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

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Abstract

I here assess the link between distributional changes in family income and child human-capital. Using a value-added model and data from a UK child cohort, I show evidence of an asymmetric effect of income gains and losses on child non-cognitive development. Only income losses are associated with a reduction in children's socio-emotional health – with one-third of the effect operating through measures of maternal well-being – while no effect is found for income gains. This is consistent with a model of human-capital formation where the quality and quantity of parental inputs react to changes in family income asymmetrically.

Keywords: Cognitive skills, Non-cognitive skills, Income changes, Human Capital, MCS, UKHLS
JEL codes: D31, J13, J24

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1 Introduction

The analysis of parental income in relation to child 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 children's human-capital development, which in turn will shape their later life outcomes. Extensive work from Heckman and coauthors from the early 2000s has emphasized how human capital is a multidimensional concept that cannot be equated to cognitive skills only (see, among others, Heckman and Rubinstein, 2001; Heckman, Stixrud and Urzua, 2006; Cunha, Heckman and Schennach, 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, Heckman and Schennach, 2010; Blanden and Machin, 2010; Ermisch, 2008; Flouri, Mavroveli and Tzavidis, 2012; Flouri, Midouhas and Joshi, 2014). Further evidence from neurobiology, developmental psychology and economics underline the fundamental role of early age experiences and family environment in shaping brain function and future development (e.g. Heim, Meinlschmidt and Nemeroff, 2003; Niccodemi *et al.*, 2022; Sumner *et al.*, 2019). 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 behavioral 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, Burns and Violato (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 behavioral problems at age 11. Other papers use the MCS to document a gradient between parental economic background and children's cognitive (Dearden, Sibieta and Sylva, 2011) and non-cognitive (Tamura, Morrison and Pikhart, 2020) development.

I here use information from the first 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 through the Strengths and Difficulties Questionnaire (SDQ), a widely recognized behavioral screening tool for children and adolescents (Goodman, Lamping and Ploubidis, 2010). Using a value-added model to assess the impact of family income gains and losses on child human capital, I find that income losses are correlated with lower residualized measures of cognitive and non-cognitive skills, while income gains only predict better cognitive performance. Consistent with the literature, results suggest that about one third of the effect of income 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. First, it is the first study to use MCS data on measures of both cognitive and non-cognitive development up to child age 15 in relationship to movements across the income distribution. As compared to other datasets, MCS has the advantage of having consistent measures of non-cognitive child development (namely, the SDQ) throughout childhood and adolescence. Second, I here use a value-added model approach to assess the contribution of income changes on the production of cognitive and non-cognitive skills from one period to the next. This approach allows me to tackle the endogeneity concerns deriving from unobserved time-invariant determinants of human capital, by keeping them constant. It additionally provides a life-event approach to the short-term evolution of human capital that allows to control for latent factors contributing to the human-capital production function. Due to the relative scarcity of longitudinal datasets containing both family income and measures of both cognitive and non-cognitive skills in children, this is a novel approach in the applied literature on family income and child human capital reviewed in Section 2. Last, and perhaps more importantly, this paper is the first (to the best of my knowledge) to relax the assumption underlying most of the empirical literature in the field, which is that income gains and losses have a symmetric effect on child development 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, by exploiting the exogenous variations coming from policy changes, such as income transfer programs. With US data, Dahl and Lochner (2012) use 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, she 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.

The timing of income shocks is also important for child development. Also using Norwegian data and separating childhood into an early, middle and late period, Carneiro *et al.* (2021) study the timing of parental income and document that higher family income is most beneficial in early childhood than in middle childhood, consistent with the self-productivity of investments in human capital. They additionally show that educational outcomes and future earnings are maximized for stable family income profiles over childhood. Paired with increasing trends in permanent and transitory income volatility in other OECD countries (Menta, Wolff and D'Ambrosio, 2021), this finding might imply a deterioration in educational outcomes over time.

In order to maximize their utility over the life-cycle, households might insure themselves against transitory and permanent income shocks in order to smooth their marginal utility and consumption

(Attanasio and Pistaferri, 2016; Meghir and Pistaferri, 2011). Carneiro and Ginja (2016) use data from the US to investigate the impact of permanent and transitory income shocks on parental investments on their children. While they find evidence of imperfect insurance against permanent income shocks, they cannot reject the hypothesis of full insurance for temporary shocks. Blundell, Pistaferri and Saporta-Eksten (2018) show that the presence of children might affect the ability of parents to self-insure after a shock in their labor earnings. Secondary earners will adjust to permanent shock in the main earner's wage by increasing their labor supply at the detriment of the time devoted to childcare, which is not fully compensated by a similar increase in the main earner's time spent with the child. Although in a different setting, Løken, Lommerud and Reiso (2018) provide some evidence on the child human-capital consequences of a decline in childcare due to the main childcare provider being pushed into work. Using variation for a 1998 welfare reform in Norway targeting single parents which imposed work requirements and time limits for income support measures, they find that the reform did not have any effect on the disposable income of single mothers. Despite the null effect on income, the lower amount of time spent at home caused the children of single mothers to perform worse in school (reduction of 0.7% of a SD per year of exposure).

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), others explore the channels mediating this relationship (Washbrook, Gregg and Propper, 2014; Yeung, Linver and Brooks-Gunn, 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, Haisken-DeNew and Shields, 2004; Gardner and Oswald, 2007; Powdthavee, 2010). Parental well-being, in turn, can shape 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, Linver and Brooks-Gunn (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 externalizing behavior; 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 externalizing behavior still persists. Washbrook, Gregg and Propper (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 behavioral and cognitive response. In this sense, a paper that comes closer to this objective is Clark, D'Ambrosio and Barazzetta (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 children's 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, Mihaly and Rockoff, 2015). With respect to other panel data models such as fixed-effects, value-added models offer the advantage of assessing the average period-to-period 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 and school quality, value-added models are less often predominant in other fields. For example, on the same dataset used in this paper, Del Bono *et al.* (2016) use 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. The first six waves of the survey were conducted at child age 9 months, 3 years, 5 years, 7 years, 11 years, and 15 years. Another wave, collected at child age 17, has been recently made available (but was not at the moment of data analysis). 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 due to the adoption of widely different scales across measurements. Cognitive skills are assessed through age-appropriate standardized 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 standardized 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 final measure of cognitive ability used in the paper is derived from the standardisation of the age-adjusted standardized 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 behavioral and emotional health of children aged 2 to 17. While originally designed to assess mental health, the SDQ has been widely used as a measure of non-cognitive skills, particularly in the context of education and labor market outcomes (e.g. Del Bono *et al.*, 2016; Del Bono, Kinsler and Pavan, 2020; Nghiem *et al.*, 2015). The SDQ has been shown to correlate highly with other measures of child non-cognitive abilities, such as the Child Behavioral Checklist (Goodman and Scott, 1999) and the Rutter scale (Goodman, 1997). Using data on a cohort of children born in England, Morris *et al.* (2021) show that parent- and teacher-reported SDQ display the highest and most consistent correlations with other measures of non-cognitive skills, such as social skills and communication. In the MCS, the SDQ questionnaire is compiled by the cohort member's main caregiver in waves 2 to 6 and by the teacher in waves 4 and 5. The questionnaire is made of 25 items, which can be divided into five different scales: emotional symptoms, conduct problems, hyperactivity/inattention, peer relationship problems, and prosocial behavior. Emotional symptoms and peer problems make up the category 'internalizing problems', while conduct problems and hyperactivity/inattention constitute the 'externalizing problems' category. Both categories are measured on a scale going from 0 to 20, which I reverse so that higher SDQ values correspond to better behavioral outcomes. As argued by Goodman, Lamping and Ploubidis (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 Appendix A for more details on the measurement and items that make up the internalizing and

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

externalizing SDQ scales. For the remainder of the paper, I will refer to SDQ as a measure of non-cognitive skills. However, it should be kept in mind that non-cognitive skills are a broad concept, covering many different aspects of the non-cognitive determinants of economic success. The SDQ can be interpreted as a measure capturing those aspects that pertain to children's socio-emotional and behavioral development.

The main child carer in the MCS is asked to report their current family take-home income at the time of the interview, net of taxes and transfers. 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 whose bounds and numerosity vary from wave to wave. Following the limits imposed by the upper and lower bounds of each income band, the data providers developed a measure of imputed income via interval regression. Among the predictors of income were respondents' age, housing tenure, region of residence, education, and labor 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 equivalized in order to account for economies of scale within the family, using the OECD household equivalence scale. While this measure has the advantage of being a continuous proxy for family income, it likely suffers from measurement error, as it not only reflects a change in the latent income of families in the survey but also changes in the socio-economic variables used in the interval regressions (which, if included as covariates in the final model specification, may lead to overcontrolling). 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 equilvalized 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 unconditional 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 Appendix A (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, Mihaly and Rockoff, 2015), which can be read as a

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

model generating from an autoregressive process of order one. This method explores the dynamics of human-capital formation by capturing the residualized 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. internalizing SDQ, externalizing 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 standardized. $L_{i,t}$ 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 equivalized imputed income and a loss (gain) is realized when child i's household income in a given period is in a lower (higher) income quintile than it was in the latest previously-observed period.[3] 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. In particular, if the absolute value of β_2 was larger in magnitude to that of β_3, then there would be evidence that income losses affect child human capital disproportionately more than income gains do.

