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THE GREAT RECESSION, HOUSEHOLD INCOME, AND CHILDREN'S TEST SCORES

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Economic downturns may have important implications for the educational attainment and human capital accumulation of children. We examine how income losses during the Great Recession were associated with children's educational performance in Ireland, one of the countries most severely affected by the global financial crisis. Using longitudinal data from a nationally representative child cohort study, collected before and after the recession at ages 9 and 13 years, we estimate panel models to examine the impact of income changes on standardized tests. We explore both objective and subjective measures of recession impact, and investigate non-linearities and effect heterogeneity using quantile regression. While income is strongly associated with educational performance overall, there is little evidence of a short-run negative impact of income shocks during the Great Recession on children's test scores.

JEL Codes: I24, I30, J10

Keywords: child development, fixed effects, Great Recession, inequality, income shocks, quantile panel regression, test scores

1. INTRODUCTION

The Great Recession is one of the major economic events of recent decades. The effects of the financial crisis were widespread and included large declines in GDP and household income in many countries. The impacts of these income losses continue to be documented across a number of domains (Ball, 2014; Bell and Blanchflower, 2011; Currie et al., 2015; Hoynes et al., 2012; Jenkins et al., 2012; Mian and Sufi, 2010). One of the channels through which the Great Recession could have long-run effects is on the educational attainment and human capital accumulation of younger cohorts who grew up during this time period (concentrated around 2007–2011 depending on the country). The economic costs of failure to

Note: This paper uses data from the “Growing Up in Ireland Child Cohort,” accessed via the Irish Social Science Data Archive—www.ucd.ie/issda.

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reach developmental potential are enormous (Heckman et al., 2013), and a comprehensive description of how the Great Recession affected household resources and children's well-being should include these channels.

The relationship between economic resources and child development is also of particular policy interest given that recent papers have found positive effects of welfare and transfer programs, which operate mainly through raising household income, on children's development (Aizer et al., 2016; Akee et al., 2010; Bastian and Michelmore, 2018; Dahl and Lochner, 2012; Milligan and Stabile, 2011). However, the evidence on transitory changes or wealth shocks is more mixed (Aughinbaugh and Gittleman, 2003; Cesarini et al., 2016; Heckman and Mosso, 2014; Rothstein and Wozny, 2013), which is one reason why it is important to provide further evidence on the impact of the recession.

There are several mechanisms through which the recession may have affected child development. First, household financial resources were substantially reduced in many countries, and household income and other measures of socioeconomic background are strongly associated with expenditure on school children (Hao and Yeung, 2015), early life learning environment (Goodman and Gregg, 2010), and other types of human capital investment such as time use (Altintas, 2016; Bono et al., 2016; Kalil et al., 2012; Putnam, 2016; Rokicki and McGovern, 2020) that positively impact educational performance. Second, the recession increased psychological distress associated with financial insecurity (Aber et al., 1997; Deaton, 2012; Haushofer and Fehr, 2014; Kiernan, 2019; McLoyd, 1990). There is already some evidence that children's emotional and behavioural health and personality traits respond positively to increases in household income (Akee et al., 2018). Moreover, research using the same data as this paper found that the recession increased behavioral problems among school children whose households were most affected (Smyth, 2015) and negatively impacted the health of young children (Briody, 2021; Reinhard et al., 2018). Mother's psychological distress may be one of the mediators in the relationship between family income and child socioemotional behavior (Noonan et al., 2018). Overall, literature reviews have documented household income gradients across a range of developmental outcomes (Blanden and Gregg, 2004; Blow et al., 2005; Cooper and Stewart, 2021; Duncan et al., 2014). Based on these findings and the evidence we have supporting the proposed mechanisms, our first research hypothesis is that reductions in family income driven by the recession negatively impacted children's educational performance.

Importantly, the effects of the Great Recession may have been heterogeneous (Dhongde et al., 2019; Gradín, 2021), most affecting those families who were least able to buffer against the impact of a reduction in wages, hours worked, social welfare benefits, or unemployment (Case et al., 2002). Given that these households are likely to be those at the lower end of the income distribution, this has important implications for widening disparities in children's wellbeing and development, as well as intergenerational transmission of disadvantage. Skill gaps across socioeconomic groups open up early but also persist in the long-run (Fletcher and Wolfe, 2016; Heckman, 2006). Children's capabilities in early life, for instance as measured by test scores, are predictive of future educational attainment and earnings, as well as health and social functioning (Currie and Thomas, 2001; Heckman et al., 2006). Initial differences in human capital can thus perpetuate

disadvantage through intergenerational transmission and restricted social mobility, and contribute to widening the socioeconomic gradient across the life cycle (Doyle et al., 2009; Duncan and Sojourner, 2013). In the UK, early life cognitive ability accounts for around 20 percent of intergenerational persistence in income (Blanden et al., 2007). Recent data show that human capital investments by families during the Great Recession were most affected among the least well-off; in the US the gap in spending on education between higher and lower income households increased by 20 percent over this time (Lunn and Kornrich, 2018). Therefore, it is important to establish whether the Great Recession further exacerbated the already substantial socioeconomic differences in test scores (Heckman and Masterov, 2007), as this could have important effects on equality of opportunity among future generations. Our second research hypothesis is that children living in households with the least resources were most affected by reductions in income.

In this paper, we contribute to the literature on the financial crisis and determinants of human capital accumulation by examining the impact of the Great Recession and household income on children's educational performance. We use survey data from a nationally representative child cohort study in Ireland, a country which was economically one of the most severely affected by the Recession, to link changes in household income to performance on school tests over time, before and after the height of the recession. Importantly for the purposes of this paper, the data are longitudinal, span the main part of the recession, contain detailed data on the financial impact of the economic downturn (Whelan et al., 2015), and include standardized tests on reading and maths. Therefore, we are able to contribute to the existing literature in several ways. First, we examine a particularly relevant context given that the recession in Ireland represented a severe income shock observed on a mass scale. While the recession was severe, it was also relatively short, meaning that we can evaluate the impact of a short-run shock rather than a permanent change in, say, income expectations or earning potential. Second, because the data contain information on the same children over time, we can account for time-invariant omitted variable bias using fixed effects (FE) models and compare the results to random effects (RE) models. Finally, the richness of our data allows us to conduct a variety of secondary analyses, including a comparison of objective and subjective recession impacts, and effect heterogeneity by baseline income and ability. We find that while RE models show a strong relationship between income and test scores, the FE models consistently show negligible and non-significant coefficient estimates for both income and subjective recession impacts. We also find little evidence that this conclusion varies by sub-group. We consider reasons for differences between RE and FE models, as well as policy implications, in the discussion.

