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Families at a Loss: The Relationship Between Income Changes and Child Human Capital

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Families at a Loss: The Relationship Between Income Changes and Child Human Capital *

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Abstract

The main scope of this paper is to assess the relationship and pathways that link gains and losses in family income to the cognitive and non-cognitive development of children. With data from the UK Millennium Cohort Study (MCS), I use a value added model to link distributional changes in family income to children's reading scores and internalising and externalising behaviour trajectories between age 3 and 15. I find that only income losses have a significant negative impact on the non-cognitive development of children and that around one third of the effect operates through channels related to mental health and well-being of mothers. Instead, movements upwards and downwards the income distribution affect cognitive outcomes symmetrically. I find evidence suggesting that past income losses matter only in conjunction with current losses in explaining residualised reading test scores and that experiencing an income loss predicts the probability of entering the bottom quintile of the distribution of cognitive and non-cognitive skills. The evidence further suggests that the bottom quintile of non-cognitive skills is "stickier" than the cognitive skills' one, with income gains having no significant effect in predicting the probability of exiting the bottom of the skills distribution.

Keywords: Cognitive skills, Non-cognitive skills, Income changes
JEL codes: D31, J13, J24

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1 Introduction

The analysis of parental income in relation to human capital is no new subject in economics. A considerable number of theoretical contributions describe how income enables parents to put in place investments that will foster their kids' human capital development, which in turn will shape their later life outcomes. Extensive work from Heckman and coauthors from the early 2000s has emphasised that human capital is a multidimensional concept that cannot be equated to cognitive skills only (see, among others, Heckman and Rubinstein, 2001; Heckman *et al.*, 2006; Cunha *et al.*, 2010). The existing empirical literature, however, has largely focused on how parents' socio-economic status affects children's cognitive abilities, often neglecting non-cognitive ones, despite the growing body of evidence proving their importance in determining later life outcomes (see Cunha *et al.*, 2010; Blanden and Machin, 2010; Ermisch, 2008; Flouri *et al.*, 2012, 2014). Further evidence from neurobiology, developmental psychology, and economics underlines the fundamental role of early age experiences and environment in shaping brain functions and future development. While there is an increasing consensus on the importance of non-cognitive skills, the evidence surrounding its determinants and, in particular, on the impact of economic shocks on the social and behavioural outcomes of children is still scarce.

Transitory economic conditions, such as income shocks, are likely to affect child human capital development. While there is an increasingly large body of evidence on the relationship between parental socio-economic status or permanent income on child human capital, relatively little is known on the role of transitory income changes. The causal evidence on the expansion of tax credit policies and child benefits shows positive effects on a range of child cognitive outcomes (Dahl and Lochner, 2012; Evans and Garthwaite, 2014; Milligan and Stabile, 2011), while evidence on non-cognitive outcomes is scarce. However, positive economic shocks might differ in nature from negative ones: insights from prospect theory (Kahneman and Tversky, 1979) suggest that individuals overweight utility losses over gains. Similarly, the realisation of income losses, together with their potential interaction with market conditions (e.g. credit constraints), may well have an asymmetric effect on the parents' ability to foster their children's human capital, either via the provision of material inputs or via the quality and quantity of their time inputs.

The main scope of this paper is to assess the relationship and pathways that link gains and losses in family income to the cognitive and non-cognitive development of children. I do so using a longitudinal dataset from the UK, the Millennium Cohort Study (MCS), which follows the lives of around 19,000 children born at the turn of the millennium and their families. An almost unique feature of the dataset is that it contains measures of both cognitive and non-cognitive development of children aged 3 to 15. The relationship between parental income and child human capital in MCS has already been the object of attention of some papers: Kelly *et al.* (2011), using cognitive and non-cognitive measures of child development from waves 2 and 3 of MCS, find evidence of an income gradient, consistently with the previous literature. Noonan *et al.* (2018) links family income to health and non-cognitive outcomes of children, finding that permanent income has a protective effect against the probability of experiencing behavioural problems at age 11. Other papers use the MCS to document a gradient between parental economic background and children's cognitive (Dearden *et al.*, 2011) and non-cognitive (Tamura *et al.*, 2020) development.

I here use information from the six available waves of MCS to investigate the relationship between cognitive and non-cognitive skills formation and family income changes. The outcomes of interest, namely cognitive and non-cognitive skills, are respectively measured through age-adjusted reading test scores and the Strengths and Difficulties Questionnaire (SDQ), a widely recognised behavioural screening tool for children and adolescents (Goodman *et al.*, 2010). Using a value added model to assess the impact of income gains and losses on child human capital, I find that income losses are correlated with lower residualised measures of cognitive and non-cognitive skills, while gains only predict better cognitive performance. Consistent with the literature, results suggest that about one third of the effect of losses on non-cognitive outcomes transits via maternal measures of well-being. Similar to Bruckauf and Chzhen (2016), I then explore mobility in and out of the bottom of the reading test-scores and SDQ distributions. I find that income losses (gains) are positively (negatively) correlated with the probability of entering the bottom quintile of the distribution of all outcomes, and that the bottom of the distribution is stickier for non-cognitive outcomes rather than cognitive ones. This paper contributes to the literature in at least three ways: it is the first study to use data on measures of both cognitive and non-cognitive development for all currently available waves of the MCS in relationship to movements across the income distribution; it uses a value added model approach to assess the contribution of income changes on the year-to-year formation of cognitive and non-cognitive skills; lastly, it relaxes the assumption underlying most of the empirical literature in this field, which is that income gains and losses have a symmetric effect on children's outcomes.

Here follows an outline of the remainder of the paper. Section 2 reviews part of the relevant literature in the field. Section 3 describes the dataset and the main variables of interest, and presents the empirical strategy. Section 4 describes the main results. Robustness checks are conducted in Section 5, to test for the sensitivity of the estimates to changes in the specification and measurement issues. Before concluding with Section 7, Section 6 shows some additional results addressing persistence and transition dynamics.

2 Literature review

There is a large literature addressing the relationship between family income and child human capital (see Dahl and Lochner, 2012, for a review). Part of this literature addresses the causal impact of income, exploiting the exogenous variations coming from policy changes (e.g. income transfer programs). With US data, Dahl and Lochner (2012) exploit discontinuities in the Earned Income Tax Credit to identify the effect of income on test scores, finding that a 1,000 dollars increase in family income raises combined math and reading test scores by 6% of a standard deviation. Using the same policy discontinuities, Evans and Garthwaite (2014) find that higher income causes lower levels of both self-reported maternal stress and biological markers associated with stress. Milligan and Stabile (2011) look at variations in income induced by child benefit policy expansion in Canada and find significant positive effects on child and mother's mental health. Blau (1999) performs a fixed effect analysis of the NLSY cohort, finding little to no effect of current income on cognitive, social, and emotional development of kids; however, he does not control for potentially endogenous transitory shocks. Dahl and Lochner (2012) improve Blau's identification strategy with an instrumental variables approach, finding larger effects. Kuehnle (2014) explores the link between income and self-reported health on the 1970 British Cohort Study. Using local unemployment rates as an instrument, he identifies a small positive causal effect of family income on children's health.

Other studies adopt a descriptive approach to document a positive association between family income and child human capital, the effect being mostly larger for cognitive rather than non-cognitive outcomes (Duncan and Brooks-Gunn, 1997). While some focus on the net effect of family income on human capital accumulation (Shea, 2000), other studies explore the channels mediating this relationship (Washbrook *et al.*, 2014; Yeung *et al.*, 2002). Income, for instance, is known to be a determinant of individual well-being, with several studies establishing a causal link between the two (Frijters *et al.*, 2004; Gardner and Oswald, 2007; Powdthavee, 2010). Parental well-being, in turn, determines parenting practices: higher well-being is associated with warmer and responsive parenting (McLoyd *et al.*, 1994; Sampson and Laub, 1994; Smith and Brooks-Gunn, 1997), with positive spillovers on children's development (Conger *et al.*, 1992; McLoyd, 1990). Looking at the correlation between a permanent and a transitory measure of income on preschool children's outcomes, Yeung *et al.* (2002) test for the presence of two main set of mediating channels, respectively linked to the 'family stress' theory and the 'investment' theory. They find that mothers' emotional affect and parenting style play a significant role in explaining the effect of income on preschool children's externalising behaviour; on the other hand, the effect of income on children's cognitive skills runs mostly through the setting up of material investments. Despite the important role of mediating factors, the authors find that a direct effect of income on cognitive skills and externalising behaviour still persists. Washbrook *et al.* (2014) find consistent results on the mediating role of parents, using a broader set of measures of maternal psychosocial functioning. Frank and Meara (2009) find that maternal depression has a large negative effect on child development and the accumulation of non-cognitive skills, while it does not seem to affect math and reading test scores. However, these papers, using only cross sectional variations in income, fail to capture the dynamics between income changes, the short-term reaction of parents in terms of well-being, and children's behavioural and cognitive response. In this sense, a paper that comes closer to this objective is Clark *et al.* (2021), who use the same cross-sectional approach to estimate the effect of mothers' financial problems (a variable capturing financial distress rather than plain income) on a variety of childhood outcomes and find that only one quarter of the effect is captured by mothers' mental health.

In this paper, I use a value added model to address the relationship between changes in income and the accumulation of child human capital over time. Value added models are an established tool in the field of economics of education and are typically used to assess the impact of teachers on kids' performance in school. In general, they can be used to evaluate the contribution of an input in the accumulation of human capital from a given point in time to a subsequent one (Todd and Wolpin, 2003, 2007; Koedel *et al.*, 2015). With respect to regressions to the mean, value added models offer the advantage of assessing the average year-to-year contribution of factors of interest to the trajectories of fairly persistent outcomes. In a way, they provide a life-event approach to the short-term evolution of human capital that, under certain assumptions, allows to control for latent factors contributing to the human capital production function. Although widely used in relationship to teachers' quality, there are only few examples of their application to different contexts. With the same dataset used in this paper, Del Bono *et al.* (2016) adopt a cumulative value-added model to show the importance of early childhood maternal time investments on child cognitive skills. Other papers use value-added models to address, for example, the effect of private schools on learning achievements (Andrabi *et al.*, 2011), the role of obesity in child non-cognitive development (Black and Kassenboehmer, 2017), the persistence of mental health issues (Roy and Schurer, 2013), or the relationship between income changes and changes in life satisfaction Boyce *et al.* (2013).

3 Data and Methodology

3.1 Data description

This paper uses data from five waves of the UK Millennium Cohort Study (MCS). MCS is a longitudinal birth cohort study following the lives of around $19,000$ children born in the UK between 2000 and 2001. Six waves of the survey have been conducted so far, at age 9 months, 3 years, 5 years, 7 years, 11 years, and 15 years. The study collects a variety of socio-economic and demographic characteristics of the cohort members and their families, as well as information on parenting and childcare. From age 3 onward, data on cognitive and non-cognitive development are also available.

