALSPAC) cohort***

We use a birth cohort of English children, ALSPAC, which recruited pregnant women resident in the Avon area of England whose expected date of delivery fell between 1<sup>st</sup> April 1991 and 31<sup>st</sup> December 1992. The enrolment sample consisted of 14,541 women (between 80 to 90 percent of all those who had a pregnancy during this period), of which 13,801 (95%) went on to become the mothers of surviving offspring at 12 months, with multiple births leading to a total of 13,971 children in the study at that age. The Avon area has a population of 1 million and includes the city of Bristol (population 0.5 million), and a mixture of rural areas, inner city deprivation, suburbs and moderate sized towns. Comparison with the 1991 census showed that the sample is broadly representative of the national population of mothers with infants less than 1 year of age (Boyd *et al.*, 2013 provides further details).

Study families were surveyed with high frequency from the time of pregnancy onwards, with mothers completing 4 postal questionnaires prior to the birth, plus a further 5 on family characteristics and a further 8 focusing on the study child in the first 4 years after the birth alone. The study also contains data from a number of other sources. Three clinical assessment visits took place when the children were 7, 8 and 9 years of age, where children were administered a range of detailed hands-on physical, psychometric and psychological

tests. A number of external sources of information have been matched to the ALSPAC children. We use records from the National Pupil Database (NPD), which contains school identifiers and results on national (Key Stage 1) school tests for all children in the state school system, and information on local deprivation at the small area level (Indices of Multiple Deprivation, IMD).

ALSPAC has certain advantages for our purposes over other national birth cohort studies. Some outcome variables measured directly during the clinical assessment visits (such as locus of control and fat mass) are not available in other studies or are measured more crudely. Many explanatory variables are measured at multiple developmental stages in early childhood including, uniquely, the period when the child was in utero. In addition, the regional census nature of the sample allows us to exploit the fact that multiple study children are nested within the same schools.

### **3.2 Analysis variables**

The variables in our analysis fall into one of four types: outcomes measures, income, distal factors and proximal factors. This section gives a brief introduction to the data used. Full details of the construction of all variables and source references are in Appendix Table A1. Descriptive statistics for all variables in the working sample are given in Appendix Table A2.

*Outcome measures.* We explore the income gradients in six different measures of developmental outcomes when the child is aged between seven to nine.

Two of these are cognitive: IQ at eight (the WISC-III UK) and Key Stage 1 (KS1) scores at seven. The latter are scores from national school tests of reading, writing and mathematics and are from national administrative data (the National Pupil Database, NPD). While the two are strongly related, we argue that IQ can be thought of more as a measure of ‘pure intelligence’ whereas Key Stage 1 is more a measure of ability to perform on school based literacy and numeracy tests.

Three are ‘non-cognitive’ outcomes: locus of control at eight; self-esteem at eight; and behaviour problems at seven. Individuals with an ‘external’ locus of control tend to attribute outcomes to luck, chance, fate or the interventions of others, whilst those with an ‘internal’ locus of control tend to believe that their own efforts are a decisive influence. ‘Internal’ individuals are expected to be more active in pursuing goals and to show greater ingenuity and persistence when confronted with obstacles than ‘external’ individuals. Locus of control and self-esteem are taken from scales completed in person by the child during an ALSPAC clinical assessment visit. Behaviour is measured by teacher-rated scores on the

well-known SDQ Total Behavioural Difficulties Scale. Unlike studies that use mother-reported behaviour scores, therefore, our measure is not subject to the potential biases arising from the fact that mothers report both the explanatory variables and the outcome (e.g. Fergusson *et al.*, 1993), although we note that children's behaviour in school may be systematically different from their behaviour at home and potential teacher bias (e.g. Johnston *et al.*, 2012) may arise. To the extent that the latter occurs at school, rather than at individual, level it will be mitigated by our use of controls for the school which children attend (discussed below).

The final measure is a physical health outcome: fat mass at age nine. This is derived from full body (DXA) scans and is an indicator of risk of obesity, which is superior to body mass index (BMI) as the scans distinguish between lean muscle and fat (Power *et al.*, 1997).

All six measures of child outcomes are normalized on child sex, cohort year and month of birth, then standardized to mean 100, standard deviation 10, on the full sample of children with non-missing values for that outcome. The original locus of control, behaviour and body fat measures are all such that higher scores indicate more adverse outcomes. We estimate models using these original variables, but to facilitate comparison we reverse the sign of the coefficients for these outcomes in the presentation of our results. Hence in all cases a coefficient of 1 on an explanatory variable is associated with an improvement of one-tenth of a standard deviation in the given outcome, where that standard deviation relates to all available valid observations (see below). Pairwise correlations between the outcomes (Appendix Table A3) range from 0.64 for IQ and KS1 to 0.02 for self-esteem and fat mass. The mean of the 15 outcome correlations is only 0.22, which provides support for the idea that child well-being is multi-dimensional and not summarised well by only one or two outcome measures.

*Income.* Our measure of family income is constructed from banded information on weekly disposable household income taken from two questionnaires at child age 33 and 47 months (the only two dates at which it is available in early childhood). We average over the two measures to reduce measurement error and use the log. This specification embodies the insights from previous work (e.g. Dearing *et al.*, 2001; Duncan *et al.*, 2010) that the relationship between income and child development is non-linear.

*Distal factors.* We consider four groupings of distal variables that capture other dimensions of a family's socio-demographic resources. They are: household demographics (family structure, family size, maternal age and race/ethnicity); labour market status (parental employment and occupation); education (parents' and maternal grandparents' highest

qualifications); and neighbourhood (local deprivation and social housing). (As non-white children make up only 4% of the birth cohort more fine-grained ethnic differences in child outcomes cannot be studied here.) The variables representing family structure, siblings and parental employment summarise the pre-natal to 47 months post-birth period. For example, the categorical maternal employment variable distinguishes mothers who worked full-time at any point between birth and 47 months; those who worked part-time only during this period; and those who did not work at all. Social housing is similarly captured by a composite variable that uses information up to 33 months post-birth. Parental education and occupation were measured during pregnancy and the local area is location at birth.

*Proximal factors.* Proximal variables are also organized into a number of groupings. These are maternal psychosocial functioning; pre-school childcare mode; health behaviours and health at birth; home learning environment; physical home environment; and school composition and quality (see Appendix Table A1).

Wherever possible we have included proximals used in previous research. For example, our measures of the home learning environment – cognitively stimulating materials and activities – are standard in research on the relationship between family background and child outcomes, and correspond closely to a number of items from the widely-used Home Observation for the Measurement of the Environment (HOME) scale. They include ownership of books and toys; maternal teaching of 10 items such as shapes, colours and the alphabet; frequency of reading and singing to the child by the mother and her partner; and trips to places such as libraries and museums. Measures are constructed from information collected at four waves between 6 and 42 months and are designed to capture both timing and intensity of experiences over the preschool period. As another example, while we do not have measures of the quality of childcare, we have very detailed data on type of childcare and hours of care, for 6 dates between 8 weeks and school entry. We then construct 12 non-mutually exclusive categorical variables measuring exposure to six types of care for the period 0 to 2 and the period 3 to school entry. Each variable has three categories for whether the child attended that type of care, not at all, less than 15 hours a week or 15+ hours per week, giving a set of 24 childcare indicators.

We also expand the set of potential proximal variables beyond those used in previous studies. Specifically, we widen the scope of maternal psychosocial functioning beyond depression and subjective financial pressure to include measures of the frequency and severity of shocks experienced by the household; the quality of the parental relationship; the extent and depth of the mother's social networks; and the mother's beliefs with regard to

personal responsibility (locus of control). Again, the majority of these variables combine information from multiple time points between pregnancy and 47 months. We include measures of breastfeeding and child's diet (the latter at age three) as additional health-related factors, and other dimensions of the physical home environment such as crowding, noise and access to a car or garden.

A final innovation is that the geographical nature of the ALSPAC cohort allows us to explore the contribution of schools in a very flexible way. We use school dummies as explanatory variables, which capture the effect on scores of attendance at a particular school, relative to the reference school. The use of school fixed effects hence captures the contribution of all factors common to a given school, including peer group composition, school resources and the quality of teaching.

### **3.3 *Missing data***

Missing data problems will occur in any analysis of longitudinal cohort data that uses a very large number of variables, because of attrition and item non-response. These problems are particularly acute in ALSPAC because of the very high frequency of follow-up of cohort members. While many birth cohorts will have administered just two or three survey instruments by the time the cohort members are 9, in ALSPAC the number is closer to 50. Non-monotone non-response is very common in ALSPAC, as respondents often miss one or more follow-ups but do not leave the study completely.

Our target sample is the 9,476 children with some information on income and at least one outcome measure. The target sample as a whole is slightly positively selected in relation to the initial sample of 13,971 in terms of observable characteristics. Using maternal education (available for virtually the whole cohort) as an indicator of socio-economic status, 35% of the initial sample have age 18 (A-levels) school qualifications or higher compared with 39% of our target sample.

Within the target sample item non-response on the outcome measures varies across outcomes. The largest sample at 8,727 is for the Key Stage 1 scores, as these are matched into ALSPAC from administrative data. The smallest sample is for behaviour problems (3,294), which are teacher assessed and results from the fact that not all teachers completed the relevant questionnaire. Even without taking into account any missingness in the 160 explanatory variables, only 1,645 observations have complete data on all six outcomes, and this sample is highly non-representative (for example, 50% of the common sample have A-

level or above). Full details in the proportion of missing data for all the analysis variables are provided in Appendix Table A2.

To exploit all the information contained in the sample we used multiple imputation by chained equations (van Buuren *et al.*, 1999). Our imputation model used all the variables that enter the analysis models and produced ten 9,476-observation rectangular datasets using the Stata command *ice* (Royston, 2004). The multiple imputation method relies on the assumption that data are missing at random (MAR), given the known characteristics of the missing individuals. While this assumption is essentially untestable we believe it appropriate in this case because of (a) the high degree of non-monotone non-response that provides later data to impute earlier missing values (b) the rich nature of the data included in the imputation and analysis models (c) the availability of the NPD data which provides school achievement information for virtually the whole sample towards the end of the analysis period and (d) our models are linear and do not contain any interaction effects that commonly lead to violation of the MAR assumption.

The bootstrap estimation procedure described in Section 2.2 was conducted separately on each imputed dataset, yielding ten sets of estimates of the path coefficients and their standard errors (the means and standard deviations of the 200 values given by the bootstrap). These ten values were then combined using Rubin's rules to yield our final estimates. The significance of each path coefficient was calculated by comparing the ratio of the coefficient to its standard error with a standard normal distribution using a two-tailed test.