The rest of this paper is structured as follows. In the next section we provide a brief summary of the existing literature. In Section III, we describe the magnitude of the economic shocks experienced during the Great Recession in Ireland. In Section IV, we describe the data and methods we adopt, and in particular our approach to accounting for heterogeneity. We present our results in Section V and discuss their interpretation in Section VI, while Section VII concludes with an overview of potential policy implications of this research.

2. LITERATURE

A large literature in public health, education, psychology, economics, and other disciplines has explored the relationship between income and financial security and measures of child behavior, cognition, and achievement. Because parental income is likely to be endogenous to child outcomes, a variety of approaches have been used to identify the effect of income separately from other factors related to family background (such as genetics and environment). These include instrumental variables (Miller and Wherry, 2019), within family comparisons (Blau, 1999), randomization in the form of lotteries (Lindahl, 2005), and natural experiments (Duncan and Sojourner, 2013). Although there is some emerging evidence from lower and middle-income countries on this subject (Kilburn et al., 2017), given the setting in which the empirical analysis in this paper is conducted, in what follows we focus our literature summary on studies based in higher-income countries.

Studies tend to explore two mechanisms through which income affects children's cognitive and health outcomes. The first is the Family Stress Model, which hypothesizes that materially disadvantaged households experience psychological distress as a result of the economic pressures they face (Masarik and Conger, 2017). Financial insecurity may lead to increases in emotional stress, changes in parental behaviors (for example, a tendency to be less nurturing and more punitive in the face of stress), and alterations to family structure due to processes such as divorce (Aber et al., 1997; Duncan et al., 2014). Neurologically, prolonged stress may interfere with children's executive functioning and development (Thompson, 2014). Recent evidence from Ireland found that job loss as a result of the Recession exacerbated child behavioral problems at ages 3–5, via increased maternal negative parenting (Mari and Keizer, 2021). The second mechanism is through resource constraints, which reduce capacity for parental investments (such as educational, nutritional, and time investments) in children. Quasi-experimental studies have found evidence for the importance of childhood nutrition as a mechanism through which income during childhood affects later-life outcomes (Hoynes et al., 2016; Levy and Duncan, 2000). Rajmil et al. (2014) find an adverse impact of the Great Recession on food intake by children, including less fruit and vegetables, fewer and lower quality meals, and intake of cheaper food. Aughinbaugh and Gittleman (2003) examine differences in the relationship between income and child outcomes in varying economic policy contexts; they find similar results in the US and UK—a small, but significant association with test scores and behavioral problems—and evidence that financial resources may be a relatively more important pathway than family stress.

When considering potential policy implications, it is important to distinguish effects of transitory income shocks from effects of changes in permanent income. In terms of permanent income, Bastian and Micheltore (2018) find that additional income during childhood increases the likelihood of completing high school and college, employment, and earnings in young adulthood. They attribute these impacts to an increase in maternal labor supply, a contributor to permanent income. Duncan et al. (2011) apply an instrumental variable approach to a set of welfare and antipoverty experiments conducted in the 1990s, and find that a \$1000 increase in annual income increases young children's achievement scores by 5–6 percent of a standard deviation. Duflo (2000) uses a difference-in-differences design to estimate

the impact of an increase in the old age pension to black South Africans on grandchildren's height-for-age, finding a large impact of income transfers to grandmothers on granddaughter outcomes, though not for grandsons. Analysis using the same data as this paper found that persistent economic vulnerability has a stronger impact on socio-emotional development than transient economic vulnerability (Watson et al., 2014). A review of the literature, which covered 61 studies using causal inference methods, including 6 randomized controlled trials, 33 quasi-experiments, and 22 longitudinal studies, found positive impacts of income on children's cognitive and socio-behavioral outcomes (Cooper and Stewart, 2021). While the magnitudes documented in that paper are relatively small, they are still non-negligible and are comparable to effect sizes associated with other types of interventions. They find support for nutrition and financial stress mechanisms, as well as evidence that income may reduce child abuse and neglect.

However, results for transitory income are more mixed. Blau (1999) uses longitudinal data from the US and applies FE and RE models to estimate the impact of income on cognitive and development outcomes, finding that the relationship with current income is small, while the relationship with permanent income is substantially larger. Akee et al. (2010) use quasi-experimental methods by exploiting the plausibly random (positive) income shocks of casino earnings. The authors find that children in affected households have higher levels of education in young adulthood and lower incidence of criminality for minor offenses, with heterogeneous effects by initial household poverty status. On the other hand, Cesarini et al. (2016) use a similar design among Swedish lottery winners and find no impact for most outcomes. The authors attribute these findings to Sweden's social safety net. Few studies examine negative income shocks on child development, with two exceptions focusing on children under the age of 5. Hidrobo (2014) uses variation in children's exposure to an economic crisis in Ecuador, finding that one year of exposure significantly decreased height-for-age z-scores and vocabulary test scores. Mari and Keizer (2021) find impacts of the recession in Ireland on child behaviour and verbal ability. To the best of our knowledge, relatively few studies have examined negative income shocks on child development outcomes during middle childhood, a key period during the transition to adolescence. In addition, both objective and subjective measures of financial shock are likely to be important in understanding household exposure to economic vulnerability (Whelan et al., 2015). For example, in their analysis of how financial circumstances in childhood affect young adults in the UK, Clark et al. (2021) find that income is a weaker predictor of worse cognitive and non-cognitive outcomes than major financial problems as reported by parents.