As far as cognitive outcomes are concerned, reading and word assessment tests are consistently available throughout waves 2 to 6. Numerical skills, on the other hand, are measured less frequently and have limited cross-wave comparability. Cognitive skills are assessed through age-appropriate standardised tests from the British Ability Scales (BAS) from waves 2 to 5. In order to capture reading and vocabulary skills, I rely on the BAS Naming Vocabulary scale for waves 2 and 3, the BAS Word Reading scale for wave 4, and BAS Verbal Similarity for wave 5 (see Hansen, 2014, for further details on the tests available for each wave). In wave 6 the only available word assessment is devised on the basis of standardised vocabulary tests developed by the Applied Psychology Unit at the University of Edinburgh in 1976 (this measure was already used to evaluate children in the same age range in the 1970 British Cohort Study). The measure of cognitive ability I use here is derived from the standardisation of the age-adjusted standardised t-scores from each of the tests described above (henceforth, referred to as 'reading test-scores' for simplicity).[1]

The measure of non-cognitive outcomes available for most waves of the MCS is the Strength and Development Questionnaire (SDQ). The SDQ is a screening test consisting of a set of age-appropriate questions assessing the behavioural and emotional health of children aged 3 to 16. The questionnaire is compiled by the cohort member's main caregiver in waves 2 to 6. Additionally, teacher-reported SDQ is available in waves 4 and 5 of MCS. The questionnaire is made of 25 items, which can be divided between five different scales: emotional symptoms, conduct problems, hyperactivity/inattention, peer relationship problems, and prosocial behaviour. Emotional symptoms and peer problems make up the category 'internalising problems', while conduct problems and hyperactivity/inattention constitute the 'externalising problems' category. Both categories are measured on a scale going from 0 to 20, which I reverse so that high values of SDQ correspond to better behavioural outcomes. As argued by Goodman et al. (2010), in low-risk samples, using these two broader categories yields better cross-sectional discriminant validity with respect to using the five SDQ scales. See Table A1 in the Appendix for more details on measurement and on the items that make up internalising and externalising SDQ.

As it is often the case in cohort studies, reported family income in MCS is not continuous, but instead limited to a discrete number of bands that vary from wave to wave. Respecting the limits imposed by the extremes of each income band, the data providers developed a measure of imputed income using interval regression. Among the predictors of income were respondent's age, housing tenure, region of residence, education, and labour market status (see Millennium Cohort Study, 2020, for a full list of predictors and more details on the imputation procedure).The measure of imputed income was then equivalised in order to account for economies of scale within the family, using the OECD household equivalence scale. While this measure allows to have a continuous income variable in the dataset, it is likely to be affected by measurement error and to

[1] The only exception is constituted by the vocabulary test at wave 6, for which only a raw score is available; I standardise it beforehand to match the same range of the standardised reading scores of the previous waves.

only partly reflect the latent income of the families in the survey. In order to limit the sensitivity of the results to this measurement issue, I build my main explanatory variables (that is, income gains and losses between consecutive periods) based on the quintiles of the equilvalised imputed income. This approach has the advantage of closely reflecting self-reported banded income, without suffering from the cross-wave differences in the definition of the bands.[2] Furthermore, it allows me to capture relatively larger variations in family income, as transitions from one income quintile to another will arguably be observed only for sufficiently large income gains or losses (I formally test whether this is indeed the case in Section 5). However, as shown more in detail in the robustness checks section, results are qualitatively similar when using the broader range of information coming from the continuous measure of imputed income provided in MCS. Transition matrices showing the raw probability of moving across quintiles of the distributions of income, reading test-scores, and SDQ from one wave to the next in the estimation sample are reported in the Appendix (Figures A1 to A4).

3.2 Empirical strategy

In this paper, I describe the evolution of children's cognitive and non-cognitive outcomes between two consecutive periods as a function of changes in household income. For this scope, I adopt a 'lagged score' value added model (Koedel *et al.*, 2015), which can be read as a model generating from an autoregressive process of order one. This method explores the dynamics of human capital formation by capturing the residualised changes in the measures of cognitive and non-cognitive skills described in Section 3.1, while accounting for their unobserved time-invariant determinants. For each of the outcomes of interest (i.e. internalising SDQ, externalising SDQ, and reading test-scores), I estimate the following regression using pooled OLS:

$$Y_{i,t} = \beta_0 + \beta_1 Y_{i,t-1} + \beta_2 L_{i,t} + \beta_3 G_{i,t} + \sum_{s=2}^{5} \gamma_s I^s_{i,t-1} + X'\delta + \zeta_t + \varepsilon_{i,t} \tag{1}$$

where $Y_{i,t}$ is one of the three outcomes of interest for individual i at time t, all of which are standardised. $L_{i,t}$ and $G_{i,t}$ are dummy variables indicating respectively whether there was a loss or a gain in household income between period $t-1$ and period t. As discussed above, income is coded as quintiles of equivalised imputed income and a loss (gain) is realised when the household the cohort member belongs to is in a lower (higher) income quintile with respect to the previous wave. By separately controlling for gains and losses in household income, income changes are allowed to have an asymmetric effect on the accumulation of cognitive and non-cognitive skills. $\{I^2_{i,t-1}, ..., I^5_{i,t-1}\}$ is a set of four dummies indicating the income band reported by the carer of child i in wave $t-1$ ($I^1_{i,t-1}$, i.e. the dummy indicating the first income band, is omitted and used as the reference

[2]The income bands extremes and the number of bands changing from wave to wave, it is a difficult task to harmonize such categories. Refer to the MCS data documentation and questionnaires for further details on the definition of income bands for each wave.

category). X is a vector of standard controls, including child and household's time-invariant characteristics such as sex, mother's age at birth, and child ethnicity; lagged characteristics and their variation between $t-1$ and t (housing tenure and its variation); covariates at time t, such as single-parent household, whether both parents participate to the labour market, and the square root of household size (see Table 1 for a full list of controls). Finally, ζ_t is a set of wave dummies. Standard errors are clustered at the child level.

Thanks to the richness of the dataset, I am able to test whether the effect of income changes on cognitive and non-cognitive outcomes is at least partly mediated by channels pertaining to the well-being of the parents. As it is often the case in cohort studies, parental variables are measured more accurately for mothers than they are for their spouse. This is because mothers tend to be the main caregiver and, hence, the main survey respondent. Furthermore, fathers might not always be present in the household at all waves and might not always coincide with the mother's partner or spouse. Because of this I focus on maternal well-being as a potential mediator of the effect of income changes on the accumulation of children's cognitive and non-cognitive skills. In order to capture mothers' physical well-being, I rely on a measure of self-assessed general health derived from the question "How would you describe your health generally?". Potential answers are "Excellent", "Very good", "Good", "Fair", and "Poor". As for psychological well-being, I use two measures to capture both the affects and the cognitive dimensions of well-being. The Kessler Psychological Distress Scale (K6), measuring affects, is a 6-items scale assessing mood and anxiety disorders in a short-term horizon. The question is introduced by the sentence "During the past 30 days, about how often did you feel..", followed by the items: "...nervous?", "...hopeless?", "...restless or fidgety?", "...so depressed that nothing could cheer you up?", "...that everything was an effort?", "...worthless?". Answers range from 1, meaning "all of the time", to 5, meaning "none of the time". Life satisfaction is used to measure cognitive well-being: respondents are faced with a scale going from 1, meaning "that you are completely dissatisfied" and 10, meaning "that you are completely satisfied" and asked to choose a number indicating how satisfied or dissatisfied they are about the way their life has turned out up to that moment.

The new specification mirrors the one described above, allowing for mothers' physical and psychological well-being to act as mediators:

$$Y_{i,t} = \beta_0 + \beta_1 Y_{i,t-1} + \beta_2 L_{i,t} + \beta_3 G_{i,t} + \sum_{s=2}^{5} \gamma_s I^s_{i,t-1} + (\Delta C_i)'\mu_1 + C'_{i,t-1}\mu_2 + \mathbf{X}'\delta + \zeta_t + \varepsilon_{i,t} \quad (2)$$

where $C_{i,t-1}$ is a vector containing the aforementioned measures of maternal well-being at time $t-1$: the Kessler K6 score, life satisfaction, and a dummy equal one if self-assessed health is either "fair" or "poor". All measures are coded in such a way that higher values reflect better outcomes. ΔC_i is a vector capturing the changes in the maternal channels, containing the standardised differences of the levels of psychological well-being between time $t-1$ and time t, and a dummy equal one if there was a worsening in the mother's self-assessed general health between the two same periods.

Conditioning on the availability of the dependent variables, the final estimation sample consists of 40,189 observations (14,394 cohort members, each observed on average for 3.8 waves).[3] Missing values of the explanatory variables were imputed using mean imputation; thus all regressions control for dummies indicating the position of the missing values for each variable.[4] Sampling weights and non-response weights provided by MCS are used throughout the analysis. Table A2 in the Appendix describes the features of the estimation sample. Around 22% of children experience a drop in their family income that moves them to a lower quintile of the income distribution; gains in family income quintile are instead experienced by around 27% of the estimation sample.

4 Results

4.1 Main regressions

Table 1 presents estimates of different specifications of the baseline model of equation (1): for each of the three dependent variables, the first column (i.e. columns 1, 3, 6) reports pooled OLS estimates of the baseline model without the lagged outcome; in columns 2, 4, and 6 instead the lagged value of the outcome variable is added to the model. Irrespective of the specification used, income losses seem to be systematically associated with lower levels of both reading test-scores and the two dimensions of SDQ. While income gains appear to foster cognitive skills, their effect on non-cognitive outcomes cannot be distinguished from zero. Comparing the first two columns for each outcome, it seems that the adoption a value added specification improves the fit of the model without qualitatively affecting the estimated coefficients.

Overall, the effect of moving to a lower income quintile is associated with a loss of about 3 to 4% of a SD of both externalising and internalising SDQ, and a loss of 3.5% of a SD in the standardised reading t-scores distribution. Although the effect sizes might look modest at first sight, the contribution of an income loss to the residualised internalising and externalising SDQ is comparable to about half the effect of being born with a weight lower than 2.5 kg, and for internalising SDQ it is not statistically different from the magnitude of the effect of being the first-born. While losses appear to play a larger role than gains in explaining residualised SDQ, pairwise Wald tests fail to reject the equality (in absolute value) of the coefficients for income gains and losses for all outcomes (the p-values of the tests are, respectively, 0.15 for externalising SDQ

[3]Note that information on the first wave a cohort member is observed are only used as lagged values in relationship to the second wave of observation. So in practice, the estimation is conducted on average on 2.8 waves per cohort member.

[4]Missingness is not a big problem in MCS: the percentage of imputed missing values is never above 5% for the main explanatory variables. Predictably, results are not sensitive to the imputation of missing values and hold also when the correspondent observations are dropped from the sample.

and 0.34 for internalising SDQ).[5]

4.2 Channels

The literature in economics and developmental psychology suggest that family income changes can affect children's human capital accumulation directly, through the provision of material inputs, and/or indirectly, through changes in parents' well-being, which can in turn affect the process of skills formation. While income gains and losses arguably reflect changes in parents' ability to provide material inputs to their children (e.g. piano lessons, books), specification (1) does not take into account other mechanisms. Table 2 uses the value added model described in specification (2) to explore the presence of mediators of the effect of income losses and gains reported in Table 1. The magnitude of the coefficients estimated in Table 1 might in fact reflect the presence of channels, such as mothers' well-being, that are likely positively correlated with income changes. As expected, the variables capturing the changes between $t-1$ and t, as well as the levels in $t-1$, of the mother's psychological and physical health explain a significant portion of the child's human capital formation trajectories and their introduction in the specification reduces on average the magnitude of the coefficients for both gains and losses. For internalising and externalising SDQ, about one third of the effect of income losses appears to transit through these channels - although the estimates are not precise enough to rule out the equality of the coefficients across specifications.