## 4. Results

### 4.1 *The income gradients*

We begin by presenting the raw income gradients. Figure 2 shows these for all of the six outcomes, estimated as the  $\delta$  from equation 1. All gradients are significant at the 1% level and show that the poorest children fair less well than their better-off counterparts. The gradient is largest for cognitive outcomes, where a unit change in (log) income is associated with an increase in IQ of 6.6 points (or 0.66 of a standard deviation), and a marginally smaller increase in academic achievement scores (Key Stage 1). The gradients in non-cognitive outcomes are around a third to a half as large as those in cognitive outcomes, with the steepest gradient in locus of control and the shallowest in self-esteem, and with behavioural problems falling somewhere between the two. The gradient in fat mass is the smallest of all six outcomes, at around 1.6 points (0.16 of a standard deviation). The finding

that it is cognitive development that is most strongly associated with early family income is in line with findings from previous research (e.g. Howe *et al.*, 2012).

[---FIGURE 2 HERE---

We turn now to presentation of the estimates to examine of the impact of different factors. We begin with high level summary of the findings of our decomposition analysis, highlighting the differential treatment of proximal and distal factors in our framework. Subsequent tables focus on more disaggregated results, and give an illustration of results in which the two types of pathways overlap. In all tables we present the path coefficients, which express the importance of the pathway in terms of the overall variation in the outcome (i.e. in standard deviation units). Larger values here correspond to greater inequalities in a way that is comparable across outcomes. In selected tables we also express the coefficients as percentages of the total income gradient in each individual outcome. These numbers help to highlight the relative importance of different pathways in accounting for a given gradient, but it is important to recognise that a small fraction of a large raw gradient may indicate greater disparities in real terms than a large fraction of a small gradient.

#### 4.2 *Summary decomposition of the role of proximal factors*

[---TABLE 1 HERE---

In terms of the model set out formally in Section 2 and Figure 1, Table 1 decomposes the raw income gradient according to:

$$\delta = \{\gamma(\beta\alpha + \lambda)\} + \{\theta\alpha + \pi\}$$

The first and second terms in curly brackets are the components of gradient which are (results in Row A), and are not (results in Row B), explained by observed proximal variables respectively. This decomposition focuses on how well measurable aspects of children's environments can explain the poorer outcomes of low-income children in total, or how far we can quantify the ultimate sources of outcome disparities. Although distal factors are included in the underlying models, this decomposition abstracts from whether it is income itself, or other correlated distal factors, that generate inequality in the relevant proximal factors. The sum of the two components is given in the final row of Table 1 and repeats the raw relationship between income and the outcome presented in Figure 2.

Row A shows that income-related differences in our observed proximal factors predict significant gradients in all six child outcomes. In size terms these are of similar magnitude for all outcomes except self-esteem and fat mass, where the predicted gradients are smaller. But when expressed as a share of the overall income gradient, the proximal

influences capture a smaller share of the gradients associated with cognitive attainment (under 40%) than for the other outcomes. On the other hand, 75% of the gradient in behaviour is explained. Under the extreme assumption that all the relationships estimated were causal the results imply that if all differences in observed proximal factors between low- and higher-income families were eliminated the income gradient in cognitive outcomes would fall by one-third, while the gradient in behaviour would fall by as much as three-quarters. The associated reductions in the other non-cognitive outcomes and fat mass lie between these numbers. Or if we assumed that all beneficial proximal processes, both observed and unobserved, are positively correlated (so that the omitted variable bias is always upwards) then these estimates would be upper bounds on the extent to which the proximal factors measured in our data drive the observed income gradients.

The next six sets of rows present the contributions of six sub-groupings of proximal influences. The poorer psychosocial functioning of low-income mothers (row i) is associated with the income gradient for all six outcomes. But its strongest association, both in absolute and relative terms, is with self esteem and behaviour, where it accounts for around 40% of the total unconditional income gradient. This is not due to maternal reporting of both child behaviour and her own mental health as, in contrast to many studies, the psychological scales in our data are completed by the mother for herself while the reports of the child's behaviour are completed by the teacher.

Row ii shows that the patterns of pre-school childcare used by higher-income families are positively associated with IQ and locus of control but not with other outcomes, and there is even some weak evidence that these same childcare patterns are negatively associated self-esteem and behaviour. Differences in health-related behaviours contribute significantly to the gradients in all domains of development, but as we might expect, their greatest importance is for the fat mass gradient, where they account for over 60% of the total. The quality of the home learning environment in low-income households is most strongly associated with deficits in cognitive and non-cognitive outcomes, but not at all with fat mass. The physical home environment accounts for little if any of the income gradients and, again, negative path coefficients for fat mass and self-esteem suggest the presence of protective factors in low-income families in this domain. We return to this protective effect in our detailed examination of particular proximals in Table 3. Finally, differences in the schools attended by low- and higher-income children (as measured by school fixed effects) play absolutely no role in accounting for any of the gradients. This may reflect that outcomes are in mid-childhood and hence early in the school career.

### 4.3 *Summary decomposition of the role of distal factors*

Table 2 looks at the role of the distal factors that are correlated with income in generating the raw income gradient. It ignores the proximal pathways and examine only how far the socio-demographic characteristics of low-income families can explain the observed raw income gradients. Estimates of the direct contribution of income are therefore comparable to reduced form OLS estimates of the effects of income on child outcomes (for example, Duncan and Brooks-Gunn, 1997, and many subsequent related papers).

Row A of the table shows this conditional role of income (i.e. through both observed proximal and unobserved proximals). It shows that the direct contribution of income to child outcomes is significant only for cognitive outcomes, where it generates differences of 0.12 to 0.14 standard deviations for a log-point change in income. So around one-fifth of the raw gradient in cognitive outcomes reflects a direct contribution of income. The remaining 80% can be attributed to other distal factors than covary with low income and independently influence children's proximal environments. For the non-cognitive and fat mass outcomes no significant direct effect of income remains, although we note that in share terms it represent a large proportion of the deficit of low-income children in self-esteem. We return to these estimates in Section 4.6, where we explore how the direct contribution of income is mediated by different proximal factors.

[---TABLE 2 HERE---

The rest of Table 2 contains the pathways often not reported in other studies. These are those that permit the contribution of income to be compared with the effect of the other correlated distal factors.

Block B shows these in four sets: household demographics, labour market status of parents, education of parents and neighbourhood. Parental education (row iii) has a substantial influence on the income gradients in all the child outcomes. It accounts for over half the gradient in fat mass and for a quarter of the behavioural gradient, the outcome for which the proportion is lowest. The gradient in cognitive outcomes predicted by differences in educational attainment between low- and higher-income families when all other distal factors (including income) are held constant is double the size of the direct income effect. But it should be noted that these education pathways are likely to capture the role of unmeasured parental cognitive ability as well as qualifications achieved. Education is also the only broad grouping of distal factors that significantly predicts gradients in all six outcomes.

Row ii shows there are substantial contributions of the differential labour market characteristics of parents (employment and occupation) to the cognitive, locus of control and behavioural outcomes even net of income and education, but this is not the case for self esteem and fat mass. Row i shows a similar pattern for differences in household demographics associated with income, although the magnitudes of the path coefficients here are generally half the size of the those associated with labour market characteristics. Row iv shows there are also independent contributions from the local neighbourhood factors associated with income to cognitive and behavioural outcomes, with again no significant pathway to self esteem. In contrast to the paths for household demographics and labour market status, we do find a significant and relatively large role for neighbourhood in predicting the fat mass gradient.

#### ***4.4 The role of specific proximal factors***

Table 3 disaggregates the associations in Table 1 and explores in more detail the gradients predicted by income-related differences in the detailed proximal factors. These estimates are the separate  $\gamma_j(\beta_j\alpha + \lambda_j)$  paths. Row A of Table 3 and the totals for each block numbered i to vi repeat the information shown in Table 1. Within each block these combined paths are disaggregated into sub-sets of proximal variables which sum to the block total. We do not present shares in this table but the final row of the table shows the unconditional income gradients which are the denominators for such calculations.

[---TABLE 3 HERE---

Table 3 shows the following. First, a small set of proximal variables is associated with all, or almost all, aspects of child development we examine. The harsher discipline of low-income mothers, their more external locus of control, and their lower rates of breastfeeding are all associated with significant deficits in five of the six outcomes. Eating patterns at age 3, provision of books and toys and maternal teaching behaviours also contribute to multiple outcome gradients.

Second, specific proximals are associated with the income gradient in some outcomes but not others. The home learning environment is most predictive of the income gradients in the cognitive domain. Income-related differences in the books and toys and the maternal teaching experienced by pre-school children both predict poorer school performance and IQ at ages 7 and 8, even conditional on the many other detailed proximal controls. Lower fathers' learning-related interactions early in life, after adjusting for maternal inputs, is associated

with the poorer school performance of low-income children. Maternal locus of control, breastfeeding and early childhood diet in low-income families also account for significant portions of the primary school gradients. There are also a number of factors that differ greatly between low- and higher-income families but that do not predict cognitive outcomes in any meaningful way.

Our comparative approach shows that an exclusive focus on cognitive development could lead to the erroneous conclusion that many of these factors do not significantly adversely affect the well-being of low-income children. Factors including maternal anxiety and depression, life events shocks, social networks and harshness of discipline make important contributions to the gradients in child behaviour problems and self esteem. Early childcare patterns are associated with later inequalities in locus of control and fat mass. Greater exposure to maternal smoking (pre- and post-natally) is important in accounting for low-income children's greater behaviour problems and risk of obesity.

Third, the table identifies a number of instances in which the experiences of low-income children are relatively protective for their well-being (denoted by a negative gradient coefficient). In some cases these negative gradients may reflect a high correlation between proximal factors coupled with an unmodelled interaction effect. For example, the negative path between educational trips and Key Stage 1 outcomes could result from a situation in which aspects of home learning environment are highly correlated and there are diminishing returns to these inputs among the most advantaged children. However, some effects suggest that behaviours of richer parents may harm their children. The lesser exposure to centre-based childcare among low-income children aged three to four is associated with fewer behaviour problems (consistent with a number of previous studies e.g. Belsky *et al.*, 2007). For fat mass the negative coefficient for the physical environment block is driven by two 'off-setting' factors, the lower probability of car access and the greater exposure to damp in the home among low-income children. It is plausible that both these factors lead to greater energy consumption, via more walking in the case of car access, and via the need to generate warmth (or possibly spend more time outdoors) in the case of homes that are cold and damp. Although insignificant, the sign of home learning environment coefficients also point to an association between lower income and increased calorie expenditure, perhaps because learning-focused environments may place a greater weight on sedentary activities, while low-income children tend to engage in more active pursuits. These patterns suggest that greater energy consumption is partially 'disguising' the consequences of poor diet among low-income children, which would result in even greater obesity rates without these off-sets. Our

estimates imply that without the protective effects of the home environment, both learning-focused and physical, the gradient in fat mass would be almost 50% larger than is actually observed.