Our heterogeneity analyses are motivated by evidence of non-linearity in the impact of income on children's outcomes in the literature. Most of this evidence focuses on heterogeneity by gender and socioeconomic status. Recent work examining the impact of the Mother's Pension program using a quasi-experimental design, found that cash transfers improved children's health and economic outcomes in adulthood, with the greatest effect for the poorest families (Aizer et al., 2016). Similarly, Milligan and Stabile (2011) exploit changes in Canada's child benefit programs, finding significant impacts of income on test scores, maternal health, and mental health. In particular, they find effects differ by gender, and that benefits

accruing to families with the least formal education drive the results. Using longitudinal data and a quasi-experimental design, Akee et al. (2018) also find large beneficial impacts of income transfers on children's emotional and behaviour health and on parental relationships, which are most pronounced for the poorest children. In our paper, we build on these results to examine differences by child ability, in addition to child gender and baseline household income, as children with lower academic ability may be least able to cope with the stress and reduced resources associated with their family being adversely affected by external circumstances.

3. IRELAND DURING THE GREAT RECESSION

While the Great Recession had a substantial effect on many countries around the world, its impact was quite different depending on the context (Salgado et al., 2014). For example, Canada and Australia did not experience a major change in GDP, while Ireland was one of the most affected higher-income countries (Chapman and Doris, 2019; Savage et al., 2019). The magnitude of the impact of the recession in Ireland compared to other countries in the OECD group is demonstrated in Appendix Figure A1 which shows the change in household income over the period 2007–2011 (OECD, 2014). Ireland was the third most affected country after Greece and Iceland, with average declines of around 6 percent in income. In contrast, some countries such as Australia and Finland saw relatively little change, and countries in Eastern Europe such as Poland actually saw average incomes increase over the time period. The OECD data also provide information on changes at different points in the income distribution; in Ireland lower income households experienced larger declines than median and top earning households, which supports the case for considering heterogeneous impacts on children from different families.

The household-level survey data we use in this paper confirm these macro-level statistics. These data are illustrated in Figure 1, which shows the change in (log) income reported by interviewed households between 2007/2008 (survey wave 1) and 2011/2012 (survey wave 2). These households are the families of the nationally representative cohort of children who were aged 9 years in 2007/2008. As part of the survey, primary caregivers were asked to report their household income in both waves, which was equivalised for household size. We divided the sample into three tertiles based on their baseline (log) household income in 2007/2008, and in Figure 1 Panel A we show the density of the change in this measure over the two waves for each of these tertiles. It is clear that a large proportion of those in the lowest income tertile experienced a substantial decline in income during this period.

We also calculated the change in (log) income from wave 1 to wave 2 categorized into three tertiles based on whether the household experienced a large loss, little to no change, or a large gain. Figure 1 panel B shows that amongst the least well-off tertile at baseline, 50 percent experienced a large loss in income. Amongst the most well-off tertile, only 15 percent experienced a large loss in income. Interestingly, a substantial proportion of households still experienced a large increase over the time period, particularly amongst the most well-off group (53 percent). This again

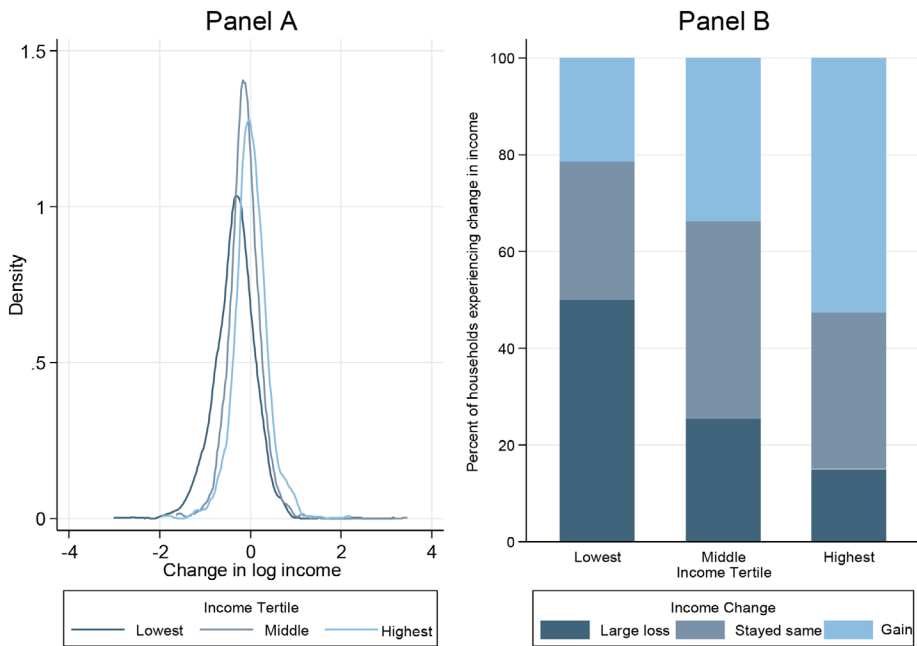


Figure 1. Distribution of changes in log equivalized household income stratified by baseline log equivalized household income tertile

Note: Data are from the Growing up in Ireland child cohort waves 1 (2007/2008) and 2 (2011/2012). [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)].

highlights the importance of taking potentially heterogeneous effects into account in the analysis.

Finally, in Figure 2, the recession impact is also evident in additional (non-income based) measures. We show, again by baseline household income tertile, the experience of adverse economic events reported at the second wave of the survey. Primary caregivers were asked whether they experienced any of the following during the recession: redundancy, reduction in hours worked, reduction in benefits (social welfare) received, and whether the household was unable to afford basic necessities, luxuries, or rent/utilities. Households across all levels of baseline income experienced substantial recession effects, however these were more prominent for the lowest income group than the highest. For example, 33 percent of those in the lowest income tertile at baseline reported a redundancy, compared to 12 percent in the highest income tertile. However, those in the highest income group were more likely to report that their hours were reduced (66 percent) compared to the lowest income group (77 percent), and this difference was present even among those who did not lose their jobs.

Overall, both the country-level aggregate data and survey data confirm large and heterogeneous effects of the recession on households, supporting the argument that Ireland is an important context in which to examine how children were affected.