The coefficients of income gains and losses for reading test-scores are instead more robust to the introduction of potential mediators, perhaps suggesting that income changes have a stronger direct effect on school performance rather than internalising or externalising behaviour. The values of the adjusted R-squared across each pair of specifications in Table 2 further shows that the introduction of channels marginally improves the model's prediction in the case of internalising and externalising SDQ, but not for test-scores. This is also consistent both with Duncan and Brooks-Gunn (1997), who suggest that cognitive skills, with respect to non-cognitive ones, rely more heavily on material inputs. Yeung *et al.* (2002)'s findings further corroborate the results presented in Table 2, in at least two ways: first, their paper shows that the effect of income instability on non-cognitive skills is mostly conveyed through maternal affects; secondly, they show that the effect on cognitive skills is in larger part mediated by material investments, rather than mothers' emotional health.

[5] Note that the effect of income quintile gains and losses can reflect both pure mobility effects and positional effects deriving from the new family income quintile at time t. As controlling for income quintiles at time t would introduce an identification problem, a possible alternative suggested by sociologists is recurring to a diagonal reference model (DRM), typically used to study social mobility (Sobel, 1981, 1985). Under a set of assumptions, DRM provide a way to disentangle origin, destination, and mobility effects. Results from this model are presented in Table A3, where the coefficients for upwards and downwards mobility along the income distribution are only statistically meaningful (and of similar magnitude to the effects shown in Table 1) for reading test-scores. However, estimates of mobility from DRM are known to suffer from a high chance of type-II error, as shown by a body of null or weak evidence on mobility effects (see, for instance, Chan, 2018; Houle and Martin, 2011; Kaiser and Trinh, Forthcoming; Schuck and Steiber, 2018; Tolsma *et al.*, 2009; Zang and Dirk de Graaf, 2016) – in contradiction with the predominant sociological theoretical frameworks.

Qualitatively similar predictions are also supported by Washbrook *et al.* (2014).

4.3 Dynamic panel data analysis

While the value added model accounts for unobserved time-invariant factors explaining the dependent variable, there might still be some unobserved time-invariant factors affecting the residualised outcome, that is the portion of the outcome that is not explained by its past value. Such residual unobserved between-individuals heterogeneity can be addressed thanks to the panel structure of the data, by including individual fixed effects and thus isolating within variation only. However, the naive combination of a value added model with fixed effects would lead to a form of dynamic panel bias known as the Nickell bias (Nickell, 1981): through the demeaning process of fixed effects regression, the demeaned lagged value of the outcome (now the endogenous regressor) can no longer be distributed independently of the error term. The deriving endogeneity produces a bias that Nickell shows to be larger in samples with “small T and large N” - situation mirroring the MCS sample. A solution to this problem is the adoption of a system generalised method of moments (GMM) estimator (Arellano and Bover, 1995; Blundell and Bond, 1998). The estimator is derived from a system of two simultaneous equations (the regression model specified in first-differences and in levels), in which the endogenous variables are instrumented with suitable lags of, respectively, their own levels and their first differences (under the assumption that the changes in the instrumenting variables are uncorrelated with the fixed effects; see Roodman, 2009). Table A4 compares the performance of pooled OLS (same as in Table 1) and system GMM.[6]. The first and second columns of each GMM specification differ for the number of GMM-style instruments used for the endogenous regressor (the lag of the outcome variable): columns 2, 5, and 8 use only the outcome’s lags of order two or greater to build the instruments, while columns 3, 6, and 9 use the same lags for all the available outcomes (i.e. Externalising and Internalising SDQ, standardised reading test-scores). The size of the autoregressive coefficient for the lagged value of each outcome in the GMM columns constitutes an indirect validity test for the specification of the model, as the coefficient lays between the FE (not shown in the table) and the OLS estimates (as shown by Hsiao, 2014, these are, respectively, a lower and an upper bound for the true value of the coefficient). The GMM estimates of gains and losses appear to be qualitatively similar to (where not of significantly larger magnitude than) the OLS ones for all outcomes. This suggests that the omission of time-invariant factors that are potentially correlated with the residualised outcome might translate into an attenuation bias at worst; as such, the coefficients from baseline

[6] I here implement the system GMM estimator in Stata v 16.0 using the `xtabond2` command developed by David Roodman (see Roodman, 2009, for an introduction to difference and system GMM and the use of `xtabond2`). All variables are considered as included instruments, except for the lag of the dependent variable. This is instead instrumented GMM-style using its own lags of order two or higher. Standard errors are estimated with a two-step procedure, with a finite-sample correction (Windmeijer, 2005). Instead of first-differences, orthogonal deviations are used in order to minimise the loss of information due to the presence of gaps in the panel (Arellano and Bover, 1995).

value-added model without individual fixed effects can be interpreted as lower bounds of the real effect of income gains and losses. Differently from the OLS estimates in columns 1 and 4, gains appear to be statistically meaningful in explaining part of the residualised outcome in all GMM specifications of Internalising and Externalising SDQ, although their magnitude is lower than that of losses (the difference between the two absolute coefficients being statistically different from zero at the 5% level in the case of Externalising SDQ).

The use of system GMM does however come with a set of stringent assumptions. A crucial one is of course that the instruments should be exogenous (that is, uncorrelated with the error term). However, the Hansen J-statistic testing for over-identifying restrictions rejects the null hypothesis of joint validity of the instruments, no matter which combination of lagged outcomes is used as GMM-style instruments. Additionally, the use of the in-levels equation in system GMM require an extra assumption to hold, that is the first differences of the instrumenting variables should be uncorrelated with the time-invariant component of the error term (i.e. the fixed effects). This is equivalent to saying that, conditionally on all other covariates, the observed deviations in the instruments from one period to the next should be taken as deviations from a sort of stationary state and, as such, they do not depend on intrinsic individual characteristics (Roodman, 2009). Given of the absence of convincing evidence in support of the identifying assumptions required by system GMM and the conservative size of the OLS estimates with respect to the dynamic panel data ones, a pooled OLS estimator of the value-added model illustrated by equation 1 will be used throughout the remainder of the paper.

5 Robustness Checks

5.1 The measurement of income

One important concern with the analysis conducted above is linked to the interpretation of the coefficients of gains (losses) for individuals at the top (bottom) income quintile in $t-1$. Due to the discrete nature of the income variable used, these individuals cannot transition upwards (downwards) the income distribution, hence gains (losses) are not defined for them. A way of getting around the issue is to replicate the estimates above using only cohort members who can potentially transition both upwards and downwards the income quintile scale, that is, excluding in each wave those individuals who were either in the top or in the bottom quintile of the household income distribution in the previous wave. Columns 1, 3, and 5 of Table A5 in the Appendix replicate the baseline value-added model for a sub-sample of cohort members whose family income is neither in the top nor in the bottom quintile around waves 2 to 5. Although the coefficients for reading test-scores are less precisely estimated, the same considerations made for Table 1 qualitatively hold.

One could take a step further and exclude from the estimation sample not only individuals whose upwards or downwards movements across the income quintile distribution are made impossible because of their position in either one of the its extremes, but also those for whom the *size* of the jump is constrained because of their position. As an example, keeping all other things constant, a cohort member who finds herself in the fourth income quintile and experience a family income gain in the next period can only transition to the fifth quintile, no matter how large the gain her family experienced. On the contrary, the gain experienced by someone going from the third to the fourth quintile is less limited by the scale of the income variable (had the relative gain been larger, such person could have potentially transitioned to the top quintile). Results for cohort members whose movements are not constrained to one-quintile jumps across the income distribution can be found in columns 2, 4, and 6 of Table A5. Although of larger magnitude, the estimated coefficients of income gains and losses are overall consistent with results in Table 1.

So far I only considered income as measured by quintiles. Despite the issues linked to its measurement (see discussion in Section 3.1), the MCS imputed measure of continuous family income has the potential to provide extra layers of information that could be useful in disentangling the effect of more sophisticated categories of gains and losses. Arguably, gains and losses based on income quintiles will likely capture larger changes in family income, while changes that are not large enough to drive a family out of their income quintile are considered as an absence of change (I formally test that this is indeed the case at the end of this section). Additionally, an analysis based on the continuous imputed measure of income would not depend on the relative position of individuals across the income distribution, but would be based on their absolute income status instead. As income in the MCS is imputed using not only banded income, but also information on educational status, age, geography and a variety of other covariates (see Millennium Cohort Study, 2020, for more details on the imputation procedure), it can be interpreted as a broader measure of socio-economic status.

First, I computed the growth rate of imputed equivalised income between one period and the next, splitting it into two variables: one, 'positive income growth', reflecting its positive values (and equal zero for all negative values) and the other, 'negative income growth', reflecting the absolute value of its negative values (and equal to zero for all positive values). I then substituted the loss and gain dummies in equation 1 with positive and negative income growth. The distribution of the income growth rate is roughly normal, centered around zero, with a long right tail. Results for this specification are illustrated in Table A6, trimming any income growth rate larger than 10 (top 0.5% of its distribution). [7] The story shown by the Table is consistent with that implied by Table 1: negative income growth hinders both cognitive and non-cognitive outcomes (although the effect is not always precisely estimated). Differently from the baseline, a positive income

[7] Note that the sample size is smaller than the baseline, because of missing values of imputed income and trimming of the right tail. Baseline results still hold in this smaller sample.

growth rate between one period and the next is now significantly associated with better measures of non-cognitive skills, although the absolute effect size is roughly one third of that of negative income growth. Another difference with the baseline results is the difference in magnitude between the gains and losses coefficients for reading test-scores: while the baseline estimates suggested symmetry of gains and losses, here the absolute values of the positive and negative income growth estimates are statistically different from each other at the 10% level – with gains affecting learning outcomes to a lesser extent than losses.

An assumption implied so far is that income gains and losses (defined by transitions across the income quintile distribution) are 'large'. However, changes in a family's relative income position could well occur even in response to relatively small changes in imputed income. I here explore the composition of income changes involved in the gain and loss dummies and their relative role in shaping human capital accumulation. In Table A7 the income quintile gain (loss) indicator is decomposed into four dummies, based on the magnitude of the continuous income growth rate associated driving the underlying upwards (downwards) quintile movement.[8] While we can almost never reject the equality of all the losses (gains) coefficients in each column, Table A7 suggests that the baseline results from Table 1 are not primarily driven by gains and losses induced by small income changes: income quintile losses (gains) associated with a -25% (25%) income growth rate or smaller (greater) are the ones to attract the most statistically significant estimates. This is somewhat unsurprising, as about 54% (80%) of all downwards (upwards) movements in the income quintile distribution involve an income growth rate of -25% or lower (25% or greater).

5.2 Omitted variables

One question that might emerge at this point concerns what are the drivers of these upwards and downwards movements across the household income distribution. Income changes are indeed likely to depend on factors such as changes in the country's social security system, in the labour market status of the parents, in the household's demographic structure, in housing tenure. However, is the process of human capital formation affected by these changes per-se, or does income have a direct way of affecting cognitive and non-cognitive outcomes? In other words, do these factors affect the outcomes only through changes in income or are they omitted variables threatening to confound its effect?