$\{I^2_{i,t-1}, ..., I^5_{i,t-1}\}$ is a set of four dummies indicating the household income quintile in wave $t-1$ ($I^1_{i,t-1}$, i.e. the dummy indicating the bottom income quintile, is omitted and used as the reference 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 labor market, and the square root of household size (see the notes in Table 1 for a full list of controls). Finally, ζ_t is a set of wave fixed-effects. 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 partners. This is because mothers tend to identify as the main caregiver and, hence, the main survey respondent. Furthermore, biological fathers might not always be present in the household at all waves and might not always coincide with the mother's partner or spouse. Therefore, I here 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

[3] For simplicity, I here assume that relative movements in the household income distribution reflect absolute movements, by equating upwards (downwards) income mobility to household income gains (losses). I will relax this assumption and test its appropriateness in Section 5

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" (see Doiron *et al.*, 2015). 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". I then use life satisfaction as a measure of 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 they are asked to choose a number indicating their level of satisfaction with 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:

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

where $C_{i,t-1}$ is a vector containing the measures of maternal well-being at time $t-1$ mentioned above: the Kessler K6 score, life satisfaction, and a dummy equal one if self-assessed health is rated as being "good" or above. All measures are coded in such a way that higher values reflect better maternal outcomes. ΔC_i is a vector capturing the changes in the maternal well-being channels, containing the standardized 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 same two periods. In this model specification, I expect β_2 and β_3 to converge toward zero, as a portion of the effect sizes displayed in Equation (1) will likely be captured by the maternal well-being channels.

Conditional 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).[4] 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.[5] Sampling weights and non-response weights provided by MCS are used throughout the analysis.[6] Table A2 in Appendix A describes the features of the estimation sample, including the percentage of imputed

[4]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.

[5]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.

[6]Results without weights (available upon request) are qualitatively similar to the weighted ones.

missing values for each variable. Around 22% of children experience downward household income mobility between ages 3 and 15; gains in family income quintile are instead experienced by around 27% of the estimation sample.

4 Results

4.1 Main results

Table 1 presents estimates of the baseline model in equation (1), with the sequential inclusion of controls. For each of the three dependent variables (panels A to C), column 1 reports pooled OLS estimates of a simplified version of the baseline model, without the lagged outcome and only controlling for the gain and loss dummies, the lagged income quintile dummies, and wave fixed-effects. Here, movements upwards the income quintile distribution are associated with better cognitive and non-cognitive outcomes, while downward movements associate with worse outcomes. Column 2 further augments the specification by controlling for the lagged value of the outcome variable. Moving from column 1 to the value-added model in column 2, the magnitude of the coefficients attached to the gain and loss dummies shrinks and starts to diverge – especially so in Panel A (externalizing SDQ), where the coefficient of losses (-0.066) becomes twice as large as that of gains (0.035) in absolute terms. The shrinkage in the coefficient is unsurprising, as the lagged outcome is controlling for unobserved time-invariant determinants of the outcome that likely correlate with family income. Introducing child-level controls in column 3 does not seem to affect the point estimates of the gain and loss dummies, which are either unchanged or slightly larger in magnitude. This suggests that the study child's characteristics are quite orthogonal to changes in family income, as one would expect. The magnitude of the coefficients for gains and losses is however reduced when including household controls in column 4 and parental controls in column 5, suggesting that part of the relationship between transitions along the income quintile distribution and changes in child human capital reflects differences in the socio-economic and demographic positioning of households in the sample. Controlling for a large set of parental and household characteristics allows to keep constant the slow-changing socio-economic conditions that affect family income. Net of the observable characteristics controlled for in column 5 of Table 1, the coefficients of the gain and loss dummies thus capture income changes that are more transitory in nature and, as such, more likely to be perceived as unexpected income shocks.

In the full model specification, the effect of moving to a lower income quintile is associated with a loss of about 3 to 4% of a standard deviation (SD from here onwards) in both externalizing and internalizing SDQ, and a loss of 3.5% of a SD in the standardized reading t-scores distribution. Although the effect sizes might look modest at first sight, the contribution of an income loss to the residualized internalizing and externalizing SDQ is comparable to 45% (column 3) to 80% (column 5) of the effect of being born with a weight lower than 2.5 kg. For reading test-scores, the magnitudes of gains and losses in column 3 is the same or larger than the effect of being the first-born (or half to two-thirds of the first-born coefficient in column 5). While losses appear to play a larger role than gains in explaining residualized SDQ, pairwise Wald tests fail to reject the equality (in absolute value) of the coefficients attached to income gains and losses for all outcomes, for conventional significance thresholds (the p-values of the tests are, respectively, 0.15 for externalizing SDQ and 0.34 for internalizing SDQ).

In order to account for unobserved time-invariant factors, I additionally present a model specification with individual fixed-effects in Appendix B. Due to the dynamic panel bias that is introduced by combining a value-added model with individual fixed-effects (Nickell, 1981), results in Appendix B feature more appropriate dynamic panel data estimators (i.e. system GMM). Given of the absence of convincing evidence in support of the identifying assumptions required by system GMM and the conservative size of OLS estimates compared 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.

Figures A5 to A7 investigate whether the timing of the income shock matters, by looking at age heterogeneity in the effects of the gain and loss dummies. Each figure shows the net effects of the coefficients of gains and losses when the model specification is augmented with interaction terms between each of the two dummies and wave fixed-effects. In order to address whether the age heterogeneity is affected by the presence of a wide set of controls, each figure presents result from two specifications: to the left, a simple model with little controls (corresponding to column 1 of Table 1); to the right, the fully specified model (column 5 of Table 1). The introduction of controls, while reducing on average the size of the coefficients, does not seem to affect their trend over time – which behaves similarly in the two panels of each figure. Figures A5 to A7 do not show evidence of strong age heterogeneity, with the marginal effects of gains and losses being mostly stable over child ages. This suggests that the baseline effects of gains and losses cannot be attributed to one specific developmental period. While remaining statistically indistinguishable from one another, point estimates are suggestive of income losses playing a larger role during adolescence for non-cognitive skills (Figures A5 to A6) and around child age 7 for cognitive skills (Figure A7).

4.2 Mechanisms

One question that need be addressed concerns the drivers of the upwards and downwards movements across the household income distribution: what are the gain and loss dummies capturing? Income changes are indeed likely to depend on a variety of factors, such as changes in the country's social security system, in the labor 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 do these factors affect the outcomes only through their effect on household income?

Table 2 is an attempt to shed light on the matter. Columns 1, 3, and 5 replicate column 5 of Table 1. Columns 2, 4, and 6 introduce a list of life events between $t-1$ and t that are likely drivers of mobility across equivalized income quintiles. Since housing tenure and its changes are already controlled for in all specifications, the remaining observable determinants of income changes are separations, job losses and job changes, and additional changes in household composition driven by siblings.[7] The coefficients of gains and losses are overall robust to the introduction of these potential mechanisms, suggesting that life events that contribute to changes in family income affect the accumulation of child human capital mostly though income changes themselves. Conditional on current employment status, changes in the parents' labor force status from one period to the next do not appear to explain changes in the residualized cognitive and non-cognitive outcomes. A parent leaving the household appears to be negatively associated with the residualized measures of non-cognitive outcomes (the association being statistically significant at the 10% level only for Internalizing 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. Externalizing problems increase with the presence of new siblings, consistent with children engaging in disruptive behaviors to capture a larger fraction of the parents' limited time resources. The results for internalizing symptoms instead hide substantial heterogeneity across gender: while boys have lower residualized internalizing SDQ when younger siblings are born, girls are only significantly affected by an older sibling leaving the household (results available upon request).[8]

The evidence on the determinants of movements along the income quintile distribution is not however informative on the channels that mediate the relationship between income gains and losses and measures of child human capital. The literature in economics and developmental psychology suggest that family income changes can affect child human-capital accumulation directly, through the provision of material inputs, and 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 other mechanisms into account. 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 column 5 of Table 1. The magnitude of the coefficients estimated in

[7] Table A3 shows how these variables contribute to the income gain and income loss dummies. As expected, most of the identified drivers of income mobility are significant predictors of income gains and losses, with signs going in the expected directions.

[8] Allowing for the births of siblings to have heterogeneous effects by family type (by interacting the sibling birth dummies with indicators for the mother being employed in the past wave and for being in a single-parent household) does not affect the coefficients attached to the gain and loss dummies. None of the interaction terms is statistically different from zero, with the exception of the one between maternal employment and the birth of one sibling: here having a mother employed in t-1 plays a protective role against the adverse cognitive effects of having a new sibling (results available upon request).

Table 1 might in fact reflect the presence of channels, such as maternal well-being, that are likely positively correlated both with income changes and child human capital. I first show, in Table A4, that downward (upward) movements along the income distribution are strongly associated with a worsening (improvement) in measures of maternal well-being. Then, in Table 2, I show that the variables capturing both the changes and the past levels of mothers' psychological and physical health explain a sizeable 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 (the latter becoming no longer significantly different from zero in columns 3 and 6). For internalizing and externalizing 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, suggesting that income changes have a stronger direct effect on school performance rather than internalizing or externalizing behavior. The values of the adjusted R-squared in columns 3, 6, and 9 of Table 2 further shows that the introduction of channels marginally improves the model's prediction in the case of internalizing and externalizing 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, Linver and Brooks-Gunn (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. Qualitatively similar predictions are also supported by Washbrook, Gregg and Propper (2014).[9]

4.3 A Stylized Model of Human-Capital Formation

Results from Tables 1 and 2 are consistent with a model of human-capital formation where income changes have a symmetric effect on child cognitive development, while negative income shocks affect child non-cognitive development to a larger extent than positive income shocks. This kind of model can be rationalized with a human-capital production function where the weights attached to standard inputs differ across cognitive and non-cognitive skills. For example, consider a human-capital production function where child c's skills 'K' (here standing for either cognitive

[9] Measures of mothers' mental and physical health could also be seen as determinants of income changes: mothers with health problems likely face larger healthcare expenditure and might be forced out of the labor market, with negative consequences on family income. To test whether mothers' health and well-being can be seen more as determinants of income rather than channels, columns 2 and 4 of Table A3 control for past levels of mothers' mental health, physical health and life satisfaction (these measures' lags are arguably less likely to suffer from reverse causality concerns than their changes from $t-1$ to t). The coefficients attached to these measures are negligible in size and mostly statistically insignificant, consistent with maternal well-being being affected by income gains and losses, rather than affecting them.