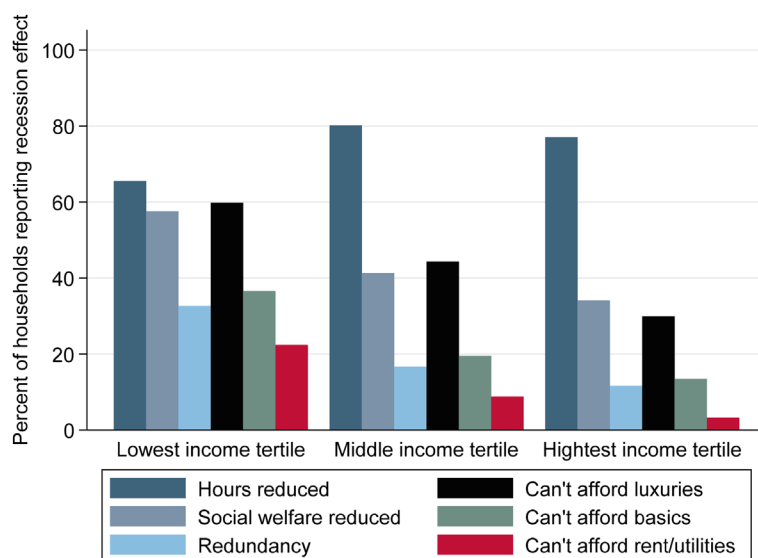


Figure 2. Additional recession impacts stratified by baseline log equivalized household income tertile
Note: Data are from the Growing up in Ireland child cohort wave 2 (2011/2012). [Colour figure can be viewed at wileyonlinelibrary.com].

4. DATA AND METHODS

We use data from the Growing Up in Ireland (GUI) study, which is a nationally representative longitudinal survey tracking the development and well-being of two cohorts of children and young people in Ireland (ESRI, 2010; Murray et al., 2011; Thornton et al., 2016). The first is the cohort of children born in 2008, who were recruited into the study when they were 9 months old. The second is the 1998 cohort of children, who were first recruited at age 9 in 2007/2008. Both cohorts were then subsequently followed up longitudinally. We focus on the 1998 cohort, as these children participated in standardized tests as part of the survey and were interviewed before and after the main impact of the recession. Data for this cohort were first collected from parents, schools, and the children themselves, aged 9 years, between September 2007 and April 2008. The second wave of interviews took place between August 2011 and March 2012, when children were aged 13.

The timing of the survey fieldwork therefore spans the recession, with the first wave of data collection occurring just before the first of the major shocks hit in Ireland in 2008, and the second wave corresponding to the deepest point of the recession, before any growth in employment was evident (Watson et al., 2014; Whelan et al., 2015). The unemployment rate for those aged 25–54, for example, stayed between 3.6 and 4.9 percent between 2003Q1 and 2008Q2 (by which point data collection for wave 1 was complete), and then began a steep rise in late 2008 to 9.7 percent in 2009Q1, 12.3 percent in 2010Q1, and 14.0 percent in 2011Q1, with the peak reached at 14.6 percent in 2012Q1 (Organization for Economic Co-operation and Development, 2022).

GUI data contain a wide range of information on the socio-demographic characteristics of children, their parents, and their schools (Williams et al., 2011). Our main exposure of interest is household income in the two waves, equivalized by household size. Equivalence scales assigned a weight of 1 to the first adult in the household, 0.66 to each subsequent adult or person aged 14+ years living in the household and 0.33 to each child aged less than 14 years. We use total gross household income, which is annual income less statutory deductions of income tax and social insurance contributions. In addition, information was collected on the subjective impact of the recession on families via the survey question “What effect did the recession have on your family?”—with the responses ranging from “No effect at all” to “A very significant effect”).

There are important features to note about the use of income as a main independent variable. It is measured on a clearly defined scale and constitutes a concrete indicator of the resources available to families. It is also a measure of the household’s socioeconomic position, and as such changes in income incorporate recession-related mechanisms including loss of employment. However, reported income may contain measurement error. Under the assumption that this error is random, this will have the effect of underestimating any impact of income on child outcomes (Hausman, 2001). Therefore, we also compare results with models where we consider the subjective assessment of recession impact, which allows families to give their own reports of how they were affected. In addition, because of the relatively short time horizon covered by the data, the results in this paper are relevant for transitory income shocks and the changes we observe do not necessarily capture changes in permanent income. These issues are important to bear in mind when interpreting results, so we return to each of them as part of the discussion in Section 5.

Summary statistics for baseline data in waves 1 and 2 are shown in Table 1. Our analysis sample consists of 6,564 children present in both waves (i.e. there are 13,128 observations in total). We restrict our attention to children with data in both waves because our empirical strategy involves examining changes within families over time to account for time-invariant unobserved heterogeneity. Sensitivity analyses with pooled models do not suggest results depend on excluding observations that are only present in a single wave. All of our descriptive statistics are weighted to be nationally representative, however weights are not used to estimate regression coefficients (Deaton, 1997; Solon et al., 2015). Nevertheless, we have verified that results are not sensitive to including weights in the regression analysis.

As shown in Table 1, mean equivalised household income in wave 1 was €19,352, or 9.7 in logs (corresponding medians were €14,000 and 9.5). These data refer to 2007/2008, before the main impact of the recession. Observed demographic characteristics include parental marital status, education, age, and employment, as well as household size, and place of residence (urban or rural). In wave 1, 33 percent of children have mothers with more than secondary qualifications, 28 percent have fathers with more than secondary qualifications, 49 percent have mothers aged 39 or less, and 45 percent live in urban areas. In wave 2, 61 percent of families reported that the recession had a significant or very significant impact on them. When we examined whether characteristics had changed from wave 1 to 2, we found that 5 percent of mothers changed their marital status between waves 1 and 2, 10 percent