#### ***4.5 The role of specific distal factors***

Table 2 showed how far distal aspects of the family and parental characteristics contribute to the income gradients in outcomes. Table 4 explores these relationships in more detail, breaking down the summary measures of family characteristics into their constituent parts. Similar to the disaggregated analyses for proximal factors, Rows A, B and the block totals i to iv repeat the information from the summary Table 2, while the rows within each block provide path coefficients for sub-groupings of distal variables that sum to the block totals.

The household demographics block totals in row i show again that differences in these characteristics between low- and higher-income families contribute significantly to four of the six income gradients. But the breakdown below also shows that different aspects of this set of factors are associated with the outcomes in different ways. Results for family structure show that the greater rates of lone parenthood in low-income families contribute significantly to steeper income gradients in children's behaviour problems, where the coefficient is comparable in size to the direct contribution of income. But there is no evidence that this is the case for the other outcomes and the negative coefficient in the IQ decomposition implies that children of lone parents do better than expected, given their other disadvantages. The siblings row reveals almost the reverse pattern: the larger family size in low-income households contributes significantly to poorer cognitive development but is slightly protective for behaviour problems.

Block ii shows that in general it is the occupational status of low-income parents that is associated with poorer child outcomes, rather than whether or not they are actually in work. In fact, the uniformly negative (if small) coefficients for maternal employment imply that the lower employment rates of low-income mothers in the preschool period are slightly beneficial for children's development, all else (including income) held equal. Inspection of the component path coefficients (not shown) revealed that it is the higher full time (as opposed to part time) employment rates of higher income mothers that drive this off-set result.

The importance of parental education (net of income) in predicting child outcomes has already been discussed. The results in block iii allow us to delve deeper and contrast the relative importance of maternal and paternal education and explore whether the qualifications

of the child's maternal grandparents have any independent association. In general, the qualifications of both parents play a role. While the maternal education coefficients are slightly larger than the paternal ones for cognitive outcomes and locus of control, the reverse is true for the remaining outcomes, particularly fat mass. Significant contributions of grandparents' qualifications to four of the six gradients provide evidence of intergenerational transmission across three generations.

Within the neighbourhood block, residence in social housing (the housing tenure row) has a particularly strong role in accounting for the gradients in school performance and in behaviour problems, but matters also for IQ and self esteem. Local area deprivation is associated with gradients in cognitive outcomes and fat mass, net of other distal influences, but does not contribute to the gradients in any of the non-cognitive outcomes.

[---TABLE 4 HERE---

#### **4.6 How the direct contribution of income is mediated**

In Table 5 we return to an examination of the direct contribution of income (presented in Row A of Tables 2 and 4). In this decomposition we bring together the overlapping sets of distal and proximal factors to examine the pathways through which income is mediated. The decompositions in this table tell us about the ways in which money (separate from other parental characteristics) impacts on the proximal environment ( $\lambda_j$ ), and which of those paths matter most for children's development ( $\gamma_j$ ). A residual part ( $\pi$ ) captures the influence of income via unobserved proximal factors, the part that remains unexplained. We use the term financial resources below when discussing the role of income in this more narrow direct sense, to help distinguish it from its role as a summary measure of social position. The results in this table correspond to the developmental psychology mediation studies such as Guo and Harris (2000), Schoon *et al.* (2010) and Yeung *et al.* (2002).

[---TABLE 5 HERE---

The top row of Table 5 presents the estimates of the direct income path presented above. The subsequent rows sum to these total contributions. Path coefficients that were less than 0.1 in magnitude (0.01 standard deviations of the outcome) and insignificant at the 10% level are omitted from the table.

The percentages in square brackets represent the coefficient as a percentage of the direct contribution of income in the first row, *not* as a percentage of the overall income gradient as in previous tables. The percentages are informative about what explains the

income-outcome association when other distal factors are conditioned out, the closest we can get to the ‘causal’ effect of income in the decomposition framework. Comparison of the percentages with their counterparts for the unconditional income gradients in Table 1 gives a sense of whether the total proximal contributions to the gradient are a good guide to the way financial resources more narrowly are mediated.

Table 5 shows that financial resources matter for cognitive outcomes via their association with the home learning environment, health behaviours and, to a lesser extent, via maternal psychosocial functioning. The percentages in the cognitive outcome columns are very similar to their counterparts in Table 1. For example, 33% and 42% of the direct income contribution to the IQ and Key Stage 1 gradients respectively is explained by observed proximal factors, and Table 1 shows that similarly 34% and 37% of the unconditional gradients are explained by the same factors. This implies that financial resources are no more but also no less important than other characteristics of low-income families in shaping the observed aspects of children’s development that matter for cognitive development.

The picture is different when we look at other outcomes. Financial resources are disproportionately predictive of the aspects of psychosocial functioning that matter for behaviour problems and fat mass. The path coefficients associated with maternal psychosocial functioning are actually larger than the overall direct contribution of income to these two gradients, and are statistically significant where the overall coefficients (in the top row) are not. The importance of the pathway from financial resources to maternal psychosocial functioning to behaviour and fat mass is partially ‘disguised’ in the aggregate estimates by other off-setting protective mechanisms associated with fewer financial resources (discussed below). Comparison of these percentages with those for the total raw gradients shown in Table 1 reveals that poorer psychosocial functioning accounts for much less, only around a third, of the unconditional gradients in behaviour and fat mass, implying that other distal factors such as education and family structure are less strongly linked to this mechanism (see also Propper *et al.*, 2007, who consider the link between income, maternal mental health and a range of physical health outcomes). The same disproportionate influence of financial resources relative to other distal factors is also apparent in Table 5 for the patterns of childcare that matter for locus of control and, to a lesser extent, the aspects of psychosocial functioning that matter for self esteem.

Table 5 reveals a number of instances in which greater financial resources are negatively associated with beneficial environments. The unconditional associations of higher income with patterns of child care problematic for behaviour, and with the home and

physical environments problematic for fat mass, were discussed above. The significant coefficients and large percentages on these paths in Table 5 imply that financial resources play an important role in contributing to these environmental differences, distinct from, say, higher education or better neighbourhood. The implication is that it is the inability of low income parents to afford certain goods and services that actually benefits their children in these respects.

Table 5 presents only one part of the complete overlapping decomposition made possible by our framework. Appendix Table A4 contains the corresponding breakdowns for the four other distal contributions summarized in Tables 2 and 4. The results illustrate how our technique allows the examination of paths such as the link between parental education, the home learning environment and cognitive outcomes; the link between household demographics (including lone parenthood), psychosocial functioning and child behaviour; and the link between neighbourhood, health behaviours and fat mass.

## **5. Discussion and conclusions**

This paper has examined the income gradients in cognitive, non-cognitive and health outcomes in middle childhood using a pathways approach informed by ecological models of child development. We exploit rich data on observed behaviours of parents and their characteristics and, in contrast to many other studies, examine six outcomes in a unified framework and allow for the uncertainty in estimates that result from missing data.

The results offer the following insights. First, we find that low-income children are disadvantaged across the full spectrum of developmental outcomes. The strongest gradients are in cognitive outcomes and the weakest in the health outcome of risk of obesity with the gradients in non-cognitive outcomes lying in the middle. Second, there are certain factors that appear consequential for children's development across the full spectrum of outcomes. Parental education accounts for at least a quarter (and in general much more) of the gradients in all six outcomes, net of differences in income and other distal family characteristics. Proximal factors that account for significant portions of the gradients in five of the six outcomes are harsh discipline, breast feeding and maternal locus of control. Third, despite the importance of some factors across all outcomes, we also find considerable evidence that the processes that are associated with income gradients in different outcomes are generally not the same. Aspects of low-income children's environments that are associated with poorer outcomes in one sphere often have no association, or even have an opposing association, with

outcomes in other spheres. For example, less stimulating home learning environments, fathers' engagement in learning and larger family sizes predict greater disparities in cognitive than in other outcomes. Gradients in children's self esteem and behaviour problems are much more strongly linked to maternal psychosocial functioning, and to lone parenthood, than are gradients in cognitive or health outcomes. Maternal health behaviours are relatively more important for fat mass than for other outcomes. Fifth, a great deal of the social inequality captured by the raw income gradients is associated with the other distal characteristics of low-income families rather than to just a lack of financial resources. The direct (or conditional) association of income is insignificant for the four non-cognitive and health outcomes (although substantive in terms of magnitude for self-esteem), and for cognitive outcomes amounts to around one-fifth of the total gradient. However, these aggregates can disguise certain paths in which financial resources play a substantial role, most notably for the maternal psychosocial characteristics such as anxiety and depression that strongly predict child behaviour problems. Finally, we find indications that low income can, in some cases, act as a protective factor. For example lack of financial resources is associated with less exposure to childcare environments linked to problem behaviour and to housing environments that lower the risk of obesity.

We have been careful to recognise the observational nature of our data and do not interpret the path coefficients as causal relationships. Unobserved heterogeneity may be important. Nevertheless, we believe our results highlight lessons for research that seeks to quantify causal links. First, it is highly unlikely that a single experiment or trial could examine the causal nature of all the relationships allowed for by our model. Our findings provide some guide to which of the myriad of possible mechanisms are most likely to be fruitful targets of intervention and which have less chance of success. They thus help to refine the hypotheses that then can be tested by expensive rigorous trials. Second, our results show that treating child human capital as a high-dimensional vector can greatly affect conclusions on the relative importance of different mechanisms. An intervention that has modest effects across multiple domains may turn out to be preferable to one that greatly improves one outcome but that has adverse consequences in another domain. So a recommendation that follows from our findings is that experiments should measure effects on as many outcomes as possible, even those that are not the primary target of the intervention. Finally, if the aim of policy is to reduce the income gradient, the effect of a mechanism on an outcome is not the only relevant relationship to consider. The path approach shows us that the effect on the gradient will depend on both this effect and the strength of the correlation

between income and the mechanism in question. So a policy to reduce income gradients will need to focus on those mechanisms that are most concentrated amongst higher income families as well as those where the mechanism has a large effect on the outcome.