'C' or non-cognitive 'NC' skills) in period t, $\theta^K_{c,t}$, depend on her past skills $\theta^K_{c,t-1}$ and a vector of parental inputs P (e.g. the parents' own cognitive and non-cognitive skills, their health, material investments, time investments), such as the following:

$$\theta^K_{c,t} = \beta\theta^K_{c,t-1} + f^K_{G,L}(P) + \epsilon_{c,t} \tag{3}$$

where $K \in \{C, NC\}$, β is the self-productivity parameter of θ^K_c between periods $t-1$ and t and $\epsilon_{c,t}$ is an idiosyncratic shock in child c's skills at time t. $f^K_{G,L}(P)$ is a skill-specific weight function that is increasing in P and whose functional form depends on the realisation of family income gains (G) or losses (L) between $t-1$ and t, such that:

$$f^K_{G,L}(P) = \begin{cases} l^K(P) & \text{if } L = 1 \\ g^K(P) & \text{if } G = 1 \\ n^K(P) & \text{if } L = G = 0 \end{cases} \tag{4}$$

with $l^K(P)$, $g^K(P)$ and $n^K(P)$ being monotonically increasing functions of P. Such functional form allows parental inputs to matter differently for cognitive and non-cognitive skills: for example, non-cognitive skills may rely more heavily on parents' mental health than cognitive ones (Menta *et al.*, 2023). This functional form additionally relaxes the assumption of symmetry in the human-capital returns to increases and decreases in parental inputs, by allowing for heterogeneous returns based on the direction of family income changes.

Last, assume that all parental inputs P depend on family income. This is a realistic assumption, as suggested by the literature on the relationship between family income and parents' human capital (Griliches and Mason, 1972), health (Ettner, 1996), time-investments (Heiland, Price and Wilson, 2017) and material investments (Carneiro and Ginja, 2016). While not all parental inputs need be increasing in income (for example Heiland, Price and Wilson, 2017, show a decrease in time investments following maternal employment), it is safe to assume that the overall quantity of parental inputs increases with the realisation of income gains and falls with the realisation of income losses, that is:

$$\frac{\mathrm{d}P}{\mathrm{d}G} > 0, \qquad \frac{\mathrm{d}P}{\mathrm{d}L} < 0 \tag{5}$$

Through the lenses of such stylized model of skills formation, the marginal effects of income gains and losses on child human capital would be given by the following derivatives:

$$\frac{\mathrm{d}\theta^K_{c,t}}{\mathrm{d}G} = \frac{\mathrm{d}g^K(P)}{\mathrm{d}P} \cdot \frac{\mathrm{d}P}{\mathrm{d}G} > 0, \frac{\mathrm{d}\theta^K_{c,t}}{\mathrm{d}L} = \frac{\mathrm{d}l^K(P)}{\mathrm{d}P} \cdot \frac{\mathrm{d}P}{\mathrm{d}L} > 0 \tag{6}$$

The marginal effect of income gains (losses) on skill K can be thus decomposed into the marginal return to parental inputs P times the change in the quantity of P after a family income gain (loss). While it is not possible to perfectly disentangle the two components of these marginal effects within the empirical framework of this paper, results in sections 4.1 and 4.2 can provide some insights on the relationships in place.

According to the stylized model above, differences in the marginal effects of gains (losses) across skills are only driven by differences in the marginal returns to parental inputs P, rather than changes in the quantity of parental inputs after a gain (loss). Column 5 of Table 1 suggests that, in the case of family income gains, returns to parental inputs might be larger for cognitive rather than non-cognitive skills $\frac{\mathrm{d}g^C(P)}{\mathrm{d}P} > \frac{\mathrm{d}g^N C(P)}{\mathrm{d}P}$. On the contrary, returns to parental inputs in the case of income losses are similar across measures of cognitive and non-cognitive skills, suggesting that $\frac{\mathrm{d}l^C(P)}{\mathrm{d}P} = \frac{\mathrm{d}l^N C(P)}{\mathrm{d}P}$. Results from Table A4 are informative on the relationship between income quintile changes and a subset of P, namely measures of maternal health and wellbeing. From the Table it emerges that income gains affect mothers' measures of mental health and wellbeing to a lower extent than do losses, suggesting that $|\frac{\mathrm{d}P}{\mathrm{d}L}| > \frac{\mathrm{d}P}{\mathrm{d}G}$ for these inputs. While this contributes to explaining the asymmetry in the marginal effects of gains and losses on child non-cognitive development, more research on the potentially asymmetric effect of income changes on parental inputs would be needed to obtain a clearer picture of the marginal returns to family income changes on child human capital.

5 Robustness Checks

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. This can be easily obtained by 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 Appendix A 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 now less precisely estimated, the same conclusions 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.

Differences in the coefficients of the gain and loss dummies might be due to underlying 'jumps' of different sizes. If losses were to be on average larger than gains, then those who experience income losses might be more likely to transition by more quintiles as compared to those who experience gains. As argued later on in this section, using the continuous imputed income measure in the MCS seems to suggest the opposite to be true, with income gains being on average larger in magnitude as compared to income losses.[10] Nevertheless, Table A6 tests whether the results are heterogeneous when splitting the gain and loss dummies into dummies indicating the number of quintiles moved. As hinted by Figure A4 in the manuscript, showing transitions in income quintiles from one period to the next, only a small fraction of the sample experiences transitions of 3 quintiles or more (2.3% of the sample). For this reason, in Table A6, these extreme transitions are pooled together with 2-quintile movements.[11] Results in Table A6 show that as the magnitude of the transitions increase, the point estimates become larger – more so for gains than for losses. Overall, income losses of small and large magnitude alike negatively affect all outcomes; income gains instead have a positive effect on child non-cognitive outcomes only when they are large enough (i.e. involving a transition of at least 2 quintiles).

Given how income is measured in the MCS, movements upwards or downwards the income distribution are likely measured with error. One may wonder if this measurement error is symmetric, i.e. whether income losses and gains are measured with the same amount of error. If this was not the case and losses were to be, say, more precisely estimated than gains, then the OLS coefficient attached to gains will likely suffer from an attenuation bias (assuming the measurement error behaves as random noise), using survey data matched with administrative records, evidence from Angel *et al.* (2019) suggests that income gains and losses in survey data should both suffer from measurement error that is larger the further an individual's income is from the median income. Given that measurement error in both gains and losses is minimized for individuals around the median income, I then test whether the asymmetric results for income losses and gains still hold when restricting the estimation sample to only families that are in the middle income quintile in

[10] This is further confirmed by evidence from a different dataset with continuous measures of income, the UK Household Longitudinal Study, reported in Appendix C.

[11] Results in Table A6 are similar when dropping the 2.3% of the sample that moves 3 quintiles or more. Similar results, albeit less precise, are again found when using income deciles instead of quintiles.

$t-1$ and that move at most one quintile upward or downward the income distribution at time t. The results from this sample restriction, displayed in Table A7, show that the coefficients of the gain dummy are never statistically different from zero and are lower in magnitude than baseline results. The coefficients for losses, on the contrary, have comparable or larger magnitude than in the baseline results. These results suggest that the asymmetric effect of gains and losses is unlikely to be driven by potential asymmetries in their measurement errors.

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 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 equivalized income between one period and the next, splitting it into two variables: one, 'positive income growth', reflecting its positive values (and equal to 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 A8, trimming any income growth rate larger than 10 (top 0.5% of its distribution). [12] The story shown by columns 1, 3, and 5 in 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). Different from the baseline, a positive income 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. However, as mentioned in Section 3.1, the MCS imputed outcome is based on a set of socio-economic covariates that are included in the model specification – for which columns 1, 2, and 5 of Table A8 are overcontrolling. When excluding those covariates that were involved in the imputation of income (see the table's footnotes for a full list), results are closer to

[12] 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.

the baseline: a one-percent drop in income is associated with lower cognitive and non-cognitive outcomes – the magnitude of the effect being 3 to 4.6 times higher than that of gains. Within each regression, the difference in absolute values between the coefficients attached to positive and negative income growth is always statistically significant at least at the 5% level. Regardless of the specification, Table A8 suggests that income gains affect learning outcomes to a lesser extent than losses, different from the symmetric effect displayed by the baseline estimates.

An assumption implied so far is that income gains and losses (defined by transitions across the income quintile distribution) are somewhat 'large'. However, changes in a family's relative income position could well occur even in response to relatively small changes in imputed income. Not only, they could also derive from opposite changes in the underlying absolute income: a family may well experience an income loss in absolute term, but still move to a higher income quintile due to a change in their relative position in the income distribution. Luckily, the latter case does not appear to be very prevalent in the MCS estimation sample, when using the imputed continuous measure of income as a proxy of latent income: only 0.5% of income quintile gains actually reflect negative income changes and 4% of income quintile losses appear to be driven by positive income changes. In order to check whether the baseline effects of income gains and losses are driven by large or small changes in the underlying absolute household 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 A9 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.[13] While we can almost never reject the equality of all the losses (gains) coefficients in each column, Table A9 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).

Finally, a problem arising from the use of self-reported measures is linked to reporting biases that might affect the estimated coefficients. In particular, the regressions exploring the relationship between income and SDQ might be affected by common-method variance, since the same respondent reports both the dependent and the independent variables. Additionally, parents' own mental health and well-being, being affected by income shocks, might lead them to report higher or lower levels of child SDQ. A way of getting around the issue would be to use an external measure of non-cognitive skills, derived from either a structured assessment administered by the interviewers (as is the case with cognitive skills in MCS) or from an informal assessment of the cohort mem-

[13] 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.

ber by a third party. The only external source of child non-cognitive skills measures available in two consecutive waves comes from the teacher survey, a self-completion module administered to teachers when the cohort member was 7 and 11 years old (waves 4 and 5, respectively). In these waves, teachers were asked to report the cohort member's SDQ. The correlation coefficient between parent-reported and teacher-reported child SDQ is 0.52 for the externalizing scale and 0.46 for the internalizing one, with the distribution of teacher-reported SDQ displaying lower variance and higher average values as compared to the distribution of parent-reported SDQ.