Table 3 is an attempt to clarify the matter. Columns 1, 3, and 5 replicate columns 2, 5, and 8 of Table 1. Columns 2, 4, and 6 introduce a list of life events between $t-1$ and t that are likely to be correlated with changes in quintiles of equivalised income. Since housing tenure and its changes are already controlled for in all specifications, remaining determinants of income changes I could control

[8] Here I chose 25%, 10%, and 5% (and their negative equivalents) as arbitrary thresholds to distinguish between different categories of income growth. Results are however robust to a battery of other thresholds and number of intervals.

for are separations, job losses and job changes, and additional changes in household composition driven by siblings. The coefficients of gains and losses are overall robust to the introduction of these potential confounders, suggesting that their omission does not contribute to the creation of an omitted variables bias. This evidence is partly in contrast with Washbrook *et al.* (2014), who find that the income gradient of non-cognitive skills and health is completely shut out by distal factors such as socio-demographic and labour market outcomes, with only one fifth of the effect of income on cognitive skills surviving the introduction of these covariates. Conditional on current employment status, changes in the parents' labour force status from one period to the next do not appear to explain changes in the residualised cognitive and non-cognitive outcomes. A parent leaving the household appears to be negatively associated with the residualised measures of non-cognitive outcomes (the association being statistically significant at the 10% level only for Internalising SDQ), while no effect is found on reading test-scores. Changes in the siblings pool composition appear to have a negative effect on child human capital accumulation, especially in the case of socio-emotional development. Externalising problems increase with the presence of new siblings, consistent with children engaging in disruptive behaviours to capture the parents' attention. The results for internalising symptoms instead hide substantial heterogeneity across gender: while boys have lower residualised internalising SDQ when younger siblings are born, girls are only significantly affected by an older sibling leaving the household.

6 Additional results

6.1 Persistence

As shown by results in Tables 1 and 2, income gains between $t-1$ and t do not seem to be statistically significant in explaining changes in non-cognitive outcomes, while income losses have a significant negative impact. One may wonder whether the same is true for past movements across family income quintiles. Table 4 investigates the role of past gains and losses, as well as current ones, and their interactions over time. The Table shows a picture similar to that of Table 1 for recent gains and losses ($Gain_t$ and $Loss_t$). While there is some evidence that past income losses decrease residualised Internalising SDQ and reading test-scores, these effects are not statistically significant. Similarly, past income gains appear to foster human capital, significantly so only for reading test scores. As household income losses seem to affect cohort members partly through parents' well-being, it seems plausible that their effect on child human capital be mostly immediate, driven by affects. As shown by Boyce *et al.* (2013), income gains typically have a positive impact on subjective well-being of a lower magnitude with respect to that of losses. An income gain between time $t-2$ and $t-1$ might not have a strong enough impact on parents' well-being to justify a positive effect on non-cognitive human capital formation at time $t-1$, but it might still enable parents to put in place material investments fostering their children's cognitive skills that will still have an effect at time t, thus explaining the positive effect of past income gains on reading test scores. There is however no evidence of complementarity between income gains in two consecutive periods: if anything they appear to have a certain degree of substitutability, as shown by the negative coefficient for the interaction between two consecutive gains. On the other hand, old income losses seem to matter only in relationship to current income losses, exacerbating their negative relationship with reading test-scores.

Results from Table 4 can be interpreted in relationship to the literature on homeostatic well-being (Cummins, 2016). As about one third of the effect of income losses on Internalising and Externalising SDQ is mediated by mothers' well-being, one might wonder whether the absence of persistence of past income losses is due to an adaptation mechanism that pushes mothers' well-being back towards its homeostatic level. I test for this possibility, by replicating Table 4 for the two outcomes reflecting mothers' psychological well-being, namely life satisfaction and the Kessler (K6) scale of affects (results available on request). As expected, I find evidence of mothers adapting to income changes both in terms of affects and cognitive well-being, with the measure of affects adapting at a faster rate than the cognitive one. Since the effect of income changes on reading test-scores does not seem to be mediated by any parental well-being channel, the well-being adaptation mechanism does not affect the persistence of past losses and gains, which matter both in absolute terms and in conjunction with current income changes.

6.2 Transition dynamics

The results presented so far are just average effects across all income quintiles. However, following the approach of Bruckauf and Chzhen (2016), it might be interesting to focus on the risk factors that predict the entry to and exit from the bottom quintile of the income distribution.[9] Table 5 reports average marginal effects derived from logistic regressions predicting the probability of entering or exiting the bottom quintile of the cognitive or non-cognitive skills distributions. Note that the estimation samples here are different: by construction, cohort members who are already at the bottom quintile of an outcome's distribution are dropped from the estimation sample of the column tagged "entry" (unless they transition into a higher quintile and then back again into the lowest one). For exit instead, the estimation sample is made up only by cohort members who already were in the bottom quintile of the outcome's distribution in $t-1$.

Controlling for the position in the income distribution in period $t-1$, a movement down the

[9] Income quintile changes may not be independent of the child's position in the distribution of cognitive and non-cognitive outcomes. I empirically test whether that is the case in the estimation sample and find little differences in the probability of experiencing income gains or losses between individuals at the bottom quintile of any outcome's distribution and those in higher quintiles. The likelihood of experiencing income gains (losses) is 0.3 pp higher (0.9* pp lower) for those at the bottom quintile of the Externalising SDQ distribution; 1** pp higher (0.4 pp lower) for those at the bottom quintile of the Internalising SDQ distribution; and 0.8 pp higher (1** pp lower) for those at the bottom quintile of the reading test-scores distribution.

income distribution quintiles is associated with a 2 pp increase of the probability of entering the bottom quintile of the externalising SDQ distribution. While losses seem to predict the probability of entering in the bottom quintile of the SDQ distributions, gains are associated with a lower likelihood of entering the bottom quintile of internalising SDQ and reading test-scores. Neither income losses nor gains seem to contribute to explaining transition dynamics out of the bottom quintile of non-cognitive outcomes (with the exception of losses for externalising SDQ). On the other hand, for reading test-scores, income gains are associated with a higher probability of exiting the outcome's bottom quintile.

7 Conclusion

This paper explores the relationship between changes in family income and the accumulation of children's cognitive and non-cognitive skills. By relaxing the assumption of a symmetric impact of losses and gains, I find that losses matter more than gains in explaining changes in non-cognitive outcomes between one wave and the next. Movements downwards the distribution of family income are associated with a decrease of 3 to 4% of a standard deviation for both SDQ and reading test-scores, an effect size comparable to that of a parent leaving the household.

The effect of losses is mediated for one third by channels reflecting mothers' well-being. Losses also predict the probability of transitioning into the bottom quintile of the distribution of both non-cognitive and cognitive abilities; for the latter, experiencing a loss hinders the probability of moving out of the bottom of the distribution. Moving upwards the family income distribution, on the contrary, is correlated with both higher probability of exiting and lower probability of entering the bottom quintile of the reading test-scores distribution. The effect of gains on reading test scores is also persistent in time: past income gains still matter for today's cognitive trajectories, consistently with the theory of family investment.

Despite the robustness of the results presented above to a battery of sensitivity tests, the empirical strategies used throughout the paper remain exposed to potential endogeneity issues. However, results are consistent with the established literature in economics and developmental psychology and contribute to uncovering some novel mechanism. From a policy perspective, the findings of this paper suggest that income transfers, while fostering cognitive skills, might not have the same effect on non-cognitive skills. The fact that human capital accumulation appears to be more sensitive to income losses might provide yet another piece of evidence in support of insurance and welfare policies to limit the negative impact of adverse economic conditions, paying particular attention to the effects on the psychological well-being of adults.

References

Andrabi, Tahir, Jishnu Das, Asim Ijaz Khwaja, and Tristan Zajonc. 2011. "Do value-added estimates add value? Accounting for learning dynamics." *American Economic Journal: Applied Economics*, 3: 29–54.

Arellano, Manuel, and Olympia Bover. 1995. "Another look at the instrumental variable estimation of error-components models." *Journal of Econometrics*, 68: 29–51.

Black, Nicole, and Sonja C. Kassenboehmer. 2017. "Getting weighed down: the effect of childhood obesity on the development of socioemotional skills." *Journal of Human Capital*, 11: 263–295.

Blanden, Jo, and Stephen Machin. 2010. "Intergenerational inequality in early years assessments." In *Children of the 21st century: The first five years.* Vol. 2, , ed. K. Hansen, H. Joshi and S. Dex, Chapter 9, 153–168. Policy Press.

Blau, David M. 1999. "The effect of income on child development." *Review of Economics and Statistics*, 81: 261–276.

Blundell, Richard, and Stephen Bond. 1998. "Initial conditions and moment restrictions in dynamic panel data models." *Journal of Econometrics*, 87: 115–143.

Boyce, Christopher J., Alex M. Wood, James Banks, Andrew E. Clark, and Gordon D.A. Brown. 2013. "Money, well-being, and loss aversion: Does an income loss have a greater effect on well-being than an equivalent income gain?" *Psychological Science*, 24: 2557–2562.

Bruckauf, Zlata, and Yekaterina Chzhen. 2016. *Poverty and Children's Cognitive Trajectories: Evidence from the United Kingdom Millennium Cohort Study.* UNICEF - Innocenti Working Paper, 14.

Chan, Tak Wing. 2018. "Social mobility and the well-being of individuals." *British Journal of Sociology*, 69: 183–206.

Clark, Andrew E., Conchita D'Ambrosio, and Marta Barazzetta. 2021. "Childhood circumstances and young adulthood outcomes: The role of mothers' financial problems." *Health Economics*, 30: 342–357.

Conger, Rand D., Katherine J. Conger, Glen H. Elder Jr., Frederick O. Lorenz, Ronald L. Simons, and Les B. Whitbeck. 1992. "A family process model of economic hardship and adjustment of early adolescent boys." *Child Development*, 63: 526–541.

Cummins, Robert A. 2016. "The theory of subjective wellbeing homeostasis: A contribution to understanding life quality." In *A Life Devoted to Quality of Life.* Vol. 60, , ed. F. Maggino, Chapter 4, 61–79. Springer.

Cunha, Flavio, James J. Heckman, and Susanne M. Schennach. 2010. "Estimating the technology of cognitive and noncognitive skill formation." *Econometrica*, 78: 883–931.

Dahl, Gordon B., and Lance Lochner. 2012. "The impact of family income on child achievement: Evidence from the earned income tax credit." *American Economic Review*, 102: 1927–56.

Dearden, Lorraine, Luke Sibieta, and Kathy Sylva. 2011. "The socio-economic gradient in early child outcomes: evidence from the Millennium Cohort Study." *Longitudinal and Life Course Studies: International Journal*, 2: 19–40.

Del Bono, Emilia, Marco Francesconi, Yvonne Kelly, and Amanda Sacker. 2016. "Early maternal time investment and early child outcomes." *Economic Journal*, 126: F96–F135.

Duncan, Greg J., and Jeanne Brooks-Gunn. 1997. *Consequences of Growing Up Poor.* Russell Sage Foundation.

Ermisch, John. 2008. "Origins of social immobility and inequality: parenting and early child development." *National Institute Economic Review*, 205: 62–71.

Evans, William N., and Craig L. Garthwaite. 2014. "Giving mom a break: The impact of higher EITC payments on maternal health." *American Economic Journal: Economic Policy*, 6: 258–90.

Flouri, Eirini, Emily Midouhas, and Heather Joshi. 2014. "The role of urban neighbourhood green space in children's emotional and behavioural resilience." *Journal of Environmental Psychology*, 40: 179–186.

Flouri, Eirini, Stella Mavroveli, and Nikos Tzavidis. 2012. "Cognitive ability, neighborhood deprivation, and young children's emotional and behavioral problems." *Social Psychiatry and Psychiatric Epidemiology*, 47: 985–992.

Frank, Richard G., and Ellen Meara. 2009. *The Effect of Maternal Depression and Substance Abuse on Child Human Capital Development.* NBER Working Paper Series, 15314.

Frijters, Paul, John P. Haisken-DeNew, and Michael A. Shields. 2004. "Money does matter! Evidence from increasing real income and life satisfaction in East Germany following reunification." *American Economic Review*, 94: 730–740.