TABLE 1
DESCRIPTIVE STATISTICS FOR WAVES 1 AND 2

	Wave 1 (2007/2008)	Wave 2 (2011/2012)
Mother married (%)	82	81
Mother employed (%)	54	59
Father employed (%)	74	66
Mother's age < =39 (%)	49	24
Mother's education (%)		
Less than secondary	29	19
Secondary	36	38
More than secondary	33	41
Father's education (%)		
Less than secondary	26	17
Secondary	23	23
More than secondary	28	31
Not in household	17	18
Urban region (%)	45	44
Household size [mean (SD)]	4.7 (1.2)	4.7 (1.2)
Household annual income (€) [mean(SD)]	19,352 (12,998)	16,087 (9,037)
Household log income (€) [mean (SD)]	9.7 (0.5)	9.6 (0.5)
Reported recession had significant or very significant effect on family (%)	–	61

Notes: Data are from the Growing up in Ireland child cohort waves 1 (2007/2008) and 2 (2011/2012). Father's employment is only known for fathers in the household. Descriptive statistics are weighted.

of mothers raised their level of education, and 20 percent of mothers changed their employment status. For fathers, 13 percent raised their education level and 13 percent changed their employment status.

Maths and reading tests were administered to study children in both waves as part of the interviews under controlled conditions (Thornton et al., 2016). They represent assessments of children's academic abilities at age 9 and age 13. Drumcondra reading and maths tests are standardised tests developed by official government agencies, and used routinely in Ireland to assess academic performance (Shiel et al., 2015). The wave 1 assessment is a curriculum-based, standardized test used to indicate level of ability in reading and maths, while the wave 2 assessment is a test of scholastic aptitude based on verbal reasoning and numerical ability items (Smyth, 2017). While the latter is not an achievement test per se, previous research has found that the Drumcondra assessment is highly predictive of outcomes in the state examinations at the middle (junior certificate) and end (leaving certificate) of secondary school in Ireland (Hannan et al., 1997). The GUI design report for wave 2 states that the Drumcondra test was chosen to provide comparability across waves (Thornton et al., 2016). Nevertheless, it is important to consider how the results based on these tests can be viewed in light of these differences. We interpret them as providing data on the ranking of children's general reading and maths ability for their age, rather than providing information on how their capacity to complete specific tasks has improved over time. Outcomes reported in the data are already standardized to a z-score with a mean of zero matched to the population, and a standard deviation of 1. In our analysis, we therefore report results which indicate the change in a child's rank, relative to their cohort. Summary statistics for test

scores according to household characteristics are shown in Figures A2–A5 in the Appendix. These figures show that households in the lower income group, the lower maternal education group, and households who experience a larger income shock between waves have children with consistently lower test scores.

To summarize our empirical approach, our outcomes of interest are the test score data in each wave of the survey, comparing before and after the recession. We consider maths and reading separately, as previous research, including using the GUI survey (McGovern, 2013), suggests potentially different human capital formation processes for each. We also stratify all of our models by sex, allowing for differential impacts on girls and boys (Nong et al., 2021), which may be especially relevant in Ireland given the prevalence of single-sex schools (Doris et al., 2013). Our main exposure of interest is log equivalized household income during the Great Recession. We model test scores as a function of income, while adjusting for the other demographic characteristics shown in Table 1. We then conduct a series of secondary analyses, including modeling exposure as the subjective measure of income change, and examine heterogeneous impacts by baseline income and ability.

Our main regression model is as follows:

$$(1) \quad \text{Test z-score}_{it} = \alpha_1 \text{Log Household Income}_{it} + X_{it}\beta_1 + Z_i\delta_1 + \varepsilon_{it}$$

with the test z-score outcome for child i at time t being a function of household income in each time period and time-varying observed characteristics in X_{it} , which include mother's marital status, mother's and father's education, and household size. Z_i is a matrix of baseline characteristics. We include variables that exhibit no or little change over time in Z_i , such as region. In our main analysis we only adjust for baseline employment status of mothers and fathers because employment status at wave 2 is potentially endogenous to household income shocks. For example, a negative income shock could lead a nonworking parent in the household to return to work. Nevertheless, we also conduct sensitivity analyzes where we adjust for mother's and father's employment status. β_1 and δ_1 are the relevant parameter vectors. ε_{it} is an idiosyncratic error term. α_1 is the coefficient of interest.

Under the maintained assumptions that the data generating process is linear in parameters, that observations are independent across individuals, relevant variance and co-variances are finite and homoscedastic, and ε_{it} is uncorrelated with explanatory variables in each time period for the same individual, we consider two approaches for estimating this model. First, a random effects (RE) model where an individual-specific intercept is assumed to be normally distributed. We consider an RE approach instead of pooled OLS after rejecting a common intercept model (Breusch and Pagan, 1980). The main identifying assumption for this RE model to provide consistent estimates of α_1 is that the individual-specific intercept is uncorrelated with explanatory variables in all time periods for the same individual. If this assumption fails (and individual-specific intercepts are in fact correlated with explanatory variables), the alternative fixed effects (FE) panel model will provide consistent estimates under the assumption that there are no time-varying omitted variables that are correlated with household income and test scores. The FE model is based on first differences (which with $t = 2$ is equivalent to the de-meaning transformation). If the RE assumption holds, both models will each provide consistent

estimates but the RE model will be more efficient. Therefore, in what follows we present results from both models and formally test for differences in coefficient estimates using a Hausman test (Hausman, 1978).

Next, we conduct a series of secondary analyses. First, we examine subjective recession experience as the exposure. We need to modify our empirical strategy because the question of interest was only asked in wave 2 of the survey. We estimate the change in test z-scores as a function of baseline characteristics and the subjective question (which is essentially measuring the change since wave 1):

$$(2) \quad \Delta \text{Test z-score}_i = \alpha_2 \text{RecessionExp}_i + X_{i,t=2007/8} \beta_2 + Z_i \delta_2 + \varepsilon_i$$

α_2 and α_3 are the coefficients of interest. This approach is comparable to a value-added model where the outcome is in first differences (Todd and Wolpin, 2003).