Table A10 compares results using teacher-reported SDQ as the dependent variable to results using parent-reported SDQ. Due to the data restriction, the analysis is carried out only for wave 5 (with lagged values referring to wave 4) and for children in the estimation sample with non-missing teacher-reported SDQ. When we replicate the baseline analysis with parent-reported SDQ in this smaller sample, the effect of losses is negative and significant at the 10% level for both outcomes, while the effect of gain is not different from zero. For teachers-reported SDQ instead, neither upwards nor downwards transitions in the income distribution appear to be significant in explaining the residualized value of the outcomes. Furthermore, the teacher who reported a cohort member's SDQ in wave 4 is unlikely to be the same respondent of the teacher survey for wave 5. While teacher-level regressions include teacher controls (gender, years of experience) and class controls (size, presence of disruptive children), the residual unobserved heterogeneity across respondents in wave 4 and 5 could partly drive the absence of results. Last, the average class size being 26.8, it is not surprising that estimates for teacher-reported SDQ be lower in magnitude than parent-reported ones.

On top of teacher-reported SDQ, I additionally provide results using child self-reported SDQ from a larger sample of children from the UK Household Longitudinal Study. Results, shown in the first four columns of Table 5, confirm the asymmetric effect of the gains and loss dummies on child SDQ. A more detailed discussion of the results in Table 5 is provided in Section 6.3.

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 3 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 are associated with lower residualized Internalizing 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 as compared to 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. Experiencing two consecutive gains in t and $t-1$ partially offsets their individual benefits on reading test-scores, consistent with a narrative of decreasing marginal returns of family income on child test-scores. This is also consistent with the evidence on two consecutive income losses: past income losses exacerbate the negative effect of current income losses on reading test-scores. This result holds important implications for socio-economic inequality and cognitive outcomes, as it provides additional evidence suggesting that simply increasing family income may not be enough to significantly improve cognitive outcomes for children in low-income families.

Results from Table 3 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 Internalizing and Externalizing 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 3 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.[14] Table 4 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 labeled "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 $t-1$, moving down one quintile of the income distribution is associated with a 2 pp increase in the probability of entering the bottom quintile of the externalizing SDQ distribution. While losses seem to predict the probability of entering in the bottom quintile of both the SDQ distributions, gains are only significantly associated with a lower likelihood of entering the bottom quintile of internalizing 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 gains for externalizing SDQ).[15] On the other hand, for reading test-scores, income gains are associated with a higher probability of exiting the outcome's bottom quintile.

6.3 External validity: Results from the UK Household Longitudinal Panel

The cohort dimension of the MCS begs the question of how general are the results of this paper. Together with the measurement issues of income, this may limit the paper's external validity. To address this concern, I replicate the main results in a different dataset: the UK Household Longitudinal Study (UKHLS). The UKHLS is a panel study, so results in this dataset would not be limited to children born in a given year (children's birth year in the estimation sample ranges between 1996 and 2011). In addition, income in the UKHLS is not banded but continuous, allowing to compute precise income changes between one period and the next. Similar to MCS, UKHLS collects information on child SDQ, with the difference that the rater is no longer the main

[14]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 Externalizing SDQ distribution; 1** pp higher (0.4 pp lower) for those at the bottom quintile of the Internalizing SDQ distribution; and 0.8 pp higher (1** pp lower) for those at the bottom quintile of the reading test-scores distribution.

[15]This perhaps counter-intuitive result suggests that the being at the bottom of the distribution of behavioral outcomes has scarring effects that might persist over time. When investigating potential sources of heterogeneity driving this result, it appears to only be driven by families whose income in $t-1$ belongs to one of the bottom two income quintiles and by younger children. For children with behavioral problems living in less well-off families, a family income gain might hinder their chances of improving their behavioral outcomes, especially so when they are younger.

carer but the child herself.[16] However, different from MCS, no measures of cognitive ability are collected for children in UKHLS. Children are however asked what they would most like to do at 16 (corresponding to the end of the lower-secondary education cycle and of compulsory education in the UK), with options ranging from being in full-time education, to getting a full-time job or an apprenticeship. Based on answers to this question, I built a dummy equal one if the child intends to stay in full-time education and zero otherwise – a variable potentially capturing some of the cognitive aspects of the child's future economic success. A more thorough description of the UKHLS and descriptive statistics are reported in Appendix C.

Table 5 adopts the same functional form of the regressions in Table A8, using data from the UKHLS. Columns 2, 4, and 6 show estimates for a full model specification, with controls matching as closely as possible those from the MCS. Columns 1, 3, and 5 instead show a simpler specification, only including child controls. Exploiting the fine-level detail of income in the UKHLS, the estimated coefficients in Table 5 refer to the absolute levels of positive and negative income growth between $t-1$ and t. Results from columns 1 and 3 of Table 5 confirm the findings from the MCS dataset: a 10% decrease in family income is associated with a decrease in child externalizing and internalizing SDQ by 3 to 4% of a SD, whereas increases in family income do not display significant associations with these outcomes. Adding more controls in columns 2 and 4 reduces the size of the coefficients, which are no longer statistically different from zero at conventional levels. A similar picture emerges in the smaller sample of children who were asked about their intentions to stay in school after age 16, although results are again not statistically different from zero. Regardless of statistical significance, Table 5 consistently displays the same qualitative evidence of an asymmetry between positive and negative income changes, with the coefficients for losses being always at least twice as large in magnitude than those of gains. Results, available upon request, are similar when collapsing continuous income into income quintiles and defining the gain and loss dummies as upwards or downward movements along the income quintile distribution.

7 Conclusion

This paper explores the relationship between changes in family income and the accumulation of child 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 SD for both SDQ and reading test-scores, a magnitude comparable to at least half of the effect of having low birth-weight or being first-born.

The effect of losses is mediated for one third by channels reflecting mothers' well-being. Losses

[16] As a result of the children being the rater of her own SDQ, potential concerns about rater bias and common-method variance voiced out in Section 5 should here be mitigated.

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 a higher probability of exiting and a lower probability of entering the bottom quintile of the reading test-scores distribution. The effect of gains on reading test scores is also persistent over time: past income gains still matter for today's cognitive trajectories, consistently with the theory of family investment. Last, I provide evidence that the asymmetric effect of income gains and losses on child non-cognitive outcomes replicates in a panel data of children in the UK born between 1996 and 2011, additionally validating the findings of this paper.

Despite the robustness of the results presented above to a battery of sensitivity tests and their replication in a different dataset, the empirical strategy of the paper remains exposed to potential endogeneity issues. Results are nevertheless coherent with the established literature in economics and developmental psychology. Similar to Yeung, Linver and Brooks-Gunn (2002) and Washbrook, Gregg and Propper (2014), I provide evidence that the effect of income instability on non-cognitive skills is mostly conveyed through maternal affects. In addition, the lower reactivity of reading test-scores to changes in maternal well-being is consistent with Duncan and Brooks-Gunn (1997) and Yeung, Linver and Brooks-Gunn (2002), who provide evidence that cognitive skills are more responsive to changes in the intensity of material investments following an income shock. 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 higher sensitivity of human-capital accumulation 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.

Results from this paper are additionally consistent with a theoretical framework of imperfect income shock insurance, perhaps due to friction in insurance and credit markets. By keeping constant the slow-changing parental socio-economic characteristics that correlate with child development, the income shocks identified in this paper are more likely to capture unexpected variations in family income. These variations are also likely transitory, as the value-added model keeps constant all the time-invariant determinants of child SDQ and reading test-scores. While the literature on consumption insurance typically finds small impacts of transitory income shocks on consumption, it should be kept in mind that income changes considered in this paper are relatively large, as they imply a shift along the income quintile distribution (precise income data from the UKHLS suggest that the average loss accounts for 11% of disposable income in $t-1$). In addition, the relationship between income losses and child human capital that does not transit through parental affects, might not only be due to reduced consumption and lower material investments, but also to a reduction in the time spent in childcare following a negative e income shock (Blundell, Pistaferri and Saporta-Eksten, 2018). Further investigation is needed to disentangle all the mechanisms that link parental income to child human capital, taking into account the possibility that financial losses and gains may not operate through identical channels.

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Figures and Tables

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

	(1)	(2)	(3)	(4)	(5)
Panel A. Externalizing SDQ					
Outcome $(t-1)$		0.672***	0.659***	0.656***	0.644***
		(0.007)	(0.007)	(0.007)	(0.007)
Gain	0.127***	0.035***	0.043***	0.031**	0.005
	(0.016)	(0.012)	(0.012)	(0.012)	(0.012)
Loss	-0.128***	-0.066***	-0.067***	-0.056***	-0.033***
	(0.016)	(0.012)	(0.012)	(0.012)	(0.012)
Adjusted R-squared	0.066	0.460	0.465	0.466	0.469
Panel B. Internalizing SDQ					
Outcome $(t-1)$		0.530***	0.528***	0.526***	0.518***
		(0.008)	(0.008)	(0.008)	(0.008)
Gain	0.108***	0.059***	0.063***	0.054***	0.020
	(0.016)	(0.013)	(0.013)	(0.014)	(0.014)
Loss	-0.128***	-0.075***	-0.076***	-0.067***	-0.039***
	(0.016)	(0.014)	(0.014)	(0.014)	(0.014)
Adjusted R-squared	0.094	0.352	0.353	0.354	0.357
Panel C. Reading test-scores					
Outcome $(t-1)$		0.318***	0.315***	0.312***	0.287***
		(0.006)	(0.006)	(0.006)	(0.006)
Gain	0.137***	0.089***	0.090***	0.078***	0.041***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Loss	-0.111***	-0.078***	-0.077***	-0.071***	-0.035***
	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)
Adjusted R-squared	0.326	0.410	0.411	0.413	0.424
Observations	40,189	40,189	40,189	40,189	40,189
Child controls	.	.	✓	✓	✓
Household controls	.	.	.	✓	✓
Parental controls	.	.	.	.	✓

Notes: Robust standard errors, clustered at the individual level, in parentheses. "Outcome $(t-1)$" represents the standardized lagged value of the dependent variable. All regressions control for survey wave dummies and dummies for the family's income quintile at time $t-1$. Child controls are the following: 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, dummies reflecting the child's ethnic background (white, mixed, Indian, Pakistani or Bangladeshi, Black, other). Household controls are country dummies (England, Wales, Scotland, NI), the squared root of household size, dummies for housing tenure at time $t-1$ (ownership, mortgage, rent, other) and its variation between $t-1$ and t. Last, parental controls are a dummies for single-parent, parental employment, and the mother's highest educational level. The parental controls category further includes the mother's age at birth of the cohort member and measures of parental involvement at child age 3 (i.e. frequency of reading to the child, regular bedtime, hours spent in front of the TV). *** p<0.01, ** p<0.05, * p<0.1.