Gardner, Jonathan, and Andrew J. Oswald. 2007. "Money and mental wellbeing: A longitudinal study of medium-sized lottery wins." *Journal of Health Economics*, 26: 49–60.

Goodman, Anna, Donna L. Lamping, and George B. Ploubidis. 2010. "When to use broader internalising and externalising subscales instead of the hypothesised five subscales on the Strengths and Difficulties Questionnaire (SDQ): Data from British parents, teachers and children." *Journal of Abnormal Child Psychology*, 38: 1179–1191.

Heckman, James J., and Yona Rubinstein. 2001. "The importance of noncognitive skills: Lessons from the GED testing program." *American Economic Review*, 91: 145–149.

Heckman, James J., Jora Stixrud, and Sergio Urzua. 2006. "The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior." *Journal of Labor Economics*, 24: 411–482.

Houle, Jason N., and Molly A. Martin. 2011. "Does intergenerational mobility shape psychological distress? Sorokin revisited." *Research in Social Stratification and Mobility*, 29: 193–203.

Hsiao, Cheng. 2014. *Analysis of Panel Data.* Cambridge University Press.

Kahneman, Daniel, and Amos Tversky. 1979. "Prospect theory: An analysis of decision under risk." *Econometrica*, 47: 263–292.

Kaiser, Caspar, and Nhat An Trinh. Forthcoming. "Positional, mobility and reference effects: How does social class affect life satisfaction in Europe?" *European Sociological Review.*

Kelly, Y., A. Sacker, E. Del Bono, M. Francesconi, and M. Marmot. 2011. "What role for the home learning environment and parenting in reducing the socioeconomic gradient in child development? Findings from the Millennium Cohort Study." *Archives of Disease in Childhood*, 96: 832–837.

Koedel, Cory, Kata Mihaly, and Jonah E. Rockoff. 2015. "Value-added modeling: A review." *Economics of Education Review*, 47: 180–195.

Kuehnle, Daniel. 2014. "The causal effect of family income on child health in the UK." *Journal of Health Economics*, 36: 137–150.

McLoyd, Vonnie C. 1990. "The impact of economic hardship on Black families and children: Psychological distress, parenting, and socioemotional development." *Child Development*, 61: 311–346.

McLoyd, Vonnie C., Toby Epstein Jayaratne, Rosario Ceballo, and Julio Borquez. 1994. “Unemployment and work interruption among African American single mothers: Effects on parenting and adolescent socioemotional functioning.” *Child Development*, 65: 562–589.

Millennium Cohort Study. 2020. *Millennium Cohort Study - User Guide (Surveys 1 to 5).* . 9^{th} ed., Centre for Longitudinal Studies.

Milligan, Kevin, and Mark Stabile. 2011. “Do child tax benefits affect the well-being of children? Evidence from Canadian child benefit expansions.” *American Economic Journal: Economic Policy*, 3: 175–205.

Nickell, Stephen. 1981. “Biases in dynamic models with fixed effects.” *Econometrica*, 1417–1426.

Noonan, Katharine, Richéal Burns, and Mara Violato. 2018. “Family income, maternal psychological distress and child socio-emotional behaviour: Longitudinal findings from the UK Millennium Cohort Study.” *SSM - Population Health*, 4: 280–290.

Powdthavee, Nattavudh. 2010. “How much does money really matter? Estimating the causal effects of income on happiness.” *Empirical Economics*, 39: 77–92.

Roodman, David. 2009. “How to do xtabond2: An introduction to difference and system GMM in Stata.” *Stata Journal*, 9: 86–136.

Roy, John, and Stefanie Schurer. 2013. “Getting stuck in the blues: persistence of mental health problems in Australia.” *Health Economics*, 22: 1139–1157.

Sampson, Robert J., and John H. Laub. 1994. “Urban poverty and the family context of delinquency: A new look at structure and process in a classic study.” *Child Development*, 65: 523–540.

Schuck, Bettina, and Nadia Steiber. 2018. “Does intergenerational educational mobility shape the well-being of young Europeans? Evidence from the European Social Survey.” *Social Indicators Research*, 139: 1237–1255.

Shea, John. 2000. “Does parents’ money matter?” *Journal of Public Economics*, 77: 155–184.

Smith, Judith R., and Jeanne Brooks-Gunn. 1997. “Correlates and consequences of harsh discipline for young children.” *Archives of Pediatrics and Adolescent Medicine*, 151: 777–786.

Sobel, Michael E. 1981. “Diagonal mobility models: A substantively motivated class of designs for the analysis of mobility effects.” *American Sociological Review*, 46: 893–906.

Sobel, Michael E. 1985. “Social mobility and fertility revisited: Some new models for the analysis of the mobility effects hypothesis.” *American Sociological Review*, 50: 699–712.

Tamura, K., J. Morrison, and H. Pikhart. 2020. “Children’s behavioural problems and its associations with socioeconomic position and early parenting environment: findings from the UK Millennium Cohort Study.” *Epidemiology and Psychiatric Sciences*, 29.

Todd, Petra E., and Kenneth I. Wolpin. 2003. “On the specification and estimation of the production function for cognitive achievement.” *Economic Journal*, 113: F3–F33.

Todd, Petra E., and Kenneth I. Wolpin. 2007. “The production of cognitive achievement in children: Home, school, and racial test score gaps.” *Journal of Human Capital*, 1: 91–136.

Tolsma, Jochem, Nan Dirk De Graaf, and Lincoln Quillian. 2009. “Does intergenerational social mobility affect antagonistic attitudes towards ethnic minorities?” *British Journal of Sociology*, 60: 257–277.

Washbrook, Elizabeth, Paul Gregg, and Carol Propper. 2014. “A decomposition analysis of the relationship between parental income and multiple child outcomes.” *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 177: 757–782.

Windmeijer, Frank. 2005. "A finite sample correction for the variance of linear efficient two-step GMM estimators." *Journal of Econometrics*, 126: 25–51.

Yeung, W. Jean, Miriam R. Linver, and Jeanne Brooks-Gunn. 2002. "How money matters for young children's development: Parental investment and family processes." *Child Development*, 73: 1861–1879.

Zang, Emma, and Nan Dirk de Graaf. 2016. "Frustrated achievers or satisfied losers? Inter- and intragenerational social mobility and happiness in China." *Sociological Science*, 3: 779–800.

Figures and Tables

Table 1: The effect of income changes on child human capital

	Externalising SDQ		Internalising SDQ		Reading test-scores	
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome $(t-1)$		0.644***		0.518***		0.287***
		(0.007)		(0.008)		(0.006)
Gain	0.019	0.005	0.016	0.020	0.049***	0.041***
	(0.016)	(0.012)	(0.016)	(0.014)	(0.013)	(0.012)
Loss	-0.027*	-0.033***	-0.052***	-0.039***	-0.035***	-0.035***
	(0.016)	(0.012)	(0.016)	(0.014)	(0.013)	(0.012)
2nd income quintile $(t-1)$	0.034	0.029	0.053**	0.031	0.072***	0.056***
	(0.026)	(0.020)	(0.026)	(0.022)	(0.019)	(0.018)
3rd income quintile $(t-1)$	0.083***	0.057***	0.110***	0.056**	0.128***	0.100***
	(0.030)	(0.021)	(0.029)	(0.023)	(0.022)	(0.020)
4th income quintile $(t-1)$	0.136***	0.079***	0.171***	0.097***	0.173***	0.132***
	(0.033)	(0.023)	(0.031)	(0.024)	(0.026)	(0.022)
5th income quintile $(t-1)$	0.188***	0.106***	0.281***	0.153***	0.247***	0.198***
	(0.038)	(0.025)	(0.036)	(0.027)	(0.029)	(0.025)
Observations	40,189	40,189	40,189	40,189	40,189	40,189
Adjusted R-squared	0.135	0.469	0.121	0.357	0.361	0.424

Notes: Outcome $(t-1)$ represents the standardised lagged value of the dependent variable. All regressions control for dummies indicating the child's gender, having a twin or being part of a triplet, having low birth-weight (< 2.5 kg), being a first-born, being in a single-parent household, and whether both parents are employed; dummies reflecting the child's ethnic background (mixed, Indian, Pakistani or Bangladeshi, Black, other), and the mother's highest educational level; mother's age at birth of the cohort member, parental involvement at age 3 (i.e. frequency of reading to the child, regular bedtime, hours spent in front of the TV), squared root of household size; dummies for house-tenure at time $t-1$ (ownership, mortgage, rent, other) and its variation between $t-1$ and t; survey wave dummies, and country dummies (England, Wales, Scotland, NI). Robust standard errors, clustered at the cohort member level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: The effect of income changes on child human capital: value added models with channels

	Externalising SDQ		Internalising SDQ		Reading test-scores	
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome $(t-1)$	0.644***	0.624***	0.518***	0.484***	0.287***	0.286***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.006)	(0.006)
Gain	0.005	-0.001	0.020	0.010	0.041***	0.039***
	(0.012)	(0.012)	(0.014)	(0.013)	(0.012)	(0.012)
Loss	-0.033***	-0.022*	-0.039***	-0.026*	-0.035***	-0.034***
	(0.012)	(0.012)	(0.014)	(0.014)	(0.012)	(0.012)
2nd income quintile $(t-1)$	0.029	0.023	0.031	0.021	0.056***	0.055***
	(0.020)	(0.019)	(0.022)	(0.021)	(0.018)	(0.018)
3rd income quintile $(t-1)$	0.057***	0.042**	0.056**	0.033	0.100***	0.097***
	(0.021)	(0.021)	(0.023)	(0.023)	(0.020)	(0.020)
4th income quintile $(t-1)$	0.079***	0.058**	0.097***	0.065***	0.132***	0.128***
	(0.023)	(0.022)	(0.024)	(0.024)	(0.022)	(0.022)
5th income quintile $(t-1)$	0.106***	0.072***	0.153***	0.104***	0.198***	0.193***
	(0.025)	(0.025)	(0.027)	(0.026)	(0.025)	(0.025)
Δ(Kessler scale)$_{t-1,t}$		-0.115***		-0.153***		-0.020***
		(0.007)		(0.008)		(0.006)
Kessler scale $(t-1)$		-0.026***		-0.037***		-0.004**
		(0.002)		(0.002)		(0.002)
Δ(Life satisfaction)$_{t-1,t}$		0.028***		0.036***		0.002
		(0.006)		(0.007)		(0.006)
Life satisfaction $(t-1)$		0.013***		0.016***		-0.002
		(0.004)		(0.004)		(0.003)
Worsening in mother's health		-0.045**		-0.068***		-0.020
		(0.021)		(0.023)		(0.019)
Mother had poor health in $t-1$		0.006		-0.049***		-0.028**
		(0.015)		(0.017)		(0.014)
Observations	40,189	40,189	40,189	40,189	40,189	40,189
Adjusted R-squared	0.469	0.483	0.357	0.385	0.424	0.425