For the heterogeneity analysis, we consider two extensions. First, we examine non-linearity in the impact of income. For example, it is possible that an effect may only occur in households with large income losses, or that the same loss affects lower income households more severely because better off families are able to buffer against income losses due to, for instance, savings or social support. Thus, we implement models where the left-hand side is test z-scores in 2011/2012 and on the right-hand side we interact recession experience with tertiles of baseline income (in wave 1):

$$(3) \quad \begin{aligned} \Delta \text{Test z-score}_i &= \gamma \text{BaselineIncome}_i + \theta \text{RecessionExp}_i \\ &+ \alpha_3 \text{RecessionExp} * \text{BaselineIncome}_i + X_{i,t=2007/8} \beta_3 + Z_i \delta_3 + \mu_{it} \end{aligned}$$

Second, we consider whether impacts may differ according to the ability of children. For example, children with lower ability might be least able to cope with the stress associated with their family being adversely affected by external circumstances. To this end, we implement panel quantile regression models that allow us to examine income impacts at each point in the ability distribution while testing for the presence of time-invariant omitted variable bias. Our approach uses conditional quantile fixed effects (Powell, 2014, 2022), which accounts for unobserved heterogeneity while still using unconditional quantiles as the units of interest. The structural quantile function (SQF) for this model can be summarized as follows:

$$(4) \quad \text{Test z-score}_{it} = \phi_i(\tau) + \alpha_4(\tau) \text{Log Household Income}_{it} + X_{it} \beta_4(\tau) + Z_i \delta_4(\tau) + u_{it}$$

We estimate quantile treatments effects (QTEs), which measure the impact of a change in income on test z-scores for a given quantile, τ . ϕ_i is a fixed effect for each child. We compare results to a pooled model based on standard quantile regression (Koenker and Bassett, 1978) without fixed effects.

5. RESULTS

5.1. Main results

We begin in Table 2 by presenting the main results for maths and reading scores from panel models based on the regression specification in Equation 1. The first panel shows results for reading, while the second panel shows results for maths. Columns 1 and 2 show results for girls, while columns 3 and 4 are for boys. Columns 1 and 3 show results from RE models, while columns 2 and 4 implement FE models.

In the summary Table 2 we only show the coefficient on log income, however all regressions include control variables and the full tables are shown in the Appendix. Standard errors are clustered at the child level to account for having multiple observations on the same child. Income is not adjusted for inflation; however, robustness checks that adjusted income for inflation using the consumer price index for Ireland showed consistent results.

Overall, the pattern for boys and girls, and for reading and maths, is the same. The coefficients in the RE models are large and statistically significant, suggesting a substantial impact of household income on children's test scores. For example, the coefficient of 0.164 for the RE model for girls reading test score implies that a 10 percent increase in household income raises test scores by approximately 0.016 standard deviations (given that the test score data is normalised to 0 with a standard deviation of 1). The magnitude of this socioeconomic gradient is similar to that in the unadjusted descriptive statistics.

In contrast, the FE coefficients are all small in magnitude, and most are not statistically significant. Although the coefficient for girls' maths score is negative and marginally significant, at 0.06 standard deviations it does not provide evidence of a strong income impact. We return to the difference between RE and FE models in the next section, however one (though not the only) interpretation is that the RE models are biased by the exclusion of unmeasured common causes of income and

TABLE 2
HOUSEHOLD INCOME AND CHILDREN'S TEST SCORES (SUMMARY TABLE)

	Girls		Boys	
	Panel random effects	Panel fixed effects	Panel random effects	Panel fixed effects
Panel A: Reading Test Score				
Log Income	0.164*** (0.023)	0.035 (0.030)	0.157*** (0.025)	0.007 (0.035)
Panel B: Maths Test Score				
Log Income	0.101*** (0.023)	-0.062* (0.036)	0.174*** (0.026)	0.051 (0.038)
Control variables	Y	Y	Y	Y
Observations	7,351	7,351	6,942	6,942

Notes: All regressions include control variables, although only the coefficient on the main independent variable is shown in this table. The full table is presented in the Appendix. A summary of the regression specification is shown in Equation 1. Standard errors are clustered at the child level and shown in parentheses.

***p < 0.01, **p < 0.05, *p < 0.1.

TABLE 3
SUBJECTIVE RECESSION IMPACT AND CHILDREN'S TEST SCORES

	Girls (OLS)	Boys (OLS)
Panel A: Reading Test Score		
Very significant effect	0.017 (0.056)	−0.066 (0.067)
Significant effect	0.024 (0.053)	−0.014 (0.064)
Small effect	0.001 (0.053)	−0.045 (0.064)
No effect (omitted)	—	—
Panel B: Maths Test Score		
Very significant effect	0.085 (0.069)	−0.010 (0.068)
Significant effect	0.048 (0.063)	0.009 (0.063)
Small effect	0.052 (0.064)	0.046 (0.064)
No effect (omitted)	—	—
Control variables	Y	Y
Observations	3,118	2,965

Notes: All regressions include control variables, although only the coefficient on the main independent variable is shown in this table. The full table is presented in the Appendix. Standard errors are clustered at the child level and shown in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

educational achievement. Coefficients on control variables shown in the Appendix are in line with expectations and previous research. Given that the RE model is potentially more efficient, we conduct a formal test of coefficient differences using an Hausman test (Hausman, 1978). χ^2 test values for girls' reading and maths are 232 and 89, respectively. χ^2 test values for boys' reading and maths are 108 and 101, respectively. All have associated p -values < 0.001 , therefore, for each outcome we can reject that the RE and FE coefficient estimates are statistically equivalent (among both boys and girls). Finally, in sensitivity analyses controlling for mother's and father's employment status in wave 2, we find results are almost identical to those in Table 2.

5.2. Secondary analyses

Subjective recession impacts

Table 3 presents results from models with subjective measures of recession impact as the main independent variable outlined in Equation (2). The omitted category is that the recession had no impact on the household. Overall, coefficient magnitudes are small and do not suggest the recession had a substantial impact.