Table 2: The effect of income changes on child human capital: income determinants and channels

	Externalizing SDQ			Internalizing SDQ			Reading test-scores		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Outcome $(t-1)$	0.644***	0.644***	0.623***	0.518***	0.517***	0.484***	0.287***	0.287***	0.286***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)
Gain	0.005	0.005	-0.001	0.020	0.019	0.009	0.041***	0.042***	0.041***
	(0.012)	(0.013)	(0.012)	(0.014)	(0.014)	(0.013)	(0.012)	(0.012)	(0.012)
Loss	-0.033***	-0.029**	-0.020	-0.039***	-0.033**	-0.021	-0.035***	-0.039***	-0.038***
	(0.012)	(0.013)	(0.012)	(0.014)	(0.014)	(0.014)	(0.012)	(0.012)	(0.012)
Parent left		-0.028	-0.010		-0.058*	-0.032		0.016	0.020
		(0.027)	(0.026)		(0.033)	(0.032)		(0.023)	(0.023)
Mother lost job		0.002	0.005		0.021	0.025		0.019	0.020
		(0.022)	(0.022)		(0.026)	(0.025)		(0.022)	(0.022)
Father lost job		0.032	0.022		0.038	0.024		0.021	0.017
		(0.036)	(0.035)		(0.041)	(0.040)		(0.032)	(0.032)
Mother changed job		-0.004	-0.012		0.020	0.010		-0.006	-0.008
		(0.012)	(0.012)		(0.013)	(0.013)		(0.011)	(0.011)
Father changed job		0.006	0.009		-0.005	-0.001		-0.011	-0.010
		(0.012)	(0.011)		(0.013)	(0.013)		(0.011)	(0.011)
1 new sibling		-0.078***	-0.083***		-0.034**	-0.041**		0.002	0.001
		(0.016)	(0.016)		(0.017)	(0.016)		(0.015)	(0.015)
2+ new siblings		-0.145**	-0.149**		-0.115*	-0.123*		-0.049	-0.052
		(0.062)	(0.061)		(0.068)	(0.067)		(0.056)	(0.056)
Any siblings left		-0.013	-0.006		-0.062**	-0.056*		-0.016	-0.015
		(0.027)	(0.026)		(0.030)	(0.029)		(0.022)	(0.022)
Δ(Kessler scale)$_{t-1,t}$			-0.115***			-0.153***			-0.021***
			(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***			0.037***			0.001
			(0.006)			(0.007)			(0.006)
Life satisfaction $(t-1)$			0.013***			0.016***			-0.003
			(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			-0.048***			-0.028**
			(0.015)			(0.017)			(0.014)
Observations	40,189	40,189	40,189	40,189	40,189	40,189	40,189	40,189	40,189
Adjusted R-squared	0.469	0.470	0.484	0.357	0.358	0.386	0.424	0.425	0.425

Notes: Outcome $(t-1)$ represents the standardized 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 $t-1$. Dummies indicating the child's family's income quintile in $t-1$ are controlled for in all columns. All regressions additionally 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 individual level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Persistence of the effect of gains and losses

	Externalizing SDQ (1)	Internalizing 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 $t-2$. For the sample of 25,377 children in the table, the unconditional probability of experiencing an income gain is 27.2% and that of experiencing an income loss is 21.1%, similar to the full estimation sample. The probabilities of experiencing two consecutive gains or losses are instead smaller (4.0% for gains and 2.3% for losses). 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 4: Transitions in and out of the outcomes bottom quintiles

	Externalizing SDQ		Internalizing SDQ		Reading test-scores	
	Entry	Exit	Entry	Exit	Entry	Exit
Gain	-0.005	-0.027*	-0.021***	-0.002	-0.014**	0.053***
	(0.005)	(0.015)	(0.007)	(0.016)	(0.006)	(0.017)
Loss	0.018***	0.024	0.014**	0.009	0.007	-0.013
	(0.005)	(0.016)	(0.007)	(0.017)	(0.006)	(0.019)
Outcome quintiles in $t-1$ (reference: 5th quintile)						
2nd quintile	0.210***		0.196***		0.124***	
	(0.012)		(0.011)		(0.007)	
3rd quintile	0.130***		0.114***		0.093***	
	(0.012)		(0.012)		(0.007)	
4th quintile	0.070***		0.062***		0.050***	
	(0.013)		(0.012)		(0.008)	
Observations	28,321	8,625	28,050	8,890	32,603	7,584
Pseudo R-squared	0.137	0.057	0.089	0.050	0.103	0.045

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.

Table 5: External validity: results from the UKHLS

	Child-reported Externalizing SDQ		Child-reported Internalizing SDQ		Intention to stay in school after age 16	
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome $(t-1)$	0.529***	0.519***	0.476***	0.464***	0.200***	0.191***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.013)	(0.013)
Positive income growth$_{t-1,t}$	-0.074	-0.097	-0.046	-0.021	0.008	-0.001
	(0.102)	(0.102)	(0.091)	(0.092)	(0.018)	(0.018)
Negative income growth$_{t-1,t}$	-0.397**	-0.196	-0.324*	-0.297	-0.047	-0.018
	(0.194)	(0.198)	(0.189)	(0.191)	(0.032)	(0.033)
Observations	11,170	11,170	11,170	11,170	5,883	5,883
Adjusted R-squared	0.297	0.301	0.247	0.246	0.111	0.122
Child controls	✓	✓	✓	✓	✓	✓
Parental controls	.	✓	.	✓	.	✓

Notes: "Outcome $(t-1)$" represents the standardized lagged value of the dependent variable. Positive income growth$_{t-1,t}$ is a continuous variable taking the positive values of the 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 the negative income growth rate, and is set to zero for positive income growth. All regressions control for survey wave dummies and dummies for the family's income quintile at time $t-1$. Child controls are age and dummies indicating the child's gender and the child's ethnicity. Household and parental controls are country dummies (England, Wales, Scotland, NI), household size, dummies for housing tenure at time $t-1$ (ownership, mortgage, rent, other) and its variation between $t-1$ and t, the parents' ages, dummies for single-parent, parental employment, and the mother's highest educational level. Robust standard errors, clustered at the individual level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix A: Additional Figures and Tables

Figure A1: Transitions along the quintiles of Externalizing SDQ

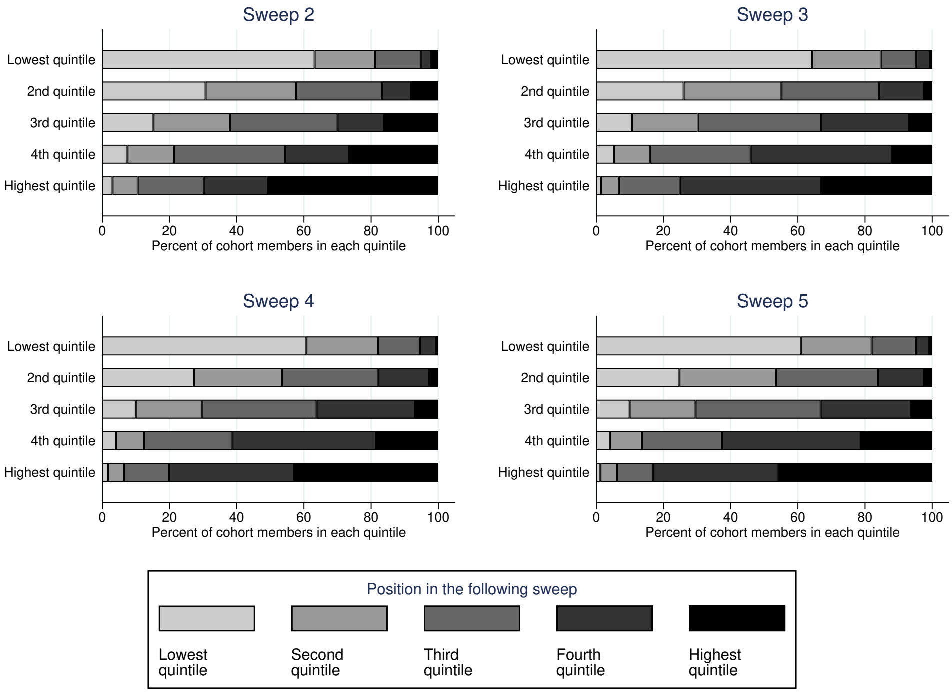
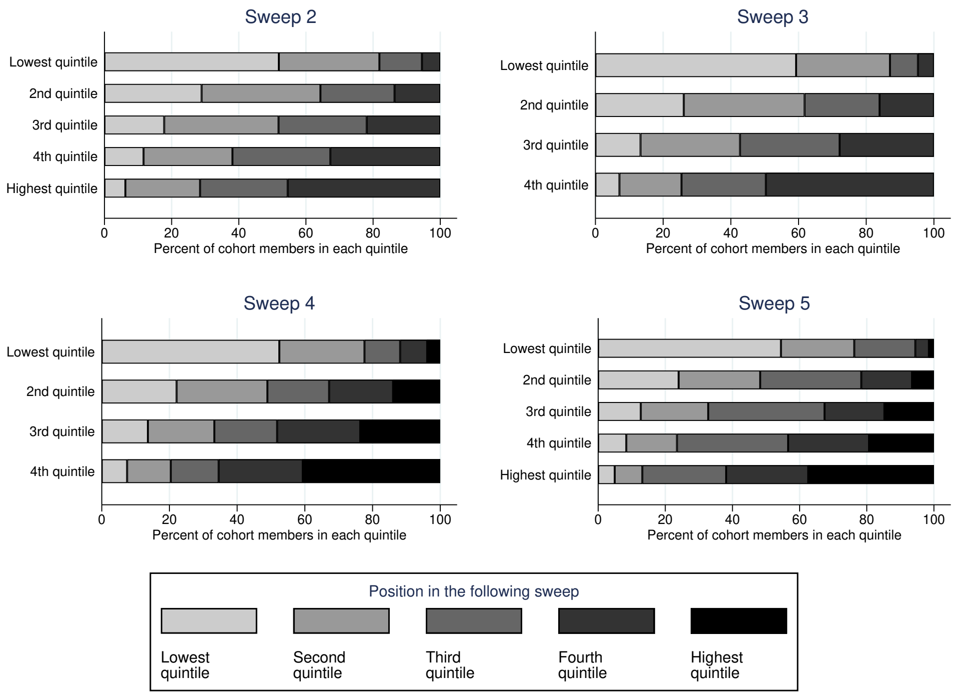