Notes: Outcome $(t-1)$ represents the standardised lagged value of the dependent variable. Δ(Kessler scale)$_{t-1,t}$ is the standardized difference of the mother's Kessler Psychological Distress Scale (K6) score between wave $t-1$ and t. Similarly, Δ(Life satisfaction)$_{t-1,t}$ is the standardized difference in the mother's life satisfaction between two consecutive waves and Life satisfaction $(t-1)$ is the level of her life satisfaction in wave $t-1$. Worsening in mother's health is a dummy equal 1 if there was a worsening in the self-reported mother's general health between wave $t-1$ and t. Mother had poor health in $t-1$ is a dummy equal 1 if the mother had either "fair" or "poor" self-reported general health in wave $t-1$. All regressions control for dummies indicating the child's gender, having a twin or being part of a triplet, having low birth-weight (< 2.5 kg), being a first-born, being in a single-parent household, and whether both parents are employed; dummies reflecting the child's ethnic background (mixed, Indian, Pakistani or Bangladeshi, Black, other), and the mother's highest educational level; mother's age at birth of the cohort member, parental involvement at age 3 (i.e. frequency of reading to the child, regular bedtime, hours spent in front of the TV), squared root of household size; dummies for house-tenure at time $t-1$ (ownership, mortgage, rent, other) and its variation between $t-1$ and t; survey wave dummies, and country dummies (England, Wales, Scotland, NI). Sampling and non-response weights used. Robust standard errors, clustered at the cohort member level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Robustness checks: Other life events as potential confounders

	Externalising SDQ		Internalising SDQ		Reading test-scores	
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome ($t-1$)	0.644***	0.644***	0.518***	0.517***	0.287***	0.287***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.006)	(0.006)
Gain	0.005	0.005	0.020	0.019	0.041***	0.042***
	(0.012)	(0.013)	(0.014)	(0.014)	(0.012)	(0.012)
Loss	-0.033***	-0.029**	-0.039***	-0.033**	-0.035***	-0.039***
	(0.012)	(0.013)	(0.014)	(0.014)	(0.012)	(0.012)
Life events between $t-1$ and t						
Parent left		-0.029		-0.058*		0.016
		(0.027)		(0.033)		(0.023)
Mother lost job		0.002		0.021		0.019
		(0.022)		(0.026)		(0.022)
Father lost job		0.032		0.038		0.021
		(0.036)		(0.041)		(0.032)
Mother changed job		-0.004		0.020		-0.006
		(0.012)		(0.013)		(0.011)
Father changed job		0.006		-0.004		-0.011
		(0.012)		(0.013)		(0.011)
1 new sibling		-0.078***		-0.034**		0.002
		(0.016)		(0.017)		(0.015)
2+ new siblings		-0.144**		-0.114*		-0.049
		(0.062)		(0.068)		(0.056)
Any siblings left		-0.012		-0.062**		-0.016
		(0.027)		(0.030)		(0.022)
Observations	40,189	40,189	40,189	40,189	40,189	40,189
Adjusted R-squared	0.469	0.470	0.357	0.358	0.424	0.425

Notes: Outcome ($t-1$) represents the standardized dependent variable at $t-1$ for SDQ, while for Reading test-scores it is the quintile rank at $t-1$. Dummies indicating the child's family's income quintile in $t-1$ are controlled for in all columns. Additionally, all regressions control for dummies indicating the child's gender, having a twin or being part of a triplet, having low birth-weight (< 2.5 kg), being a first-born, being in a single-parent household, and whether both parents are employed; dummies reflecting the child's ethnic background (mixed, Indian, Pakistani or Bangladeshi, Black, other), and the mother's highest educational level; mother's age at birth of the cohort member, parental involvement at age 3 (i.e. frequency of reading to the child, regular bedtime, hours spent in front of the TV), squared root of household size; dummies for house-tenure at time $t-1$ (ownership, mortgage, rent, other) and its variation between $t-1$ and t; survey wave dummies, and country dummies (England, Wales, Scotland, NI). Sampling and non-response weights used. Robust standard errors, clustered at the cohort member level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Persistence of the effect of gains and losses

	Externalising SDQ (1)	Internalising SDQ (2)	Reading test-scores (3)
Outcome_{t-2}	0.535***	0.451***	0.224***
	(0.009)	(0.012)	(0.007)
Gain_t	0.007	0.006	0.052***
	(0.020)	(0.022)	(0.017)
Loss_t	-0.038*	-0.057***	-0.055***
	(0.020)	(0.022)	(0.017)
Gain_{t-1}	0.034	0.021	0.042*
	(0.027)	(0.029)	(0.023)
Loss_{t-1}	0.003	-0.045	-0.021
	(0.026)	(0.029)	(0.023)
$\text{Gain}_t \times \text{Gain}_{t-1}$	0.000	0.004	-0.087**
	(0.044)	(0.046)	(0.038)
$\text{Gain}_t \times \text{Loss}_{t-1}$	-0.037	-0.004	0.000
	(0.037)	(0.044)	(0.033)
$\text{Loss}_t \times \text{Gain}_{t-1}$	0.021	0.020	-0.047
	(0.037)	(0.043)	(0.033)
$\text{Loss}_t \times \text{Loss}_{t-1}$	0.012	0.071	-0.087*
	(0.053)	(0.062)	(0.047)
Observations	25,377	25,377	25,377
Adjusted R-squared	0.362	0.253	0.462

Notes: Outcome_{t-2} represents the standardized dependent variable at $t-2$. All regressions control for income quintile dummies for waves $t-2$ and $t-1$. Additionally, all regressions control for dummies indicating the child's gender, having a twin or being part of a triplet, having low birth-weight (< 2.5 kg), being a first-born, being in a single-parent household, and whether both parents are employed; dummies reflecting the child's ethnic background (mixed, Indian, Pakistani or Bangladeshi, Black, other), and the mother's highest educational level; mother's age at birth of the cohort member, parental involvement at age 3 (i.e. frequency of reading to the child, regular bedtime, hours spent in front of the TV), squared root of household size; dummies for house-tenure at time $t-1$ (ownership, mortgage, rent, other) and its variation between $t-1$ and t; survey wave dummies, and country dummies (England, Wales, Scotland, NI). With respect to the tables above, the levels of time varying controls refer to wave $t-2$ and both the changes between $t-2$ and $t-1$, and between $t-1$ and t were controlled for. Sampling and non-response weights used. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Transitions in and out of the outcomes bottom quintiles

	Externalising SDQ		Internalising SDQ		Reading test-scores	
	Entry	Exit	Entry	Exit	Entry	Exit
Gain	-0.002	-0.017	-0.015**	0.004	-0.014**	0.053***
	(0.005)	(0.016)	(0.006)	(0.016)	(0.006)	(0.017)
Loss	0.019***	0.037**	0.015**	0.009	0.007	-0.013
	(0.005)	(0.018)	(0.007)	(0.017)	(0.006)	(0.019)
Outcome quintiles in $t-1$ (reference: 5th quintile)						
2nd quintile	0.227***		0.214***		0.124***	
	(0.011)		(0.012)		(0.007)	
3rd quintile	0.127***		0.126***		0.093***	
	(0.012)		(0.012)		(0.007)	
4th quintile	0.067***		0.066***		0.050***	
	(0.013)		(0.013)		(0.008)	
Observations	31,955	8,230	30,925	9,256	32,603	7,584
Pseudo R-squared	0.147	0.147	0.0926	0.0926	0.103	0.103

Notes: The coefficients shown in the Table are average marginal effects derived from logistic regressions. The "Entry" and "Exit" columns represent respectively logistic regression where the outcome variable is the probability of moving in and out of the bottom quintile of the distribution of the outcome of reference. All regressions control for dummies indicating the child's gender, having a twin or being part of a triplet, having low birth-weight (< 2.5 kg), being a first-born, being in a single-parent household, and whether both parents are employed; dummies reflecting the child's ethnic background (mixed, Indian, Pakistani or Bangladeshi, Black, other), and the mother's highest educational level; mother's age at birth of the cohort member, parental involvement at age 3 (i.e. frequency of reading to the child, regular bedtime, hours spent in front of the TV), squared root of household size; dummies for house-tenure at time $t-1$ (ownership, mortgage, rent, other) and its variation between $t-1$ and t; survey wave dummies, and country dummies (England, Wales, Scotland, NI). Sampling and non-response weights used. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix: Additional Figures and Tables