Heterogeneous impacts by income

We examine whether there is a non-linear relationship between income and test scores. Our models thus far have considered log income, which acknowledges

diminishing returns, but nevertheless imposes log-linearity, assuming constant proportional impacts. We investigated whether there were asymmetries (income losses being different from income gains) or polynomial-type income effects, but were unable to find any evidence that these were present. Therefore, in the following analysis we focus on establishing whether income impacts may have differed by family. Better-off households may have been able, for example, to draw on savings or other assets following a change in earnings. Alternatively, lower income households may have had some protection from financial difficulty through social welfare; for example, the percentage of families who reported that at least 20 percent of their income came from social welfare increased from 13 percent to 19 percent over the two waves. Previous research has found that volatility may itself be important for child educational outcomes (Gennetian et al., 2018). As the potential mechanisms through which recession impacts operate are endogenous, and we do not have an available identification strategy, the following analysis is a description of the relevant associations rather than a causal analysis.

We consider the change in maths and reading test scores for three tertiles of household income at baseline (in wave 1 at $t = 2007/2008$), interacted with their subjective assessment of how the recession impacted on their family, separately for boys and girls. We show the marginal effect on the change in test scores of being in a household which experienced a very significant effect of the recession compared to a household which experienced no effect of the recession, for each of the three income tertiles at baseline.

Overall, there is little evidence of heterogeneity in recession impacts in Figure 3. Confidence intervals are wide and include 0 for all outcomes and groups. Comparing families with different incomes at baseline, there is no clear indication that those from less-well off households were differentially affected. Only the coefficient for boys' reading scores is marginally significant (at the 10 percent level). The coefficient magnitude for this group is substantial though, as it implies that boys in the lowest income tertile whose families experienced a very significant recession impact had a change in reading scores which was 0.23 standard deviations lower than boys in the lowest income tertile whose families experienced no significant recession impact. However, given that the overall pattern does not consistently show that lower income families are worst affected by the recession, we are cautious in our interpretation of this result. We also implemented a similar model with baseline income interacted with actual income change (instead of the subjective report) but reached the same conclusion.

Heterogeneous impacts by ability

Finally, we examine whether there is heterogeneity by child, specifically whether children of varying ability are differentially affected by the recession. For example, children with lower ability may require a higher level of investment to attain the same achievement level, and are therefore relatively more disadvantaged by a reduction in parental resources. This could arise as a result of dynamic complementarities in the human capital production function (Cunha and Heckman, 2007, 2008). To this end, we implement quantile regression models which allow us to examine the impact of income at each point in the ability distribution. As before, we compare pooled (RE) and FE quantile panel models.

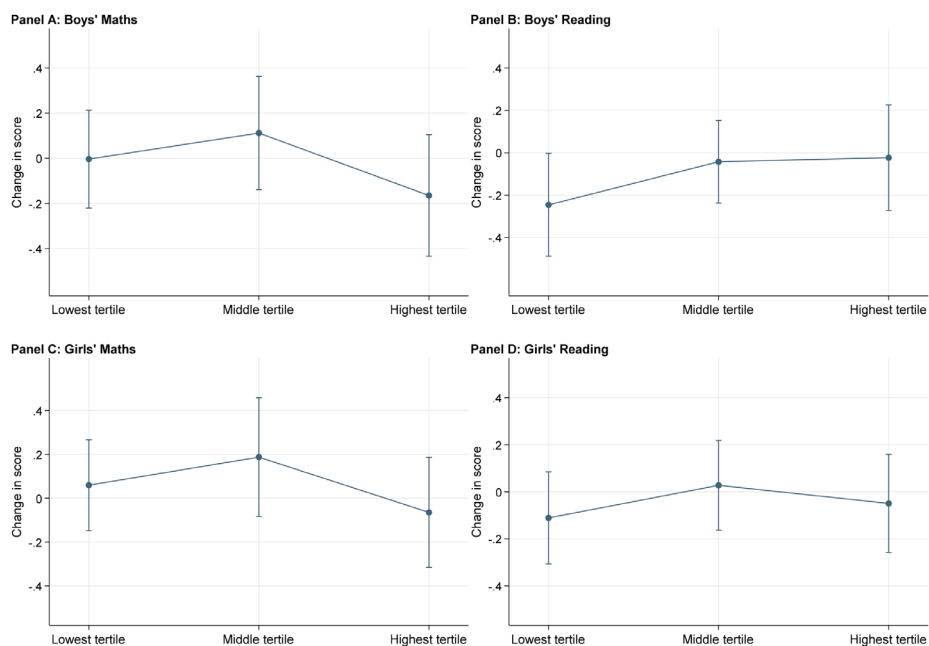


Figure 3. Subjective recession effects by baseline income for boys' and girls' reading and maths scores

Notes: The graph shows the marginal effect of being in a household which experienced a very significant effect of the recession compared to a household which experienced no effect of the recession on the change in test scores for each of the three income tertiles at baseline. [Colour figure can be viewed at wileyonlinelibrary.com].

The pooled quantile estimates (with standard errors clustered by child [Parente and Santos Silva, 2016]) are shown in Figure 4. For girls, there is little evidence that the relationship differs according to ability, with the relevant confidence interval including the OLS estimate at each quantile. Estimates for boys are similar, although there is some indication that the association of household income with test scores is lower for boys of higher ability, especially for maths. For example, for boys' maths test scores, those at the highest end of the ability distribution (the highest conditional quantiles) are expected to have test scores which are 0.01 standard deviation units lower for a 10 percent reduction in household income. In contrast, for boys at the lower end of the ability distribution (the lowest conditional quantiles), the corresponding association is larger, a reduction of 0.03 standard deviation units for a 10 percent reduction in household income.