Figure A2: Transitions along the quintiles of Internalizing SDQ



Notes: Please note that the 4th quintile of Internalizing SDQ coincides with its 5th quintile in Sweeps 3 and 4: in the two waves, both quintiles are equal to 20 – the maximum value on the Internalizing SDQ scale.

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

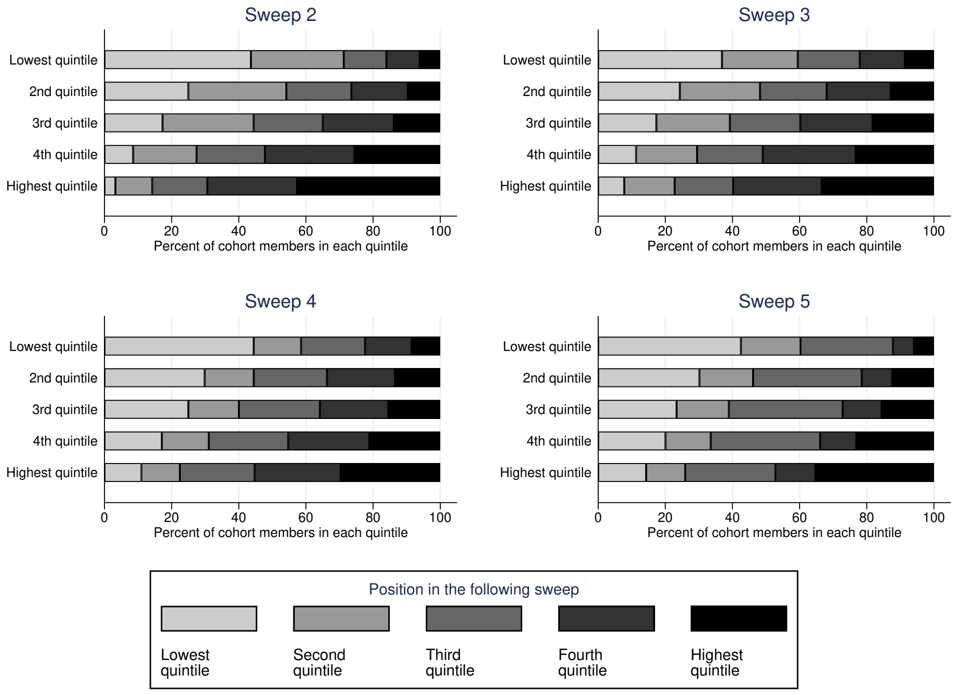


Figure A4: Transitions along the quintiles of household income

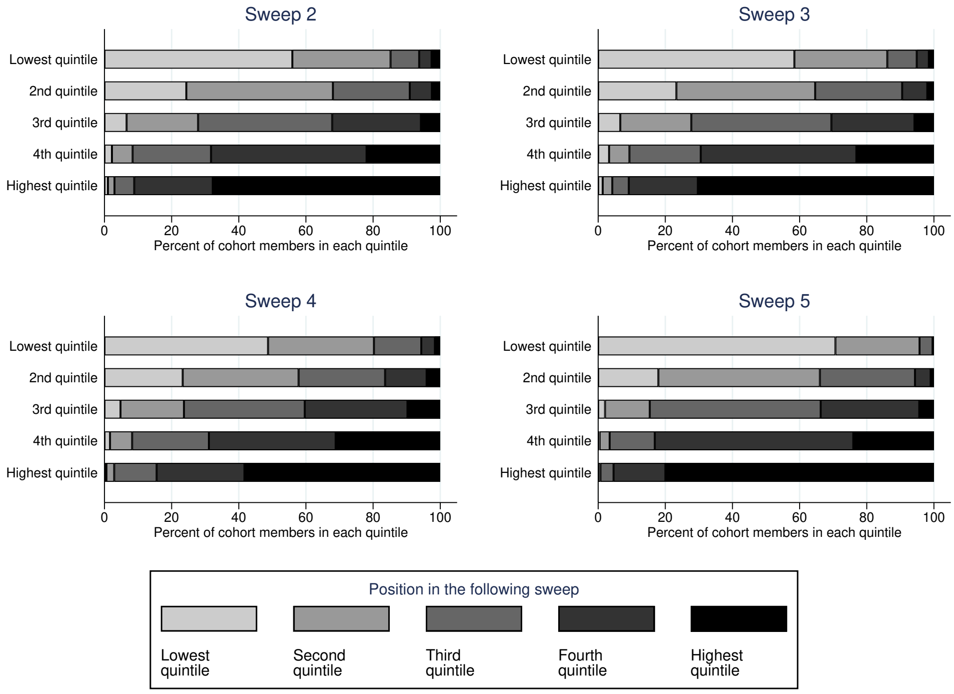
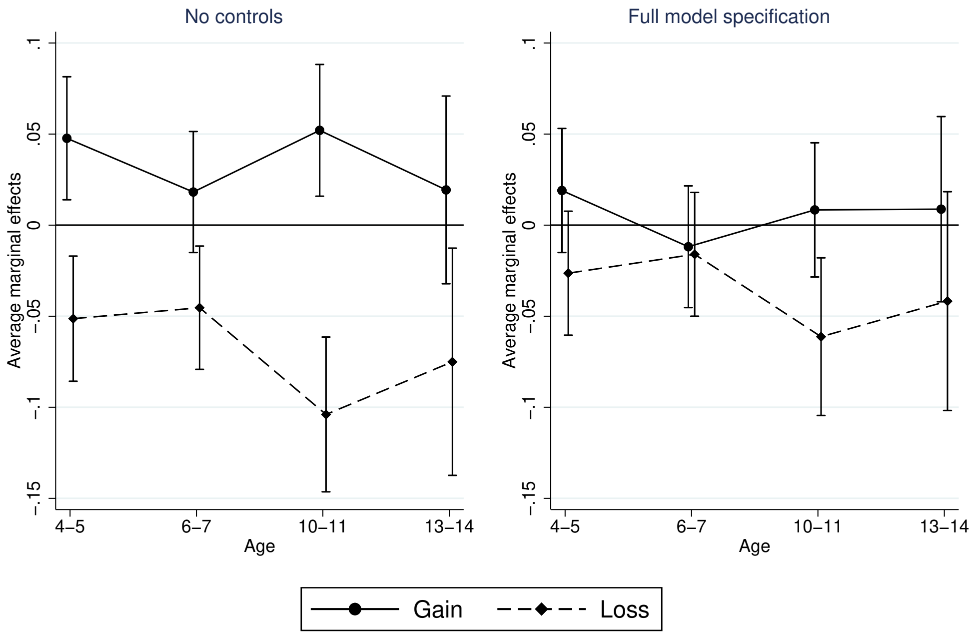
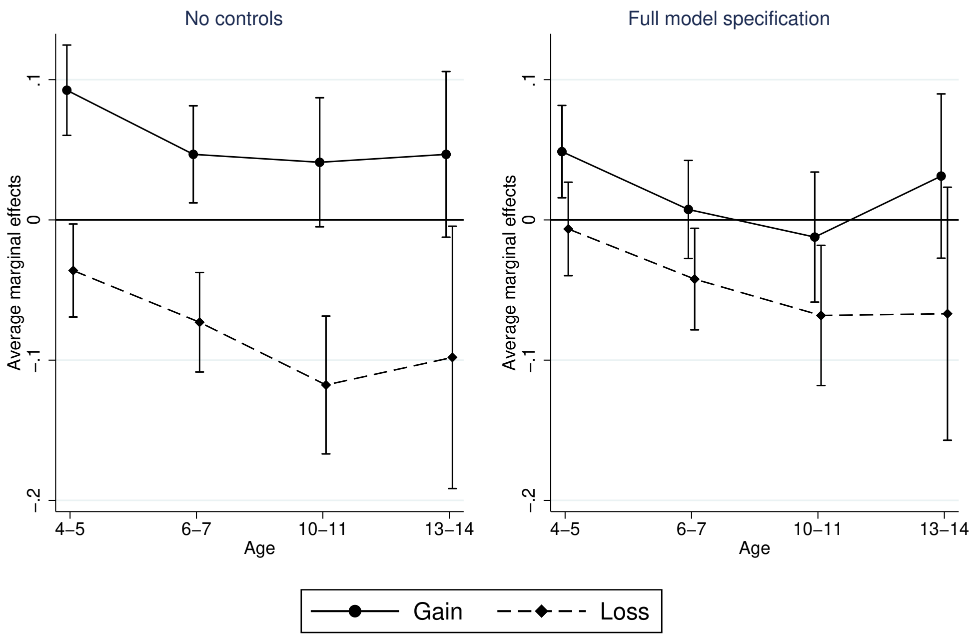