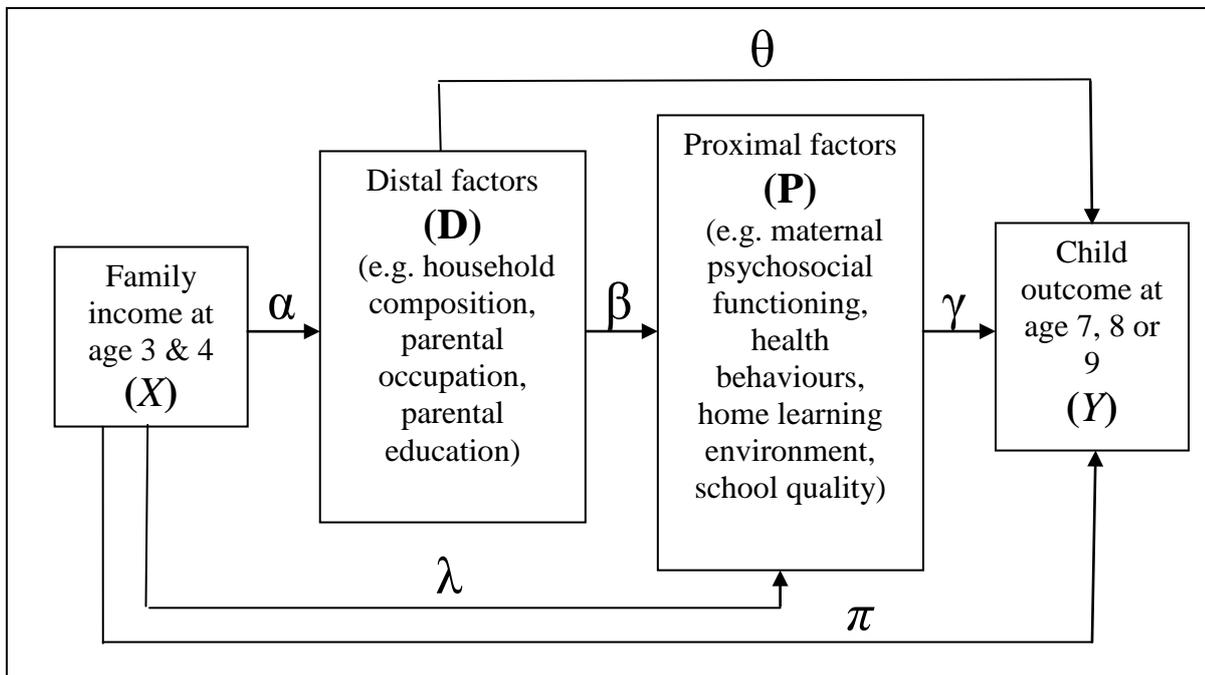
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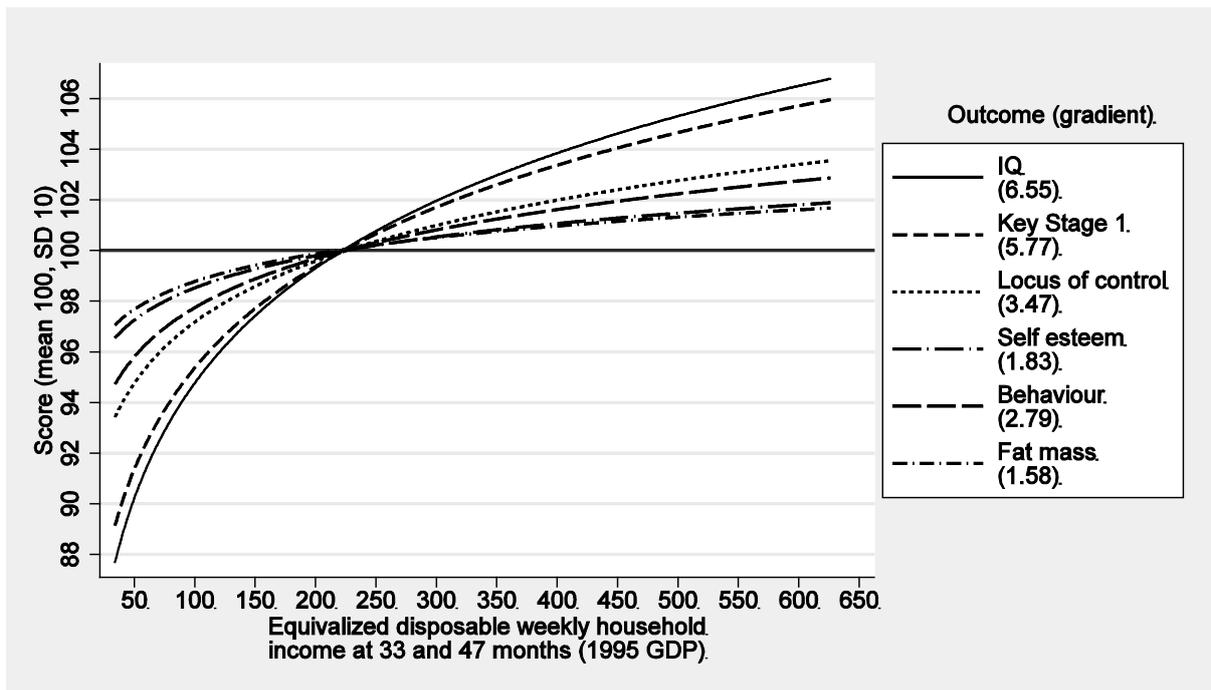
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Figure 1. Income gradient decomposition path diagram



*Note.* The diagram represents a system of OLS equations in which the end point of an arrow is a (vector of) dependent variable(s), the beginning of the arrow is a (vector of) explanatory variable(s) and the Greek letters are the associated (vectors/matrices of) coefficients.

Figure 2. The income gradients in child outcomes in middle childhood



Notes. Higher scores reflect more favourable outcomes on all 6 measures. Gradients are  $\delta$  from the OLS regression:  $outcome_i = cons + \delta \ln(income)_i + e_i$ . All gradients statistically significant at the 1% level.

**Table 1. Summary decomposition 1: Contribution of proximal factors**

	Child outcome measure					
	Cognitive		Non-cognitive			Health
	IQ	KS1	Locus of control	Self esteem	Behav- iour	Fat mass
A. Total contribution of proximal factors (sum i to vi): $\gamma(\beta\alpha + \lambda)$	<b>2.22**</b> [33.9%]	<b>2.16**</b> [37.4%]	<b>2.04**</b> [58.9%]	<b>0.80*</b> [43.8%]	<b>2.11**</b> [75.5%]	<b>0.93**</b> [59.2%]
i. Maternal psychosocial functioning	0.55** [8.3%]	0.60** [10.3%]	0.51* [14.8%]	0.81** [44.4%]	1.09** [38.9%]	0.55** [34.9%]
ii. Pre-school childcare	0.23* [3.6%]	0.09 [1.6%]	0.47** [13.6%]	-0.16 [-8.8%]	-0.25 <sup>†</sup> [-9.0%]	0.20 [12.7%]
iii. Health & health behaviours	0.55** [8.3%]	0.66** [11.4%]	0.63** [18.1%]	0.06 [3.1%]	0.89** [31.9%]	0.95** [60.3%]
iv. Home learning environment	0.67** [10.2%]	0.74** [12.7%]	0.42* [12.0%]	0.51** [27.9%]	0.37* [13.4%]	-0.27 [-17.0%]
v. Physical home environment	0.14 [2.1%]	0.08 [1.4%]	-0.06 [-1.8%]	-0.43 <sup>†</sup> [-23.8%]	0.06 [2.0%]	-0.55* [-34.5%]
vi. School fixed effects	0.09 [1.4%]	0.00 [0.0%]	0.08 [2.2%]	0.02 [0.8%]	-0.05 [-1.6%]	0.04 [2.8%]
B. Unexplained by proximal factors: $(\theta\alpha + \pi)$	<b>4.33**</b> [66.1%]	<b>3.61**</b> [62.6%]	<b>1.42**</b> [41.1%]	<b>1.03*</b> [56.2%]	<b>0.68</b> [24.5%]	<b>0.64</b> [40.7%]
Unconditional income gradient (A+B): $\delta$	<b>6.55**</b> [100%]	<b>5.77**</b> [100%]	<b>3.47**</b> [100%]	<b>1.83**</b> [100%]	<b>2.79**</b> [100%]	<b>1.58**</b> [100%]

Notes: N = 9476. Numbers in the higher row of each pair are the path coefficients shown in equation 5. Numbers in square brackets express the coefficient as a proportion of the unconditional income gradient given at the bottom of the table. All outcomes standardized to mean 100, standard deviation 10. Higher scores indicate more favourable outcomes on all measures. The unconditional income gradient is the difference in the outcome associated with a 1 unit change in the log of income. See Appendix Table A1 for definitions of all variables and contents of groupings. Standard errors (not shown) calculated by non-parametric bootstrap.

\*\* p<.01; \* p<.05; <sup>†</sup> p<.10.

**Table 2. Summary decomposition 2: Contribution of correlated distal factors**

	Child outcome measure					
	Cognitive		Non-cognitive			Health
	IQ	KS1	Locus of control	Self esteem	Behav-iour	Fat mass
A. Direct contribution of income: $\gamma\lambda + \pi$	<b>1.41**</b> [21.5%]	<b>1.15**</b> [19.9%]	<b>0.58</b> [16.6%]	<b>0.75</b> [40.9%]	<b>0.45</b> [16.1%]	<b>0.22</b> [14.1%]
B. Total contribution of distal factors (sum i to iv): $(\gamma\beta_k + \theta_k)\alpha_k$	<b>5.14**</b> [78.5%]	<b>4.62**</b> [80.1%]	<b>2.89**</b> [83.4%]	<b>1.08*</b> [59.1%]	<b>2.34**</b> [83.9%]	<b>1.36**</b> [85.9%]
i. Household demographics	0.55** [8.4%]	0.48** [8.3%]	0.38* [11.0%]	0.15 [8.0%]	0.32* [11.3%]	-0.18 [-11.7%]
ii. Labour market status	0.79** [12.1%]	0.94** [16.3%]	0.75* [21.7%]	0.23 [12.8%]	0.66* [23.8%]	0.12 [7.3%]
iii. Education	3.09** [47.1%]	2.05** [35.6%]	1.60** [46.2%]	0.58** [31.7%]	0.66** [23.5%]	0.88** [55.7%]
iv. Neighbourhood	0.72** [10.9%]	1.15** [20.0%]	0.16 [4.6%]	0.12 [6.6%]	0.71** [25.3%]	0.55* [34.5%]
Unconditional income gradient (A+B): $\delta$	<b>6.55**</b> [100%]	<b>5.77**</b> [100%]	<b>3.47**</b> [100%]	<b>1.83**</b> [100%]	<b>2.79**</b> [100%]	<b>1.58**</b> [100%]