Figure A1: Transitions along the quintiles of Externalising SDQ

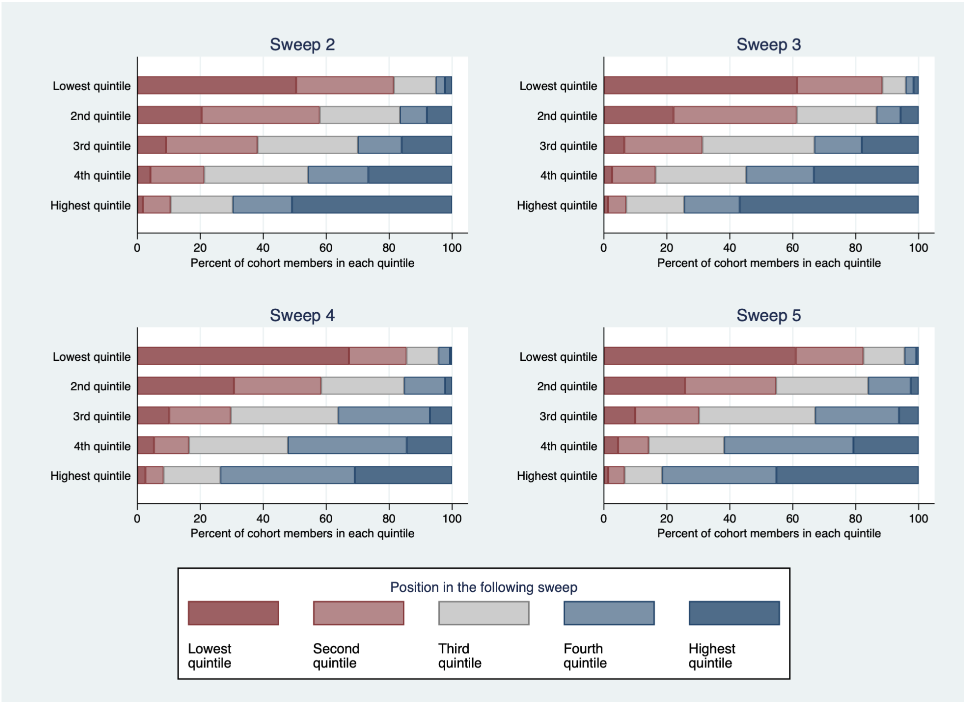

Figure A2: Transitions along the quintiles of Internalising SDQ

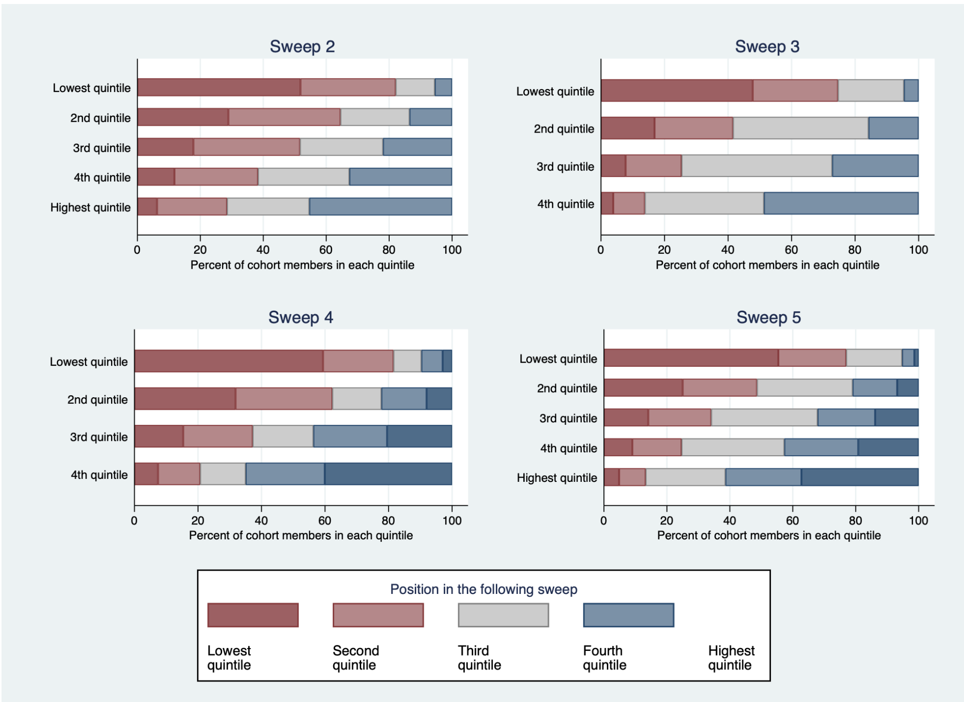

Figure A3: Transitions along the quintiles of reading test-scores

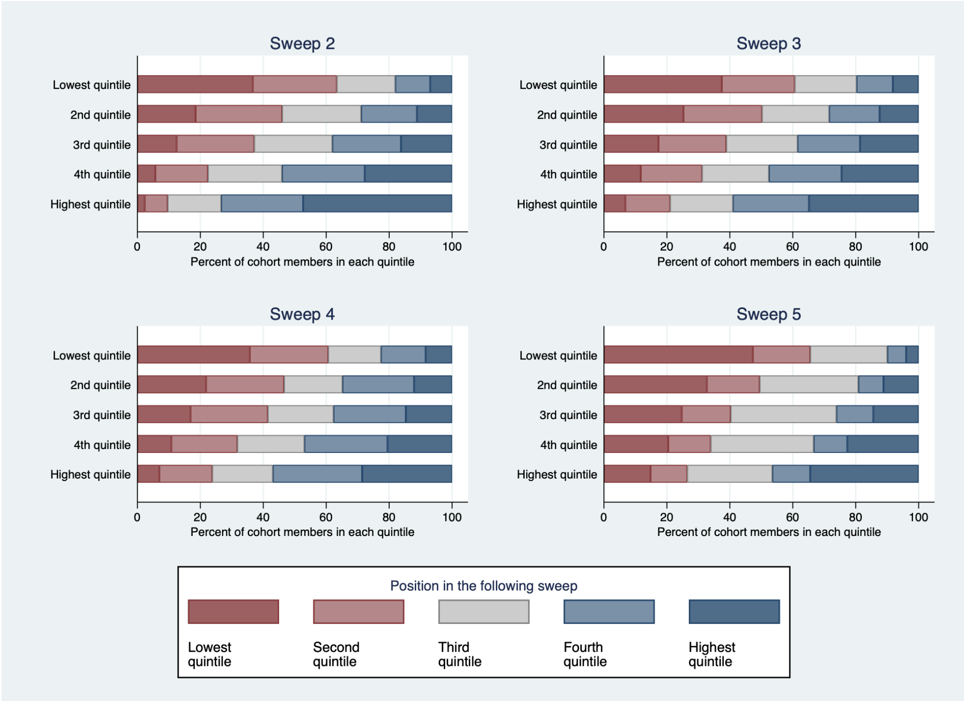

Figure A4: Transitions along the quintiles of household income

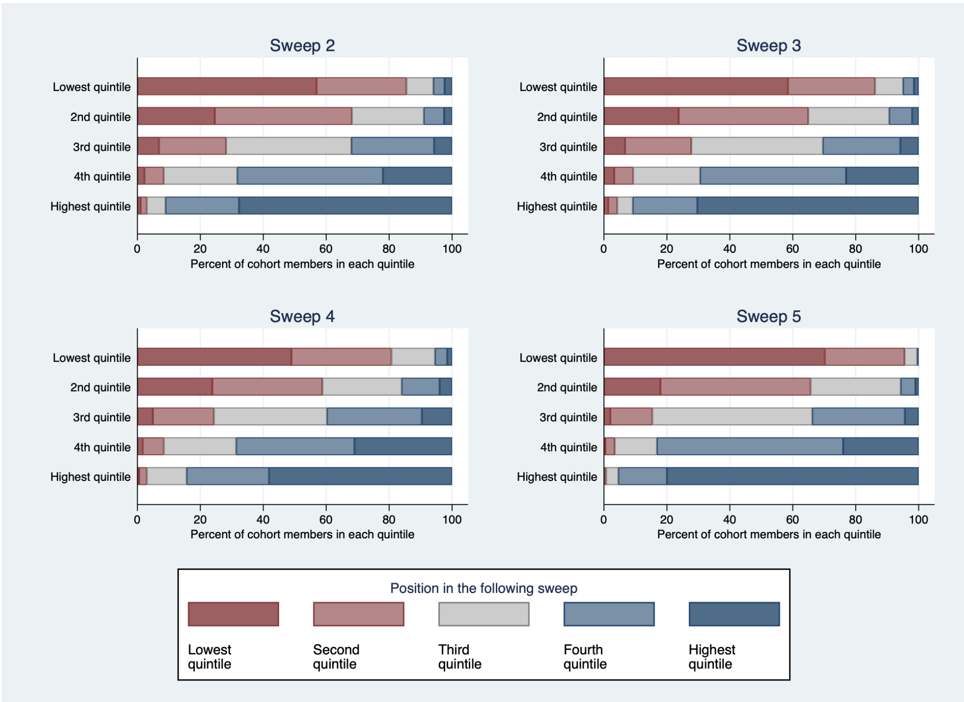

Table A1: The Strengths and Difficulties Questionnaire

Please think about this child's behaviour over the last 6 months if you can:

This child:	NOT TRUE	SOMEWHAT TRUE	CERTAINLY TRUE
Emotional health:			
Often complains of headaches, stomachaches or sickness	0	1	2
Has many worries, often seems worried	0	1	2
Is often unhappy, down-hearted or tearful	0	1	2
Is nervous or clingy in new situations, easily loses confidence	0	1	2
Has many fears, is easily scared	0	1	2
Total emotional health score: 0-10			
Conduct problems:			
Has temper tantrums or hot tempers	0	1	2
Is generally obedient, usually does what adults request	2	1	0
Often fights with other children or bullies them	0	1	2
[a]Often lies or cheats	0	1	2
[b]Steals from home/school/elsewhere	0	1	2
Total conduct problems score: 0-10			
Hyperactity/Inattention:			
Is restless, overactive, cannot stay still for long	0	1	2
Constantly fidgets or squirms	0	1	2
Is easily distracted, concentration wandered	0	1	2
[c]Thinks things out before acting	2	1	0
Sees tasks through to the end, good attention span	2	1	0
Total hyperactivity score: 0-10			
Peer relationship problems:			
Is rather solitary, tends to play alone	0	1	2
Has at least one good friend	2	1	0
Is generally liked by other children	2	1	0
Is picked on or bullied by other children	0	1	2
Gets on better with adults than with other children	0	1	2
Total peer relationship problems score: 0-10			
Total internalising behaviour = emotional + peer relationship (0-20)			
Total externalising behaviour = behaviour + hyperactivity (0-20)			

[a] Changed to "Often argumentative with adults" in the questionnaire for 3-4 years old.

[b] Changed to "Can be spiteful to others" in the questionnaire for 3-4 years old.

[c] Changed to "Can stop and think things out before acting" in the questionnaire for 3-4 years old.

Table A2: Descriptive statistics

Variables	**Mean**	**SD**	**Min**	**Max**
Outcomes				
Externalising SDQ	15.347	3.539	0	20
Internalising SDQ	17.029	2.991	1	20
Reading test-scores	54.669	11.904	20	80
Lagged outcomes				
Externalising SDQ	14.694	3.677	0	20
Internalising SDQ	17.206	2.702	1	20
Reading test-scores	55.261	11.150	20	80
Income changes				
Loss in income quintile between $t-1$ and t	0.218	.	0	1
Gain in income quintile between $t-1$ and t	0.271	.	0	1
Child characteristics				
Low birthweight (<2.5 kg)	0.069	.	0	1
First born	0.414	.	0	1
Twin or triplet	0.023	.	0	1
White	0.880	.	0	1
Mixed	0.035	.	0	1
Indian	0.017	.	0	1
Pakistani or Bangladeshi	0.029	.	0	1
Black	0.026	.	0	1
Other ethnicity	0.012	.	0	1
Female	0.496	.	0	1
Household characteristics				
Single parent	0.225	.	0	1
One working parent	0.352	.	0	1
Two working parents	0.508	.	0	1
Square root of household size	2.113	0.296	1.414	4
England	0.821	.	0	1
Wales	0.048	.	0	1
Scotland	0.090	.	0	1
Northern Ireland	0.040	.	0	1
Ownership $(t-1)$	0.052	.	0	1
Mortgage $(t-1)$	0.605	.	0	1
Rented $(t-1)$	0.318	.	0	1
Other $(t-1)$	0.025	.	0	1
No ownership/mortgage between $t-1$ and t	0.342	.	0	1
Lost house ownership between $t-1$ and t	0.025	.	0	1
Parental investment at age 3				
Up to one hour of TV per day	0.217	.	0	1
More than 1 hour of TV, less than 3 hours	0.623	.	0	1
More than 3 hours of TV per day	0.159	.	0	1
Regular bedtime	0.816	.	0	1
Read every day to the child	0.630	.	0	1
Read more than once per week, not every day	0.312	.	0	1
Read less than twice per month	0.058	.	0	1
Mother's characteristics				
Mother's age at birth	28.977	5.709	18	58
No educational qualifications	0.138	.	0	1
Less than O-level	0.019	.	0	1
GCSE or O-level	0.466	.	0	1

A-level or equivalent	0.099	.	0	1
Diploma of higher education	0.095	.	0	1
University degree or higher	0.182	.	0	1
Mother's well-being				
Δ(Kessler scale)$_{t-1,t}$	0.221	3.743	-24	24
Kessler scale $(t-1)$	3.430	3.825	0	24
Δ(Life satisfaction)$_{t-1,t}$	-0.125	2.030	-10	9
Life satisfaction $(t-1)$	7.599	1.866	1	10
Mother's health worsened	0.068	.	0	1
Mother has poor health $(t-1)$	0.143	.	0	1
Life events between $t-1$ and t				
One additional sibling	0.128	.	0	1
Two or more additional siblings	0.011	.	0	1
One or more siblings left household	0.052	.	0	1
No change in siblings composition	0.809	.	0	1
One parent left	0.063	.	0	1
Mother lost job	0.055	.	0	1
Father lost job	0.026	.	0	1

All descriptive statistics refer to the main estimation sample of 40,189 observations.