Figure A5: Age heterogeneity of the effect of gains and losses on internalizing SDQ



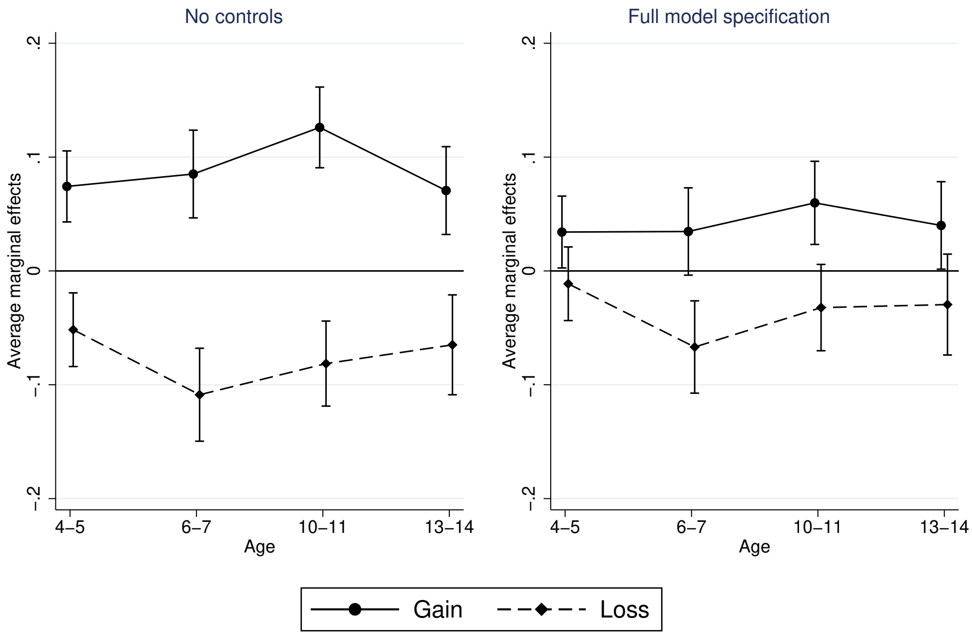
Notes: spikes are for 90% confidence intervals.

Figure A6: Age heterogeneity of the effect of gains and losses on internalizing SDQ



Notes: spikes are for 90% confidence intervals.

Figure A7: Age heterogeneity of the effect of gains and losses on reading test-scores



Notes: spikes are for 90% confidence intervals.

Table A1: The Strengths and Difficulties Questionnaire

Please think about this child's behavior 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 internalizing behavior = emotional + peer relationship (0-20)			
Total externalizing behavior = behavior + 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				
Externalizing SDQ	15.347	3.539	0	20
Internalizing SDQ	17.029	2.991	1	20
Reading test-scores	54.669	11.904	20	80
Lagged outcomes				
Externalizing SDQ	14.694	3.677	0	20
Internalizing 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
OECD equivalized annual income (MCS imputed)				
$ln(Income_t)$	9.075	0.590	5.682	10.657
$ln(Income_{t-1})$	8.994	0.653	5.351	10.657
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: The determinants of income changes

	Gain		Loss	
	(1)	(2)	(3)	(4)
Parent left	0.003	0.003	0.200***	0.200***
	(0.010)	(0.010)	(0.012)	(0.012)
Mother lost job	0.021**	0.021**	0.094***	0.094***
	(0.010)	(0.010)	(0.012)	(0.012)
Father lost job	-0.041***	-0.042***	0.218***	0.218***
	(0.015)	(0.015)	(0.018)	(0.018)
Mother changed job	-0.000	-0.001	-0.010*	-0.010
	(0.006)	(0.006)	(0.006)	(0.006)
Father changed job	0.007	0.007	0.008	0.008
	(0.006)	(0.006)	(0.006)	(0.006)
1 new sibling	-0.020***	-0.020***	0.044***	0.044***
	(0.007)	(0.007)	(0.007)	(0.007)
2+ new siblings	-0.001	-0.001	0.076***	0.075***
	(0.023)	(0.023)	(0.025)	(0.025)
Any siblings left	-0.058***	-0.058***	0.057***	0.056***
	(0.011)	(0.011)	(0.011)	(0.011)
Kessler scale ($t-1$)		-0.000		0.001**
		(0.001)		(0.001)
Life satisfaction ($t-1$)		-0.000		-0.002
		(0.001)		(0.001)
Mother had poor health in $t-1$		-0.009		-0.002
		(0.007)		(0.007)
Observations	40,189	40,189	40,189	40,189
Adjusted R-squared	0.282	0.282	0.237	0.238

Notes: Dummies indicating the child's family's income quintile in $t-1$ are controlled for in all columns. All regressions additionally 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 individual level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: The role of income changes on measures of maternal well-being

	Δ(Kessler scale)$_{t-1,t}$ (1)	Δ(Life satisfaction)$_{t-1,t}$ (2)	Mother's health worsened (3)
Gain	-0.028*	0.054***	-0.010**
	(0.015)	(0.013)	(0.004)
Loss	0.048**	-0.071***	0.010**
	(0.015)	(0.014)	(0.004)
Observations	40,189	40,189	40,189
Adjusted R-squared	0.231	0.293	0.047

Notes: 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. Dummies indicating the child's family's income quintile in $t-1$ are controlled for in all columns. All regressions additionally 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 individual 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

	Externalizing SDQ		Internalizing 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 standardized 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 individual level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: The measurement of income: gains and losses by number of quintiles moved

	Externalizing SDQ (1)	Internalizing SDQ (2)	Reading test-scores (3)
Outcome $(t-1)$	0.644***	0.517***	0.287***
	(0.007)	(0.008)	(0.006)
Gain: 2+ quintiles	0.041*	0.069***	0.050**
	(0.022)	(0.024)	(0.022)
Gain: 1 quintile	-0.002	0.010	0.039***
	(0.013)	(0.015)	(0.013)
Loss: 1 quintile	-0.038***	-0.041***	-0.036***
	(0.013)	(0.015)	(0.013)
Loss: 2+ quintiles	-0.023	-0.049*	-0.035
	(0.024)	(0.025)	(0.023)
Observations	40,189	40,189	40,189
Adjusted R-squared	0.469	0.357	0.424

Notes: Outcome $(t-1)$ represents the standardized lagged value of the dependent variable. Dummies indicating the child's family's income quintile in $t-1$ are controlled for in all columns. All regressions control for dummies for 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 individual level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: The measurement of income: one-quintile movements from the middle quintile

	Externalizing SDQ (1)	Internalizing SDQ (2)	Reading test-scores (3)
Outcome $(t-1)$	0.663***	0.522***	0.290***
	(0.013)	(0.016)	(0.013)
Gain	-0.008	-0.021	-0.022
	(0.023)	(0.026)	(0.024)
Loss	-0.044	-0.054	-0.062**
	(0.030)	(0.036)	(0.028)
Observations	7,451	7,451	7,451
Adjusted R-squared	0.459	0.342	0.414

Notes: Outcome $(t-1)$ represents the standardized lagged value of the dependent variable. Dummies indicating the child's family's income quintile in $t-1$ are controlled for in all columns. All regressions control for dummies for 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 individual level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A8: The measurement of income: continuous income growth rate

	Externalizing SDQ		Internalizing SDQ		Reading test-scores	
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome $(t-1)$	0.644***	0.653***	0.518***	0.523***	0.287***	0.304***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.006)	(0.006)
Positive income growth$_{t-1,t}$	0.019**	0.032***	0.019**	0.035***	0.016**	0.036***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
Negative income growth$_{t-1,t}$	-0.047	-0.108***	-0.063*	-0.135***	-0.079**	-0.167***
	(0.034)	(0.033)	(0.036)	(0.036)	(0.034)	(0.033)
Observations	39,722	39,722	39,722	39,722	39,722	39,722
Adjusted R-squared	0.469	0.467	0.357	0.356	0.423	0.415
Socio-economic controls:	✓	.	✓	.	✓	.

Notes: Outcome $(t-1)$ represents the standardized 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, dummies reflecting the child's ethnic background (mixed, Indian, Pakistani or Bangladeshi, Black, other), 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; survey wave dummies, and country dummies (England, Wales, Scotland, NI). Columns 1, 3, and 5 additionally control for parental socio-economic variables that are included in the computation of the MCS imputed measure of income: dummies for parental employment and the mother's highest educational level; mother's age at birth of the cohort member; and dummies for house-tenure at time $t-1$ (ownership, mortgage, rent, other) and its variation between $t-1$ and t. Sampling and non-response weights used in all columns. Robust standard errors, clustered at the individual level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: The measurement of income: gains and losses by continuous income growth rate

	Externalizing SDQ (1)	Internalizing 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 standardized 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 individual level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A10: Robustness checks: Teacher- and parents-reported SDQ at child age 11

	Externalizing SDQ		Internalizing SDQ	
	Parent	Teacher	Parent	Teacher
Outcome (age 7)	0.644***	0.517***	0.519***	0.317***
	(0.017)	(0.021)	(0.022)	(0.022)
Gain	-0.013	0.011	0.013	0.009
	(0.043)	(0.050)	(0.049)	(0.059)
Loss	-0.071*	0.011	-0.084*	0.004
	(0.042)	(0.052)	(0.049)	(0.055)
Observations	3,437	3,437	3,436	3,436
Adjusted R-squared	0.491	0.398	0.333	0.168
School controls	No	Yes	No	Yes

Notes: As teacher-reported SDQ is available only for waves 4 and 5 (respectively, age 7 and 11), all regressions in this Table are limited to wave 5 and use lagged variables from wave 4. The standard list of child, parent, and household controls is added to all specifications. Teacher-level regressions additionally control for teacher and class characteristics, namely the teacher's gender and years of experience (both in general and at the current school), the number of children in the class, and whether there are any disruptive children in the class. Robust standard errors, clustered at the individual level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix B: Dynamic panel data analysis

While the value-added model in the main model specification accounts for unobserved time-invariant factors explaining the dependent variable, there might still be some unobserved time-invariant factors affecting the residualized 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 generalized 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 B1 compares the performance of pooled OLS (same as in Table 1) and system GMM.[1]. 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. Externalizing and Internalizing SDQ, standardized 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 residualized outcome might translate into an attenuation bias at worst; as such, the coefficients from the baseline 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

[1] 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 minimize the loss of information due to the presence of gaps in the panel (Arellano and Bover, 1995).

of the residualized outcome in all GMM specifications of Internalizing and Externalizing 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 Externalizing 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, conditional on all other covariates, the observed deviations in the instruments from one period to the next should be taken as deviations from a stationary state and, as such, they should 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, the preferred estimator for this paper is pooled OLS, from the value-added model illustrated by equation 1.