See notes to Table 1. \*\* p<.01; \* p<.05; † p<.10

**Table 3. Detailed decomposition 1: Contribution of proximal factors**

Path coefficient	Child outcome measure					
	Cognitive		Non-cognitive			Health
	IQ	KS1	Locus of control	Self esteem	Behav- iour	Fat mass
<b>A. Total contribution of proximal factors</b> (sum $\alpha_i$ to $\alpha_{vi}$ ): $\sum_j \gamma_j (\beta_j \alpha + \lambda_j)$	<b>2.22**</b>	<b>2.16**</b>	<b>2.04**</b>	<b>0.80*</b>	<b>2.11**</b>	<b>0.93**</b>
<b>i. Maternal psychosocial functioning</b>	<b>0.55**</b>	<b>0.60**</b>	<b>0.51*</b>	<b>0.81**</b>	<b>1.09**</b>	<b>0.55**</b>
Of which:						
Maternal anxiety/depression	0.04	0.09*	0.10 <sup>†</sup>	0.16*	0.19**	-0.08
Life event shocks	-0.06 <sup>†</sup>	-0.01	0.02	0.05	0.16**	0.06 <sup>†</sup>
Subjective financial distress	0.06	0.12	-0.07	0.26	-0.04	0.20
Quality of parental relationship	-0.01	-0.13*	-0.07	-0.06	-0.22*	-0.07
Frequency of smacking at 3	0.09**	0.05**	0.09**	0.14**	0.11**	0.00
Maternal social networks	0.05	0.10	0.07	0.11	0.47**	0.19 <sup>†</sup>
Maternal locus of control	0.37**	0.37**	0.37**	0.14	0.43*	0.24*
<b>ii. Pre-school childcare</b>	<b>0.23<sup>†</sup></b>	<b>0.09</b>	<b>0.47**</b>	<b>-0.16</b>	<b>-0.25<sup>†</sup></b>	<b>0.20</b>
Of which:						
Birth to age 3	0.17	0.06	0.37**	0.00	0.04	0.25*
Age 3 to school entry	0.06	0.03	0.10	-0.16	-0.29	-0.05
<b>iii. Health &amp; health behaviours</b>	<b>0.55**</b>	<b>0.66**</b>	<b>0.63**</b>	<b>0.06</b>	<b>0.89**</b>	<b>0.95**</b>
Of which:						
Health at birth	0.08**	0.07**	0.03 <sup>†</sup>	0.03	0.03	-0.04*
Smoking	-0.18*	0.00	0.14	0.02	0.46**	0.39**
Breast feeding	0.24**	0.14**	0.17 <sup>†</sup>	0.00	0.22*	0.16 <sup>†</sup>
Eating patterns at 3	0.41**	0.45**	0.29*	0.02	0.19	0.45**
<b>iv. Home learning environment</b>	<b>0.67**</b>	<b>0.74**</b>	<b>0.42*</b>	<b>0.51**</b>	<b>0.37*</b>	<b>-0.27</b>
Of which:						
Books and toys	0.51**	0.35**	0.13	0.27*	0.30*	-0.14
Maternal teaching	0.16**	0.16**	0.04	0.12*	0.14*	-0.06
Maternal reading/singing	-0.11 <sup>†</sup>	0.00	0.02	-0.07	0.00	0.01
Paternal reading/singing	0.13	0.41**	0.18	0.10	0.04	-0.05
Trips to library, museums, etc	-0.02	-0.17**	0.04	0.08	-0.11	-0.04
<b>v. Physical home environment</b>	<b>0.14</b>	<b>0.08</b>	<b>-0.06</b>	<b>-0.43<sup>†</sup></b>	<b>0.06</b>	<b>-0.45*</b>
Of which:						
Car ownership	0.01	0.03	-0.02	-0.21	0.20	-0.33*
Has garden	-0.04	-0.04	-0.05	-0.06	-0.10	-0.01
Noise	0.04	0.03	0.05	0.00	0.10	-0.03
Crowding	0.18	0.07	0.10	-0.11	-0.06	0.00
Damp/condensation/mould	-0.05	-0.01	-0.14 <sup>†</sup>	-0.05	-0.08	-0.18**
<b>vi. School fixed effects</b>	<b>0.09</b>	<b>0.00</b>	<b>0.08</b>	<b>0.02</b>	<b>-0.05</b>	<b>0.04</b>
<b>B. Unexplained by proximal factors: <math>\theta\alpha</math></b>	<b>4.33**</b>	<b>3.61**</b>	<b>1.42**</b>	<b>1.03*</b>	<b>0.68</b>	<b>0.64</b>
Unconditional income gradient (A+B): $\delta$	<b>6.55**</b>	<b>5.77**</b>	<b>3.47**</b>	<b>1.83**</b>	<b>2.79**</b>	<b>1.58**</b>
Observations	9476	9476	9476	9476	9476	9476

See notes to Table 1. \*\* p<.01; \* p<.05; <sup>†</sup> p<.1

**Table 4 Detailed decomposition 2: Contribution of correlated distal factors**

	Child outcome measure					
	Cognitive		Non-cognitive			Health
	IQ	KS1	Locus of control	Self esteem	Behav- iour	Fat mass
A. Direct contribution of income: $\gamma\lambda + \pi$	<b>1.41**</b>	<b>1.15**</b>	<b>0.58</b>	<b>0.75</b>	<b>0.45</b>	<b>0.22</b>
B. Total contribution of distal factors (sum i to iv): $(\gamma\beta_k + \theta_k)\alpha_k$	<b>5.14**</b>	<b>4.62**</b>	<b>2.89**</b>	<b>1.08*</b>	<b>2.34**</b>	<b>1.36**</b>
i. Household demographics	<b>0.55**</b>	<b>0.48**</b>	<b>0.38*</b>	<b>0.15</b>	<b>0.32*</b>	<b>-0.18</b>
Of which:						
Family structure	-0.23*	0.06	0.03	0.14	0.46**	-0.15
Siblings	0.40**	0.33**	0.07	0.16*	-0.14 <sup>†</sup>	-0.08
Mother's age at birth	-0.01	-0.02	-0.06**	-0.05	0.01	-0.02
Ethnicity	0.38**	0.10 <sup>†</sup>	0.33**	-0.10	-0.02	0.07
ii. Labour market status	<b>0.79**</b>	<b>0.94**</b>	<b>0.75*</b>	<b>0.23</b>	<b>0.66*</b>	<b>0.12</b>
Of which:						
Mother's employment	-0.13*	-0.11*	-0.12	-0.12	-0.10	-0.06
Father's employment	-0.09	0.07	0.03	0.17	0.13	0.07
Mother's occupation	0.33**	0.38**	0.44**	0.08	0.17	0.16
Father's occupation	0.69**	0.61**	0.47**	0.10	0.46*	-0.05
iii. Education	<b>3.09**</b>	<b>2.05**</b>	<b>1.60**</b>	<b>0.58**</b>	<b>0.66**</b>	<b>0.88**</b>
Of which:						
Mother's qualifications	1.44**	0.97**	0.81**	0.13	0.23	0.22
Father's qualifications	1.27**	0.95**	0.58*	0.43*	0.36	0.43**
Grandparents' qualifications	0.38**	0.14*	0.21**	0.02	0.08	0.23**
iv. Neighbourhood	<b>0.72**</b>	<b>1.15**</b>	<b>0.16</b>	<b>0.12</b>	<b>0.71**</b>	<b>0.55*</b>
Of which:						
Local deprivation	0.24**	0.27**	0.02	-0.18	-0.17	0.23*
Housing tenure	0.47**	0.88**	0.14	0.30 <sup>†</sup>	0.88**	0.31
Unconditional income gradient (A+B): $\delta$	<b>6.55**</b>	<b>5.77**</b>	<b>3.47**</b>	<b>1.83**</b>	<b>2.79**</b>	<b>1.58**</b>

See notes to Table 1. \*\* p<.01; \* p<.05; <sup>†</sup> p<.1

**Table 5. Decomposition of the direct contribution of income**

	Child outcome measure					
	Cognitive		Non-cognitive			Health
	IQ	KS1	Locus of control	Self esteem	Behaviour	Fat mass
Direct contribution of income : $\gamma\lambda + \pi$	<b>1.41**</b>	<b>1.15**</b>	<b>0.58</b>	<b>0.75</b>	<b>0.45</b>	<b>0.22</b>
	[100%]	[100%]	[100%]	[100%]	[100%]	[100%]
Of which explained by: $(\gamma_j\lambda_j)$						
Maternal psychosocial functioning	0.12	0.17 <sup>†</sup>	0.10	0.42**	0.54**	0.34**
	[8.4%]	[14.4%]	[17.7%]	[56.0%]	[120.3%]	[152.5%]
Pre-school childcare	-	-	0.22*	-0.11	-0.23*	-
			[38.8%]	[-14.7%]	[-51.0%]	
Health & health behaviours	-	0.16**	0.11 <sup>†</sup>	-	0.15 <sup>†</sup>	-
		[14.1%]	[19.1%]		[32.5%]	
Home learning environment	0.13*	0.11*	-	0.16*	-	-0.14*
	[9.1%]	[9.5%]		[21.7%]		[-63.2%]
Physical home environment	-	-	-	-0.13	-	-0.17*
				[-17.4%]		[-75.3%]
School fixed effects	-	-	-	-	-	-
Unexplained: $\pi$	0.94**	0.66**	-	0.25	-0.12	0.11
	[66.5%]	[57.6%]		[33.5%]	[-26.3%]	[50.2%]

Notes: N = 9476. Numbers in the higher row of each pair are selected path coefficients shown in equation 5. Numbers in square brackets express the coefficient as a proportion of the direct contribution of income given in the first row of the table. Standard errors (not shown) calculated by non-parametric bootstrap.

\*\* p<.01; \* p<.05; <sup>†</sup> p<.10.