Table A3: Estimates of income mobility on cognitive and non-cognitive outcomes from a Diagonal Reference Model

	Externalising SDQ (1)	Internalising SDQ (2)	Reading test-scores (3)
Outcome $(t-1)$	0.644***	0.517***	0.287***
	(0.007)	(0.008)	(0.006)
Gain	-0.017	-0.010	0.038*
	(0.017)	(0.024)	(0.021)
Loss	-0.011	-0.009	-0.032
	(0.018)	(0.025)	(0.021)
Estimated effects for the immobile			
Bottom income quintile	-0.055***	-0.073***	-0.098***
	(0.021)	(0.022)	(0.017)
2nd income quintile	-0.037***	-0.048***	-0.042***
	(0.014)	(0.016)	(0.013)
3rd income quintile	0.005	-0.004	0.004
	(0.012)	(0.016)	(0.012)
4th income quintile	0.037***	0.032**	0.035***
	(0.012)	(0.013)	(0.010)
Top income quintile	0.050***	0.094***	0.102***
	(0.013)	(0.013)	(0.013)
Weight for income in t	0.664*	0.620*	0.061
	(0.387)	(0.353)	(0.309)
Weight for income in $t-1$	0.336	0.380	0.939***
	(0.387)	(0.353)	(0.309)
Observations	40,189	40,189	40,189
AIC	91,452.44	99,253.61	92,443.78

Notes: The table displays maximum likelihood estimates for a diagonal reference model (Sobel, 1981), with the 'origin' variable being the family income quintile at time t and the 'destination' variable the income quintile in $t-1$. The dummies 'Gain' and 'Loss', defined as in the empirical strategy section, here can be interpreted, respectively, as indicators of upward and downward mobility. The table reports coefficients for the immobile categories, i.e. those individuals whose family income quintile does not change between $t-1$ and t (note that the sum of these coefficients is constrained to zero). Estimated weights are one the inverse of the other, and represent the relative importance of the origin vs destination variables. Outcome $(t-1)$ represents the standardised lagged value of the dependent variable. All regressions control for dummies indicating the child's gender, having a twin or being part of a triplet, having low birth-weight ($<$ 2.5 kg), being a first-born, being in a single-parent household, and whether both parents are employed; dummies reflecting the child's ethnic background (mixed, Indian, Pakistani or Bangladeshi, Black, other), and the mother's highest educational level; mother's age at birth of the cohort member, parental involvement at age 3 (i.e. frequency of reading to the child, regular bedtime, hours spent in front of the TV), squared root of household size; dummies for house-tenure at time $t-1$ (ownership, mortgage, rent, other) and its variation between $t-1$ and t; survey wave dummies, and country dummies (England, Wales, Scotland, NI). Sampling and non-response weights used in all columns. Robust standard errors, clustered at the cohort member level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Income changes and child human capital: Pooled OLS and GMM regressions

	Externalising SDQ			Internalising SDQ			Reading test-scores		
	OLS	GMM		OLS	GMM		OLS	GMM	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Outcome $(t-1)$	0.644***	0.301***	0.332***	0.518***	0.330***	0.331***	0.287***	0.104***	0.090***
	(0.007)	(0.014)	(0.014)	(0.008)	(0.014)	(0.013)	(0.006)	(0.010)	(0.009)
Gain	0.005	0.031**	0.025**	0.020	0.027**	0.026*	0.041***	0.066***	0.067***
	(0.012)	(0.012)	(0.012)	(0.014)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)
Loss	-0.033***	-0.063***	-0.057***	-0.039***	-0.045***	-0.043***	-0.035***	-0.073***	-0.079***
	(0.012)	(0.012)	(0.012)	(0.014)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)
2nd income quintile $(t-1)$	0.029	0.074***	0.076***	0.031	0.067***	0.069***	0.056***	0.121***	0.110***
	(0.020)	(0.020)	(0.019)	(0.022)	(0.021)	(0.021)	(0.018)	(0.018)	(0.018)
3rd income quintile $(t-1)$	0.057***	0.139***	0.145***	0.056**	0.117***	0.120***	0.100***	0.222***	0.221***
	(0.021)	(0.021)	(0.021)	(0.023)	(0.023)	(0.023)	(0.020)	(0.020)	(0.020)
4th income quintile $(t-1)$	0.079***	0.224***	0.222***	0.097***	0.180***	0.180***	0.132***	0.313***	0.312***
	(0.023)	(0.023)	(0.023)	(0.024)	(0.024)	(0.023)	(0.022)	(0.023)	(0.023)
5th income quintile $(t-1)$	0.106***	0.323***	0.316***	0.153***	0.255***	0.257***	0.198***	0.463***	0.467***
	(0.025)	(0.025)	(0.025)	(0.027)	(0.026)	(0.026)	(0.025)	(0.025)	(0.025)
Observations	40,189	40,189	40,189	40,189	40,189	40,189	40,189	40,189	40,189

Notes: Outcome $(t-1)$ represents the standardised lagged value of the dependent variable. Columns 2, 5, and, 8 use a system GMM estimator where the lagged outcome is instrumented with its own lags of order two or greater. The remaining GMM columns additionally use the lags of order two or greater of the other two outcomes as instruments (e.g. Internalisng and Externalising SDQ in column 9). As the panel presents gaps, orthogonal deviations are used instead of first differences for all GMM estimations. All regressions control for dummies indicating the child's gender, having a twin or being part of a triplet, having low birth-weight ($<$ 2.5 kg), being a first-born, being in a single-parent household, and whether both parents are employed; dummies reflecting the child's ethnic background (mixed, Indian, Pakistani or Bangladeshi, Black, other), and the mother's highest educational level; mother's age at birth of the cohort member, parental involvement at age 3 (i.e. frequency of reading to the child, regular bedtime, hours spent in front of the TV), squared root of household size; dummies for house-tenure at time $t-1$ (ownership, mortgage, rent, other) and its variation between $t-1$ and t; survey wave dummies, and country dummies (England, Wales, Scotland, NI). Sampling and non-response weights used only in columns (1), (4), and (7). Robust standard errors, clustered at the cohort member level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: The measurement of income: relaxing the scale constraints of the income quintiles distribution

	Externalising SDQ		Internalising SDQ		Reading test-scores	
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome $(t-1)$	0.652***	0.658***	0.518***	0.528***	0.286***	0.289***
	(0.008)	(0.009)	(0.009)	(0.010)	(0.007)	(0.008)
Gain	0.009	0.011	0.028*	0.031	0.025*	0.039**
	(0.014)	(0.018)	(0.015)	(0.019)	(0.014)	(0.018)
Loss	-0.041**	-0.048***	-0.041**	-0.044**	-0.028*	-0.051***
	(0.017)	(0.018)	(0.019)	(0.021)	(0.016)	(0.018)
3rd income quintile $(t-1)$	0.027	0.026	0.036*	0.032	0.037**	0.062***
	(0.017)	(0.019)	(0.020)	(0.021)	(0.016)	(0.018)
4th income quintile $(t-1)$	0.048**	0.051**	0.085***	0.097***	0.066***	0.090***
	(0.019)	(0.024)	(0.021)	(0.026)	(0.019)	(0.024)
Observations	25,326	19,948	25,326	19,948	25,326	19,948
Adjusted R-squared	0.459	0.458	0.341	0.349	0.406	0.412

Notes: Outcome $(t-1)$ represents the standardised lagged value of the dependent variable. All regressions control for dummies indicating the child's gender, having a twin or being part of a triplet, having low birth-weight (< 2.5 kg), being a first-born, being in a single-parent household, and whether both parents are employed; dummies reflecting the child's ethnic background (mixed, Indian, Pakistani or Bangladeshi, Black, other), and the mother's highest educational level; mother's age at birth of the cohort member, parental involvement at age 3 (i.e. frequency of reading to the child, regular bedtime, hours spent in front of the TV), squared root of household size; dummies for house-tenure at time $t-1$ (ownership, mortgage, rent, other) and its variation between $t-1$ and t; survey wave dummies, and country dummies (England, Wales, Scotland, NI). Sampling and non-response weights used in all columns. Robust standard errors, clustered at the cohort member level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: The measurement of income: continuous income growth rate

	Externalising SDQ (1)	Internalising SDQ (2)	Reading test-scores (3)
Outcome $(t-1)$	0.644***	0.518***	0.287***
	(0.007)	(0.008)	(0.006)
Positive income growth$_{t-1,t}$	0.019**	0.019**	0.016**
	(0.008)	(0.008)	(0.008)
Negative income growth$_{t-1,t}$	-0.047	-0.063*	-0.079**
	(0.034)	(0.036)	(0.034)
Observations	39,722	39,722	39,722
Adjusted R-squared	0.469	0.357	0.423

Notes: Outcome $(t-1)$ represents the standardised lagged value of the dependent variable. Positive income growth$_{t-1,t}$ is a continuous variable taking the positive values of the MCS imputed income growth rate between $t-1$ and t, and is set to zero for negative values. Similarly, Negative income growth$_{t-1,t}$ reflects the absolute value of negative income growth rates, and is set to zero for positive income growth. Note that the estimation sample here is smaller than the main one due to conditioning on the availability of the continuous measure of income and trimming values of income growth above 10 (around the top 0.5%). Dummies indicating the child's family's income quintile in $t-1$ are controlled for in all columns. Additionally, all regressions control for dummies indicating the child's gender, having a twin or being part of a triplet, having low birth-weight (< 2.5 kg), being a first-born, being in a single-parent household, and whether both parents are employed; dummies reflecting the child's ethnic background (mixed, Indian, Pakistani or Bangladeshi, Black, other), and the mother's highest educational level; mother's age at birth of the cohort member, parental involvement at age 3 (i.e. frequency of reading to the child, regular bedtime, hours spent in front of the TV), squared root of household size; dummies for house-tenure at time $t-1$ (ownership, mortgage, rent, other) and its variation between $t-1$ and t; survey wave dummies, and country dummies (England, Wales, Scotland, NI). Sampling and non-response weights used in all columns. Robust standard errors, clustered at the cohort member level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: The measurement of income: gains and losses by continuous income growth rate

	Externalising SDQ (1)	Internalising SDQ (2)	Reading test-scores (3)
Outcome $(t-1)$	0.645***	0.518***	0.288***
	(0.007)	(0.008)	(0.006)
Gain			
$\geq 25\%$	0.008	0.018	0.035***
	(0.013)	(0.015)	(0.013)
$[10\%, 25\%)$	-0.006	0.015	0.074***
	(0.029)	(0.031)	(0.022)
$[5\%, 10\%)$	-0.045	0.048	-0.019
	(0.053)	(0.071)	(0.047)
$< 5\%$	0.107	0.102	0.089
	(0.082)	(0.082)	(0.063)
Loss			
$\leq -25\%$	-0.042***	-0.050**	-0.035**
	(0.016)	(0.019)	(0.016)
$(-25\%, -10\%]$	-0.013	-0.030	-0.024
	(0.020)	(0.021)	(0.018)
$(-10\%, -5\%]$	-0.042	-0.001	-0.080**
	(0.036)	(0.040)	(0.036)
$> -5\%$	-0.059	-0.054	-0.017
	(0.045)	(0.050)	(0.046)
Observations	39,825	39,825	39,825
Adjusted R-squared	0.469	0.357	0.423

Notes: Outcome $(t-1)$ represents the standardised lagged value of the dependent variable. The income quintile gain and loss dummies are here decomposed into a set of dummies based on the value of the continuous income growth rate between $t-1$ and t. The reference category (no change) here includes also small income changes (income growth rates between -5% and +5%). Note that the estimation sample here is smaller than the main one (loss of 364 observations) due to conditioning on the availability of the continuous measure of income. Dummies indicating the child's family's income quintile in $t-1$ are controlled for in all columns. Additionally, all regressions control for dummies indicating the child's gender, having a twin or being part of a triplet, having low birth-weight (< 2.5 kg), being a first-born, being in a single-parent household, and whether both parents are employed; dummies reflecting the child's ethnic background (mixed, Indian, Pakistani or Bangladeshi, Black, other), and the mother's highest educational level; mother's age at birth of the cohort member, parental involvement at age 3 (i.e. frequency of reading to the child, regular bedtime, hours spent in front of the TV), squared root of household size; dummies for house-tenure at time $t-1$ (ownership, mortgage, rent, other) and its variation between $t-1$ and t; survey wave dummies, and country dummies (England, Wales, Scotland, NI). Sampling and non-response weights used in all columns. Robust standard errors, clustered at the cohort member level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.