References

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Table B1: Income changes and child human capital: Pooled OLS and GMM regressions

	Externalizing SDQ			Internalizing 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 standardized 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 Externalizing 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 individual level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix C: The UK Household Longitudinal Study

C1 Data description

The UK Household Longitudinal Study (UKHLS) is a nationally representative survey of households in the United Kingdom that has been conducted annually since 2009. It is a multi-disciplinary study that covers a wide range of topics, including economics, social policy, health, and well-being. The survey is designed to provide longitudinal data on a range of factors affecting households in the UK, including income, employment, education, housing, family dynamics, health, and social participation. The UKHLS is the successor to the British Household Panel Survey (BHPS), which was conducted annually from 1991 to 2008.

The UKHLS collects information on children and youth, with special questionnaires administered to either the parents or the children themselves. While no standard measures of cognitive skills are available for children in the UKHLS, non-cognitive measures are. In particular, child self-reported SDQ is available in the youth questionnaire, administered to children from 10 to 15 years of age. Child-reported SDQ is a reliable measure of socio-emotional and behavioral development (Goodman, Lamping and Ploubidis, 2010), based on the same items as the parent-reported SDQ questionnaire (the difference being that the subject is no longer "your child" but the respondent herself). While no test-scores or standard measures of child cognitive outcomes are available in the UKHLS, children are asked what they would most like to do at 16 (corresponding to the end of the lower-secondary education cycle and of compulsory education in the UK), with options ranging from being in full-time education, to getting a full-time job or an apprenticeship. Based on answers to this question, I built a dummy equal one if the child intends to stay in full-time education and zero otherwise – a variable potentially capturing some of the cognitive aspects of the child's future economic success.

Several questions are asked to UKHLS household members about their personal income, from labor, private benefits, investments, social benefits, or other sources. Answers to the income question are not banded, so respondents are asked to report precise income figures. Net household monthly income is then derived as the sum of net monthly incomes from all household members. I use this as a starting point to build a measure of disposable household income, which is adjusted for inflation and equivalized using the OECD equivalence scale for comparison purposes with the MCS.

C2 Descriptive statistics

Table C1 displays descriptive statistics for the outcomes and main independent variables used in Table 5. The distribution of SDQ is quite similar to that of carer-reported SDQ in the MCS.

The average income loss between one period and the next is 11% of past income, while the average income gain is 17%. In addition to what shown by Table C1, I investigate the structure of income changes in the UKHLS in order to provide additional evidence on the size of income changes underlying movements across the income distribution. Firstly, Figure C1 plots the absolute value of the difference in equivalent household income in between t and $t-1$ in the sample of 11,170 observations in the UKHLS used in Tables 5 and C1. Positive and negative income differences almost perfectly overlap, suggesting that gains and losses are quite symmetric in their absolute magnitude. When looking instead at a relative measure of income change, the growth rate of income between $t-1$ and t, its distribution behaves quite normally around zero, with positive income growth values displaying a longer tail than negative ones. This suggests that income gains entail on average larger relative income increases as compared to gains. It might however still be the case that, for income changes that imply a transition from one quintile to another of the income distribution, losses might on average be larger than gains. Figure C2 shows that this is not the case: small (absolute) values of the income growth rate are relatively more frequent for income quintile losses than for income quintile gains.

Taken together, the evidence on continuous income in the UKHLS and that on discrete income from the MCS suggest that the asymmetric effects of gains and losses documented in the paper are not driven by underlying income changes that are larger for losses than for gains. In absolute terms, there appear to be no differences in the magnitude of gains and losses; in relative terms, it is income gains that tend to be larger than losses in both of the datasets used here.

References

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Figure C1: The distribution of absolute income changes

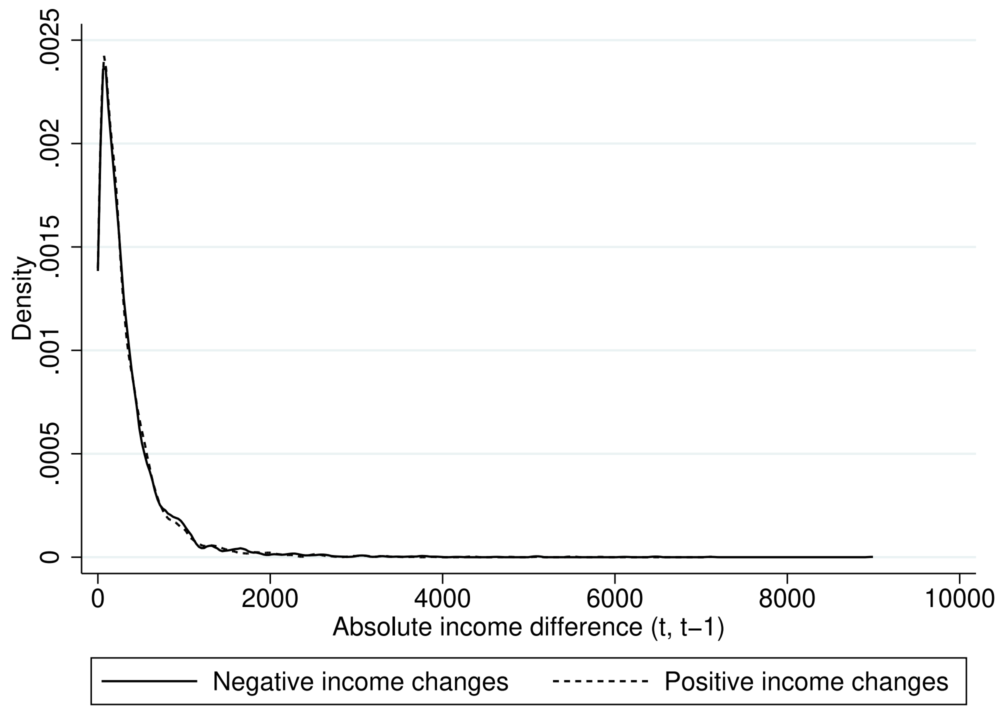

Figure C2: The distribution of income growth rate in the UKHLS, by change in income quintile

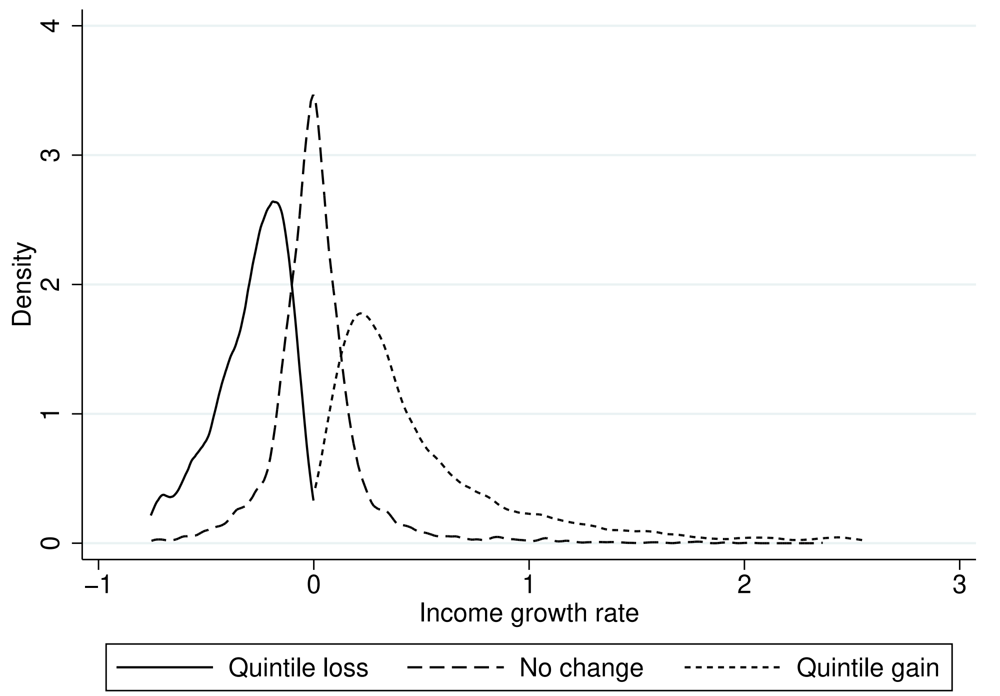

Table C1: Descriptive statistics

Variables	**Observations**	**Mean**	**SD**	**Min**	**Max**
Outcomes					
Externalizing SDQ	11,170	14.03	3.63	0	20
Internalizing SDQ	11,170	15.19	3.42	1	20
School after age 16	5,883	0.81	.	0	1
Lagged outcomes					
Externalizing SDQ	11,170	14.21	3.65	0	20
Internalizing SDQ	11,170	15.83	3.28	0	20
School after age 16	5,883	0.64	.	0	1
Income changes					
Positive income growth$_{t-1,t}$	11,170	0.17	0.33	0	2.56
Negative income growth$_{t-1,t}$	11,170	0.11	0.16	0	0.76