## **Appendices**

## Appendix A

**Table A1. Variables used in analysis**

Variable	Description/comments
	Child outcomes <sup>a</sup>
IQ	Raw total IQ score from the Wechsler Intelligence Scale for Children (WISC-III UK; Wechsler, Golombok and Rust 1992). The WISC-III UK was at the time the most up-to-date version of the WISC, the most widely used individual ability test world-wide. The short form of the scale was administered to the children at age 8 during a clinical assessment visit by ALSPAC's psychology team. The total score is derived as the sum of scores on five verbal sub-tests: information, similarities, arithmetic, vocabulary and comprehension; and five performance sub-tests: picture completion, coding, picture arrangement, block design and object assembly.
KS1 (School performance)	Derived from standardized national Key Stage 1 tests administered to all children in public schools at the end of Year 3 (when most children are aged 7). The three sub-tests cover reading, writing and mathematics. Attainment levels for the sub-tests are converted to points using the guidelines provided by the Department for Education and Skills and averaged.
Locus of control	Taken from the shortened version of the Nowicki-Strickland Internal-External scale (NSIE scales) for preschool and primary children (Nowicki and Duke 1974a). The scale consists of 12 questions read out to the child by an examiner during an ALSPAC clinical assessment visit at age 8, each requiring a yes/no answer. Responses were coded 0 or 1 and summed to create a total score. $\alpha = 0.47$ .
Self esteem	Taken from the 12-item shortened form of Harter's Self Perception Profile for Children (Harter 1985). The scale was administered during the ALSPAC clinical assessment visit at age 8. Items were scored from 1 to 4 and summed to give a total. $\alpha = 0.75$ .
Behaviour	Taken the Strengths and Difficulties Questionnaire (SDQ; Goodman 1997). This instrument has been shown to be a good predictor of conduct, emotional, hyperactivity and any psychiatric disorders in children of the age examined here (Goodman et al. 2000). Completed by teachers in Year 3. The SDQ comprises 4 sub-scores, each derived from the responses to 5 questions, relating to hyperactivity, emotional symptoms, conduct problems and peer problems. Items are scored from 0 to 2 and summed to create a total behaviour score. $\alpha = 0.87$ .
Fat mass	Total body fat mass in grams adjusted for age of child in months, sex, height and height squared. Direct measures of the fat mass of children obtained at an ALSPAC clinical assessment visit at age 9, using dual-energy X-ray absorptiometry (DXA), a highly accurate method involving a full body scan (Morrison et al. 1994).
	Income
Log real equivalized weekly disposable household income at 33 and 47 months	Constructed from banded information on weekly disposable household income at child ages 33 and 47 months. Median values for the bands imputed using data on a comparable sample from the nationally representative Family Expenditure Survey. Converted to real values using the 1995 RPI as a base and equivalized using the OECD modified scale. We also impute the value of housing benefit for families who do not directly receive housing payments. Variable is average of two measures.

Distal factors

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**Household demographics**

Family structure      Dummy equal to 1 if the mother did not live with a partner at any of 4 dates between birth and 47 months

Siblings      Dummy equal to 1 if younger sibling present in the household at 47 months. Number of older siblings in the household at 47 months (top-coded at 3).

Mother's age at birth      Mother's age at the birth of the study child

**Labour market status**

Mother's employment      Mother ever worked full-time between birth and 47 months; worked part-time only; did not work at all.

Father's employment      Mother's partner was out of work never; once; more than once at any of seven dates between the pregnancy and 47 months.

Mother's and father's occupations      Defined from information gathered during pregnancy on current or last job. Responses are coded from 1 to 6 using OPCS job codes: 1 = professional; 2 = managerial/technical; 3 = skilled non-manual; 4 = skilled manual; 5 = semi-skilled; 6 = unskilled.

**Education**

Mother's and father's qualifications      Collected during pregnancy. Coded: 1 = CSE/no qualifications; 2 = Vocational/O-level; 3 = A-level; 4 = Degree.

Grandparents' qualifications      Separate variables for maternal grandmother and grandfather. Coded as parental qualifications.

**Neighbourhood**

Local deprivation      Rank of the Index of Multiple Deprivation (IMD) for the local electoral ward (around 5500 persons) of residence of the child at birth. The IMD is derived from 6 composite indicators in the domains of Income; Employment; Health Deprivation and Disability; Education, Skills and Training; Housing; and Geographical Access to Services. See <http://www.communities.gov.uk/documents/citiesandregions/pdf/131306.pdf>

Housing tenure      Always in owner-occupied accommodation between birth and 33 months; ever in public housing between birth and 33 months; other.

Ethnicity      Child is non-white.

Proximal factors

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**Maternal psychosocial functioning**

Maternal anxiety/depression      Crown-Crisp Experiential Index (CCEI; Crown and Crisp, 1979). Self-assessed questionnaire completed by mothers at 6 dates spanning the early period of pregnancy to 33 months. Variable is average of the 6 measures.

Life event shocks      Derived from questions on whether each of 41 life events had occurred in recent months, and if so, how strongly the mother was affected. Responses scored on a 5-point scale from 0 (did not happen) to 5 (affected me a lot) and summed. Measure is the average score over four dates between 8 and 47 months post-birth, and so captures both the frequency and severity of shocks. Example items: A friend or relative was ill; You had problems at work; You argued with your partner; You moved house; You had a major financial problem.

Subjective financial distress      Constructed from responses to five items asking how difficult the mother currently finds it to afford food, clothing, heating, rent or mortgage and things she needs for the child. Responses scored from 0 (not difficult) to 3 (very difficult) and summed. Measure is the average of three scores taken at child age 8, 21 and 33 months.

Quality of parental relationship      Three sub-scores, all derived from information in early childhood. Affection score: derived from responses to 6 items related to how frequently

	<p>the mother and partner engage in behaviours like kissing or hugging, making plans and talking over their feelings. Responses scored from 0 to 3, summed and averaged over 3 dates between 8 and 47 months post-birth.</p> <p>Aggression score: derived from questions on how frequently the mother and her partner argued in the past 3 months, and whether 5 events such as hitting, throwing things and walking out of the house in anger occurred in the same period. Total score ranges from 0 to 14, final variable is an average over scores at 8 and 33 months.</p> <p>Shared activities score: constructed in a similar manner, using 5 items (each scored from 0 to 3) on how frequently the parents took part in activities together such as going out for a drink, a meal or to the cinema in the last 3 months.</p>
Frequency of smacking at 3	How often the mother smacks the child when he or she is naughty at 33 months. Responses are scored 1 (never), 2 (once a month or less), 3 (once a week), or 4 (daily).
Maternal social networks	<p>Two sub-scales, each administered during pregnancy and again at 21 months.</p> <p>Social networks: derived from 10 items, each scored from 0 to 3, relating to the number and strength of the mother's relationships with friends and relatives.</p> <p>Social support: same format, but here the 10 items relate to perceived levels of emotional, financial and instrumental support. Measures are average scores for each scale over the two time points.</p>
Maternal locus of control	Measured using the Adult Nowicki-Strickland Internal-External scale (ANSIE; Nowicki and Duke, 1974b). 12-item scale completed by mothers during the pregnancy.
<b>Pre-school childcare</b>	
Birth to age 3	<p>Six separate categorical variables indicating care by: the father; another relative or friend; nannies and babysitters; child minders; centre-based care; and other.</p> <p>Childcare mode was recorded at 8 weeks, 8, 15 and 24 months. For each type, we distinguish whether it was used at any date and if so, whether it was ever used for more than 15 hours per week.</p>
Age 3 to school entry	<p>Six separate categorical variables indicating care by: relatives (including the father); nannies; child minders; playgroups; nurseries; and other modes of care.</p> <p>Categories: not used at all; 15 hours a week or less; more than 15 hours a week.</p>
<b>Health &amp; health behaviours</b>	
Health at birth	<p>Birth weight in kilograms.</p> <p>Indicators for child was born pre-term (&lt;37 weeks gestation); whether the child was low birth weight (&lt; 2.5 kg) but not pre-term.</p>
Smoking	<p>Mother smoked at all in pregnancy.</p> <p>Smoker in the child's household at age 4.</p>
Breast feeding	Never; < 3 months; 3 to 6 months; 6 to 12 months; > 12 months.
Eating patterns at 3	<p>Derived from a mother-completed postal questionnaire on the child's consumption of 43 different foodstuffs at 38 months. Four 'dietary types' constructed by North et al. (2000) using principal components analysis.</p> <p>Junk food: loads heavily on convenience foods such as french fries, burgers, fried foods and takeaway meals and on foods like chips, candy, cookies, chocolate and carbonated drinks.</p> <p>Healthy food: loads on vegetables, salad, fruit, fish, rice, pasta and pulses and on vegetarian substitutes for meat products.</p> <p>Traditional food: represents the traditional British 'meat and two veg' diet, loading heavily onto consumption of meat and poultry, potatoes, root vegetables, green vegetables and legumes.</p>

Snack food: relates in general to foods that require little cooking, such as puddings, cakes, cheese, bread and fruit.

Note: the purpose of these dietary types is to provide a summary of the child's eating patterns in general: they are not designed to measure specific factors such as calorie or fat content directly.

### Home learning environment

#### Books and toys

Age at which the child is first recorded as owning at least 10 books: 6, 18, 30 or 42 months, or not at all by 42 months. (Only 6% of children own less than 10 books by age 3.)

Toy score: derived from the number of 12 different toys (such as blocks, jigsaws and interlocking toys) the child has at age 2.

#### Maternal teaching

Derived from questions on whether the mother teaches the child each of 10 items such as numbers, shapes, rhymes and the alphabet. Items are scored from 0 to 3 according to whether the child is first taught: not at all, by 42 months, by 30 months or by 18 months, then summed. (Lack of variation in the age 3 teaching items means that this method better distinguishes the experiences of children.)

#### Maternal and paternal reading/singing

Frequency the parent reads to and sings songs to the child at 18 and 42 months. Each scored from 0 to 8 (score of 8 indicates that the parent reads and sings to the child every day). Set to zero...

#### Trips to library, museums, etc.

Frequency child is taken to visit the library and other places of interest such as museums between the ages of 18 and 42 months. Score for each ranges from 0 to 6 (6 indicating visits of at least once a week at all three dates of measurement).

### Physical home environment

#### Car ownership

Household without use of car at 8, 21 or 33 months.

#### Has garden

Household without access to garden or yard at 8, 21 or 33 months.

#### Noise

Noise from inside of outside household is a serious problem at 21 or 33 months.

#### Crowding

Average number persons per room in household at 8, 21 and 33 months.

#### Damp/ condensation/ mould

Damp, condensation or mould is a serious problem at 8, 21 or 33 months.

### School fixed effects

#### School dummies

Defined only for cases in which at least 5 non-missing values of the outcome measure are observed within the same school. Children in schools with less than 5 valid observations are grouped together in a single category, and children whose school IDs are missing are similarly grouped in a separate single category. Over 70 percent of the sample children are in schools with at least 20 valid observations, and 40 to 50 percent are in schools with at least 50 valid observations.

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a. Outcomes are normalized on child sex, cohort year and month of birth, and then standardized to mean 100 standard deviation 10 on the maximum available sample. The locus of control, behaviour and fat mass measures are such that higher scores indicate more adverse outcomes. Coefficients associated with these outcomes are reversed in sign in the presentation of results.

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**Table A2. Descriptive statistics for all variables**

Variable	Mean	Std. Dev.	Min	Max	Fraction non-missing <sup>a</sup>
<b>Child outcomes<sup>b</sup></b>					
IQ	100.18	9.92	66.02	129.00	0.60
Key Stage 1 (KS1)	100.82	9.27	60.86	124.37	0.92
Locus of control	99.89	9.98	70.36	125.25	0.57
Self esteem	100.03	9.98	59.37	119.79	0.62
Behavior at 7	99.90	9.93	85.27	152.10	0.35
Fat mass	99.91	9.83	74.83	158.35	0.65
<b>Income</b>					
Average weekly disposable income <sup>c</sup>	222.54	100.32	34.99	625.57	1.00
<b>Distal variables</b>					
<b>Household demographics</b>					
Family structure: single mother by 47 months	0.14	0.35	0	1	1.00
Siblings: younger sibling by 47 months	0.41	0.49	0	1	0.92
Siblings: number of older siblings at 47 months	0.95	1.11	0	3	0.92
Mother's age at birth	28.57	4.70	15	44	1.00
Child is non-white	0.04	0.19	0	1	0.95
<b>Labour market status</b>					
Mother's employment: not employed pre-school	0.25	0.43	0	1	0.87
Mother's employment: part-time only pre-school	0.55	0.50	0	1	0.87
Mother's employment: full-time pre-school	0.20	0.40	0	1	0.87
Father's employment: always in work to age 4	0.81	0.39	0	1	0.66
Father's employment: out of work at 1 date by age 4	0.10	0.30	0	1	0.66
Father's employment: out of work > 1 date by age 4	0.09	0.29	0	1	0.66
Mother's occupation	2.85	1.07	1	6	0.81
Partner's occupation	3.00	1.31	1	6	0.88
<b>Education</b>					
Mother's qualifications	2.37	0.92	1	4	0.97
Partner's qualifications	2.44	1.04	1	4	0.94
Grandmother's qualifications	1.76	0.78	1	3	0.72
Grandfather's qualifications	2.00	1.02	1	4	0.68
<b>Neighbourhood</b>					
Local deprivation: Rank of ward IMD score	4536	2523	0	8379	0.91
Housing tenure: owner-occupied birth to 33 months	0.75	0.43	0	1	0.99
Housing tenure: ever in social housing	0.16	0.37	0	1	0.99
Housing tenure: other birth to 33 months	0.09	0.28	0	1	0.99
<b>Proximal variables</b>					
<b>Maternal psychosocial functioning</b>					
Maternal depression/anxiety	11.51	6.26	0	41.50	1.00
Life event shocks	2.87	1.91	0	18.92	1.00
Subjective financial distress	3.12	3.20	0	15	0.99
Quality of parental relationship: affection	14.99	2.88	0	18	0.96
Quality of parental relationship: aggression	3.92	2.82	0	14	0.93
Quality of parental relationship: shared activities	5.98	2.54	0	15	0.93
Frequency of smacking at age 3	2.29	0.72	1	4	0.87
Maternal social networks sub-score	23.39	3.64	3	29	0.98
Maternal social support sub-score	20.28	4.62	1.5	30	0.96
Maternal locus of control	4.20	2.13	0	12	0.83

Variable	Mean	Std. Dev.	Min	Max	Fraction non-missing <sup>a</sup>
<b>Pre-school childcare</b>					
Birth to age 3 (dummy variables)					
Partner 1-15 hrs pwk	0.49	0.50	0	1	0.99
Partner > 15 hrs pwk	0.42	0.49	0	1	0.99
Friend/relative 1-15 hrs pwk	0.33	0.47	0	1	1.00
Friend/relative > 15 hrs pwk	0.08	0.27	0	1	1.00
Child minder 1-15 hrs pwk	0.06	0.24	0	1	1.00
Child minder > 15 hrs pwk	0.11	0.31	0	1	1.00
Nanny 1-15 hrs pwk	0.06	0.23	0	1	1.00
Nanny > 15 hrs pwk	0.05	0.21	0	1	1.00
Nursery 1-15 hrs pwk	0.08	0.28	0	1	1.00
Nursery > 15 hrs pwk	0.04	0.19	0	1	1.00
Other 1-15 hrs pwk	0.02	0.15	0	1	1.00
Other > 15 hrs pwk	0.01	0.09	0	1	1.00
Age 3 to school entry					
Partner/friend/relative 1-15 hrs pwk	0.15	0.35	0	1	0.89
Partner/friend/relative > 15 hrs pwk	0.06	0.23	0	1	0.89
Child minder 1-15 hrs pwk	0.06	0.23	0	1	0.89
Child minder > 15 hrs pwk	0.05	0.22	0	1	0.89
Nanny 1-15 hrs pwk	0.02	0.13	0	1	0.89
Nanny > 15 hrs pwk	0.02	0.15	0	1	0.89
Playgroup 1-15 hrs pwk	0.35	0.48	0	1	0.89
Playgroup > 15 hrs pwk	0.01	0.12	0	1	0.89
Nursery 1-15 hrs pwk	0.32	0.47	0	1	0.89
Nursery > 15 hrs pwk	0.13	0.34	0	1	0.89
Other 1-15 hrs pwk	0.05	0.22	0	1	0.89
Other > 15 hrs pwk	0.19	0.39	0	1	0.89
<b>Health &amp; health behaviors</b>					
Birth weight (kg)	3.42	0.55	0.65	5.64	0.99
Gestation < 37 weeks	0.05	0.22	0	1	1.00
Low birth weight (<2.5kg) and not pre-term	0.02	0.14	0	1	0.99
Mother smoked in pregnancy	0.25	0.43	0	1	0.95
Smoker in household age 4	0.38	0.49	0	1	0.89
Never initiated breastfeeding	0.25	0.43	0	1	0.98
Breastfed < 3 months	0.24	0.43	0	1	0.98
Breastfed 3-6 months	0.17	0.37	0	1	0.98
Breastfed 6-12 months	0.24	0.43	0	1	0.98
Breastfed > 12 months	0.10	0.30	0	1	0.98
Junk food score at age 3	-0.09	2.95	-7.43	29.96	0.76
Healthy food score at age 3	-0.05	2.72	-6.46	22.80	0.76
Traditional food score at age 3	0.01	2.51	-7.93	17.01	0.76
Snack food score at age3	0.07	1.95	-9.31	12.16	0.76
<b>Home learning environment</b>					
Child first owned 10+ books at 6 months	0.19	0.39	0	1	1.00
Child first owned 10+ books at 18 months	0.47	0.50	0	1	1.00
Child first owned 10+ books at 30months	0.20	0.40	0	1	1.00
Child first owned 10+ books at 42 months	0.07	0.26	0	1	1.00
Child never owned 10+ books by 42 months	0.06	0.24	0	1	1.00
Toy score at age 2	15.21	2.22	1	20	0.90
Maternal teaching score	27.32	2.47	11	30	0.92
Maternal reading and singing score at 18 mths	7.02	1.42	0	8	0.94
Maternal reading and singing score at 42 mths	6.28	1.89	0	8	0.92

Variable	Mean	Std. Dev.	Min	Max	Fraction non-missing <sup>a</sup>
Paternal reading and singing score at 18 mths	4.55	2.28	0	8	0.90
Paternal reading and singing score at 42 mths	4.35	2.05	0	8	0.86
Outings to library score	1.42	1.60	0	6	0.83
Outings to museums/places of interest score	2.01	1.86	0	6	0.84
<b>Physical home environment</b>					
Without access to car at 8, 21 or 33 months	0.11	0.32	0	1	0.99
Without access to garden at 8, 21 or 33 months	0.07	0.26	0	1	0.99
Noise serious problem at 21 or 33 months	0.08	0.26	0	1	0.98
Average crowding index (persons per room)	0.79	0.31	0.19	9.0	0.98
Damp/mould/condensation ever serious problem	0.13	0.33	0	1	0.99
<b>Average within-school scores<sup>d</sup></b>					
Average IQ in school	99.42	2.61	88.55	107.62	0.48
Average Key Stage 1 score in school	100.48	2.57	65.23	108.35	0.79
Average locus of control score in school	100.36	2.16	89.57	108.17	0.46
Average self esteem score in school	99.97	1.73	92.19	106.57	0.50
Average behavior score in school	99.86	2.38	90.65	110.79	0.26
Average fat mass score in school	100.10	1.62	94.28	108.11	0.52

*Notes.* Variables with minimum of 0 and maximum of 1 are dummy variables. See Appendix Table A1 for variable definitions.

- a. Statistics defined over the full sample with non-missing income and at least one child outcome measure (N = 9476).
- b. Outcomes are standardized to mean 100, standard deviation 10 on the full sample of observations available. Differences in the mean and standard deviation of the working samples are due to the dropping of cases with missing household income. For locus of control, behavior and fat mass higher scores indicate more adverse outcomes.
- c. Equalized. 1995 prices. Measure is logged in regression analysis.
- d. Defined only for children with at least 4 other non-missing peers' scores. For illustrative purposes only, school dummies are used in multivariate analysis.

Table A3. Correlations between outcome measures

	IQ	KS1	Locus of control	Self esteem	Behaviour	Fat mass
IQ	1 N = 5708					
KS1	0.64 N = 5162	1 N = 8727				
Locus of control	0.33 N = 4907	0.28 N = 4883	1 N = 5390			
Self esteem	0.18 N = 5346	0.21 N = 5295	0.22 N = 5055	1 N = 5857		
Behaviour	0.29 N = 2515	0.37 N = 2959	0.14 N = 2365	0.22 N = 2567	1 N = 3294	
Fat mass	0.08 N = 4946	0.10 N = 5536	0.06 N = 4681	0.02 N = 5072	0.08 N = 2605	1 N = 6113

(p = 0.088)

*Note.* All correlations are significant at the 1% level unless otherwise marked.

**Table A4a. Decomposition of the contribution of household demographics**

	Child outcome measure					
	Cognitive		Non-cognitive			Health
	IQ	KS1	Locus of control	Self esteem	Behav- iour	Fat mass
Total contribution of household demographics : $(\gamma\beta_k + \theta_k)\alpha_k$	<b>0.55**</b> [100%]	<b>0.48**</b> [100%]	<b>0.38*</b> [100%]	<b>0.15</b> [100%]	<b>0.32*</b> [100%]	<b>-0.18</b> [-100%]
Of which explained by: $(\gamma_j\beta_{jk}\alpha_k)$						
Maternal psychosocial functioning	-	-	-	0.08* [55.5%]	0.12** [38.6%]	-
Pre-school childcare	-	-	-	-	-	-
Health & health behaviours	-	0.06* [11.9%]	0.06 <sup>†</sup> [15.0%]	-	0.09* [29.7%]	0.13** [69.0%]
Home learning environment	0.17** [30.2%]	0.31** [65.2%]	0.17** [43.7%]	0.14* [95.9%]	-	-
Physical home environment	-	-	-	-0.07 <sup>†</sup> [-45.2%]	-	-0.08* [-44.6%]
School fixed effects	-	-	-	-	-	-
Unexplained: $\theta_k\alpha_k$	0.25 [45.7%]	-	-	-	-	-0.24 [-130.4%]

**Table A4b. Decomposition of the contribution of labour market status**

	Child outcome measure					
	Cognitive		Non-cognitive			Health
	IQ	KS1	Locus of control	Self esteem	Behav- iour	Fat mass
Total contribution of labour market status : $(\gamma\beta_k + \theta_k)\alpha_k$	<b>0.79**</b> [100%]	<b>0.94**</b> [100%]	<b>0.75*</b> [100%]	<b>0.23</b> [100%]	<b>0.66*</b> [100%]	<b>0.12</b> [100%]
Of which explained by: $(\gamma_j\beta_{jk}\alpha_k)$						
Maternal psychosocial functioning	0.09** [11.8%]	0.09** [10.0%]	0.08 <sup>†</sup> [10.9%]	0.09* [39.9%]	0.09 <sup>†</sup> [13.6%]	0.06 <sup>†</sup> [55.7%]
Pre-school childcare	0.07 <sup>†</sup> [8.2%]	-	0.12* [16.2%]	-	-	-
Health & health behaviours	-	0.09* [9.2%]	0.09* [12.4%]	-	0.18** [26.4%]	0.16** [140.9%]
Home learning environment	0.07* [8.6%]	0.06 <sup>†</sup> [6.6%]	-	0.05 <sup>†</sup> [21.0%]	-	-
Physical home environment	-	-	-	-	-	-0.07* [-64.3%]
School fixed effects	-	-	-	-	-	-
Unexplained: $\theta_k\alpha_k$	0.48* [60.8%]	0.67** [71.8%]	0.40 [53.2%]	0.20 [86.3%]	0.36 [54.2%]	-

**Table A4c. Decomposition of the contribution of education**

	Child outcome measure					
	Cognitive		Non-cognitive			Health
	IQ	KS1	Locus of control	Self esteem	Behaviour	Fat mass
Total contribution of education : $(\gamma\beta_k + \theta_k)\alpha_k$	<b>3.09**</b> [100%]	<b>2.05**</b> [100%]	<b>1.60**</b> [100%]	<b>0.58**</b> [100%]	<b>0.66**</b> [100%]	<b>0.88**</b> [100%]
Of which explained by: $(\gamma_j\beta_{jk}\alpha_k)$						
Maternal psychosocial functioning	0.26** [8.6%]	0.22** [10.9%]	0.21** [13.1%]	0.14** [24.2%]	0.14* [20.7%]	-
Pre-school childcare	-	-	0.14** [8.4%]	-0.08 <sup>†</sup> [-14.5%]	-0.13* [-19.4%]	-
Health & health behaviours	0.33** [10.8%]	0.20** [9.5%]	0.23** [14.5%]	-	0.19* [29.0%]	0.42** [48.2%]
Home learning environment	0.22** [7.1%]	0.15** [7.3%]	0.10 [6.2%]	0.10 <sup>†</sup> [18.0%]	-	-
Physical home environment	-	-	-	-	-	0.03* [3.2%]
School fixed effects	-	-	-	-	-	-
Unexplained: $\theta_k\alpha_k$	2.15** [69.7%]	1.51** [73.7%]	0.87** [54.2%]	0.50** [87.0%]	0.44* [67.7%]	0.35* [39.6%]

**Table A4d. Decomposition of the contribution of neighbourhood**

	Child outcome measure					
	Cognitive		Non-cognitive			Health
	IQ	KS1	Locus of control	Self esteem	Behaviour	Fat mass
Total contribution of neighbourhood : $(\gamma\beta_k + \theta_k)\alpha_k$	<b>0.72**</b> [100%]	<b>1.15**</b> [100%]	<b>0.16</b> [100%]	<b>0.12</b> [100%]	<b>0.71**</b> [100%]	<b>0.55*</b> [100%]
Of which explained by: $(\gamma_j\beta_{jk}\alpha_k)$						
Maternal psychosocial functioning	0.05 <sup>†</sup> [6.6%]	0.08** [6.5%]	0.08* [49.4%]	0.08** [66.1%]	0.20** [28.0%]	0.08** [15.4%]
Pre-school childcare	-	-	-	-	0.12** [17.3%]	-
Health & health behaviours	-	0.15** [13.3%]	0.14* [86.1%]	-	0.29** [40.3%]	0.19** [34.3%]
Home learning environment	0.09** [12.2%]	0.10** [9.0%]	-	0.05 <sup>†</sup> [44.6%]	0.12** [17.3%]	-
Physical home environment	-	-	-	-0.19 <sup>†</sup> [-159.5%]	-	-0.25* [-45.5%]
School fixed effects	-	-	-	-	-	-
Unexplained: $\theta_k\alpha_k$	0.51** [71.7%]	0.77** [66.7%]	-	0.11 [86.8%]	-	0.49* [90.1%]

Notes: N = 9476. Numbers in the higher row of each pair are selected path coefficients shown in equation 5. Numbers in square brackets express the coefficient as a proportion of the total contribution of the distal grouping given in the first row of each sub-table. Standard errors (not shown) calculated by non-parametric bootstrap.

\*\* p<.01; \* p<.05; <sup>†</sup> p<.10.

## Appendix B: Illustrative example of path model

Consider a decomposition model between income and an outcome with a single distal factor other than income (e.g. parental education) and a single proximal factor (e.g. the frequency a parent reads to the child). The raw income gradient in the outcome is 6.3 points, implying a log-point change in income is associated with a 0.63 standard deviation improvement in the outcome. The parameters of the structural equations (numbered as in Section 2.2) are presented below.

$$Y_i = 70 + 6.3(\delta)\text{Income}_i + e_i \quad (5)$$

$$Y_i = 75 + 5(\gamma)\text{Reading}_i + 3(\theta)\text{Education}_i + 2(\pi)\text{Income}_i + \mu_i \quad (1)$$

$$\text{Reading}_i = -0.15 + 0.3(\beta)\text{Education}_i + 0.5(\lambda)\text{Income}_i + \eta_i \quad (2)$$

$$\text{Education}_i = -1.5 + 0.4(\alpha)\text{Income}_i + \nu_i \quad (3)$$

The table below shows the way the underlying parameters can be combined to focus on different aspects of the income gradient.

Component	Formula	Calculation	Path coefficient	% of raw gradient
Total gradient	$\gamma\beta\alpha + \gamma\lambda + \theta\alpha + \pi$ $= \delta$	$(5 \times 0.3 \times 0.4) + (5 \times 0.5) + (3 \times 0.4) + 2$	6.3	100%
<b>Decomposition 1</b>				
<b>A. Total proximal contribution (sum of i and ii)</b>	$\gamma(\beta\alpha + \lambda)$	$5 \times [(0.3 \times 0.4) + 0.5]$	<b>3.1</b>	<b>49%</b>
i. Income-proximal contribution	$\gamma\lambda$	$(5 \times 0.5)$	2.5	40%
ii. Distal-proximal contribution	$\gamma\beta\alpha$	$(5 \times 0.3 \times 0.4)$	0.6	9%
<b>B. Total unexplained contribution (sum of iii and iv)</b>	$\theta\alpha + \pi$	$(3 \times 0.4) + 2$	<b>3.2</b>	<b>51%</b>
iii. Income-unexplained contribution	$\pi$	2	2	32%
iv. Distal-unexplained contribution	$\theta\alpha$	$(3 \times 0.4)$	1.2	19%
<b>Decomposition 2</b>				
<b>C. Direct income contribution (sum of i and iii)</b>	$\gamma\lambda + \pi$	$(5 \times 0.5) + 2$	<b>4.5</b>	<b>72%</b>
i. Income-proximal contribution	$\gamma\lambda$	$(5 \times 0.5)$	2.5	40%
iii. Income-unexplained contribution	$\pi$	2	2	32%
<b>D. Total distal contribution (sum of ii and iv)</b>	$(\gamma\beta + \theta)\alpha$	$[(5 \times 0.3) + 3] \times 0.4$	<b>1.8</b>	<b>28%</b>
ii. Distal-proximal contribution	$\gamma\beta\alpha$	$(5 \times 0.3 \times 0.4)$	0.6	9%
iv. Distal-unexplained contribution	$\theta\alpha$	$(3 \times 0.4)$	1.2	19%

The first decomposition focuses on the portion of the raw income gradient that can be explained by proximal factors. The total proximal contribution in row A is a measure of how far the income gradient is predicted to fall if all unconditional associations between proximal factors and income were eliminated – in this example it equates to the elimination of the correlation between income and parental reading. This decomposition focuses on the extent to which differences in the measured immediate environments of children can explain the

income gradient, abstracting from whether it is income or other distal factors that are the source of these environmental differences. Here, the greater reading in higher-income families generates a gradient of 3.1 points, or 49% of the raw gradient.

The total proximal contribution reflects two processes. First, income has a direct relationship with reading, holding education constant ( $\lambda$ ). The path coefficient of 2.5 implies that equalising income across families while leaving education unchanged is associated with a change in reading behaviour that reduces the overall predicted gradient by 40%. This is less than the total contribution of reading behaviour because lower income families also tend to have less education (captured by  $\alpha$ ), which itself exerts an independent influence on reading behaviour ( $\beta$ ). 0.6 points, or 9% of the overall gradient, is generated by the association of education with reading, combined with the concentration of low-educated parents in poorer families.

3.2 points, or 51%, of the raw gradient is attributed to other differences between low and higher income families besides reading behaviour. Some of these differences are conditionally associated with education – 19% of the total gradient is explained by something low- and high-educated parents do differently even when income is held constant. Finally, 32% of the raw gradient is accounted for by unobserved processes that are directly linked to income. The  $\pi$  coefficient implies that equalising income, while holding reading and education constant, is predicted to reduce the observed gradient by 2 points.

The second decomposition focuses on the extent to which income itself generates the observed gradient, separate from the confounding influence of other distal characteristics. The component C gives this “direct” effect of income, abstracting from whether it operates through measured proximal factors or unobserved processes. This is the type of income effect that is the focus of experimental and other causal analyses. In this example, equalising income across families, holding education constant, is predicted to lower the observed gradient by 72%. The division of this direct effect into 40% via the effect on reading behaviour and 32% via other unmeasured processes corresponds to the object of inquiry in the meditational studies of the conditional effect of income (e.g Guo and Harris 2000).

Component D, the part of the observed gradient that is due to the confounding of income with other distal factors, is the part that is normally treated as a nuisance in studies aiming to isolate the effect of income on outcomes. Inspection of this component provides evidence on the question: if it is not money itself that generates the poorer outcomes of low-income children, what is it? In this example education is the only potential confounder (accounting for the remaining 28% of the gradient), but in a realistic application education will compete with other distal characteristics such as family structure and labour market experiences. Further, each confounding distal contribution can be further decomposed into explained and unexplained components. The numbers for this example imply that a third of the overall gradient generated by education differences is due to the association between education and reading (0.6/1.8), while two-thirds is due to the association between education and unmeasured environmental influences that matter for the outcome.