There is a difficulty with implementing FE models in a quantile context because when indicators for each child are included in the model the interpretation of the quantiles (and the resulting rank) changes. Then the quantity under consideration is the quantile, or relative rank of the child, conditional on the child's baseline ability. Therefore, children at the top of the unconditional quantile could be at the bottom of the conditional quantiles, and vice versa. For example, consider a child who scores near the top of the unconditional distribution but whose score declines relative to their result in the previous wave. She would therefore rank high on the unconditional quantile, but could rank low on the conditional quantile once fixed

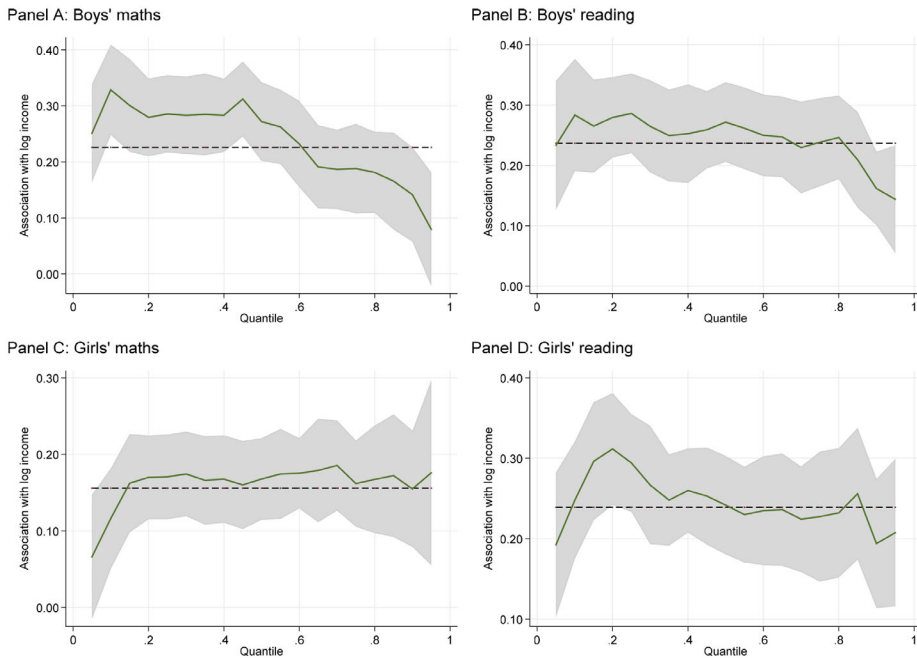


Figure 4. Pooled quantile results for boys' and girls' reading and maths scores. [Colour figure can be viewed at wileyonlinelibrary.com].

effects are included in the model. Therefore, we implement the approach suggested by Powell (2022, 2014), which allows us to take advantage of the FE for identification purposes only, i.e. to account for time invariant heterogeneity, but to otherwise consider ability quantiles which are not conditional on the fixed effects themselves.

These (non-additive) FE quantile panel results are shown in Table 4. There is no evidence of an income impact at any point in the ability distribution, neither for boys nor girls, and neither for reading nor maths. The magnitude of the coefficients are relatively small and are not statistically significant at any quantile in the distribution.

6. DISCUSSION

Overall, our results suggest a clear pattern. For boys and girls, and for maths and reading, RE models indicate a significant and relatively large association between income changes and children's test scores. There is little evidence of non-linearities or heterogeneity by ability, except perhaps some indication that boys from lower income households are most affected by the recession (in terms of reading), and some indication that boys with higher ability are least affected. The RE models would therefore suggest that household income has an important impact on children's human capital accumulation. In contrast, FE models consistently show negligible and non-significant coefficient magnitudes for both our exposures of income and subjective recession effects. Analysis of changes in income

TABLE 4
QUANTILE FIXED EFFECTS REGRESSION RESULTS

	25th percentile Girls	Median Girls	75th percentile Girls	90th percentile Girls	25th percentile Boys	Median Boys	75th percentile Boys	90th percentile Boys
Panel A: Reading Score								
Log Household Income	0.002 (0.064)	0.049 (0.058)	0.098 (0.062)	0.071 (0.069)	0.078 (0.070)	0.069 (0.077)	0.044 (0.155)	0.049 (0.083)
Panel B: Maths Score								
Log Household Income	−0.034 (0.072)	0.033 (0.056)	−0.021 (0.085)	0.016 (0.254)	0.068 (0.104)	0.089 (2.881)	0.015 (0.076)	−0.006 (1.551)
Control variables	Y	Y	Y	Y	Y	Y	Y	Y
Observations	7,351	7,351	7,351	7,351	6,942	6,942	6,942	6,942

Notes: All regressions include control variables, although only the coefficient on the main independent variable is shown in this table. A summary of the regression specification is shown in **Equation 4**. Estimates are based on non-additive fixed effect quantile panel models (Powell, 2014, 2022). Standard errors are clustered at the child level and shown in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

and quantile fixed effect estimates do not show any evidence that this conclusion varies by sub-group.

Given that these two approaches reach different conclusions, it is important to try to reconcile these findings. There are three potential explanations. First, as we outlined above, the FE models account for unobserved heterogeneity that takes the form of time-invariant omitted variable bias. Therefore, one explanation for the difference between coefficients in the two models is that the additional identifying assumption for the RE model (that the individual-specific intercept is uncorrelated with model covariates) does not hold. It is reasonable to suspect there may be factors that affect both human capital accumulation and household income (Hoogerheide et al., 2012; Maani and Kalb, 2007; Tamm, 2008). For example, family characteristics such as parenting beliefs may be positively associated with both. These variables are often difficult to measure and adjust for, and therefore we may prefer the FE estimates because they are robust to (one type of) omitted variable bias. If it is the case that these factors are important, it suggests the RE estimates may be biased upwards because of these omitted factors (and substantially so based on a comparison of the coefficient magnitudes in the different models). One candidate for an omitted variable is long-run wealth (the total financial resources available to a family over an extended time period, often referred to as permanent income). The RE model does not account for a potential correlation between long-run wealth and income, whereas the FE model does, at least to the extent that wealth is time invariant. From this perspective, we are unable to test the hypothesis that wealth (long run family resources) matters for children's human capital, and that it is this process that drives differences in children's test scores, rather than temporary income shocks which do not appear to have an important impact, at least in the context which we examine.

Second, the FE estimates could partially reflect measurement error. Our main independent variable of interest is income, and self-reported income is often measured with error. If this measurement error is random, we would expect coefficient estimates to be attenuated when the independent variable is affected (Hausman, 2001), and this attenuation can be substantial in fixed effect models

(McGovern, 2019). The degree of bias caused by measurement error depends on the extent to which outcomes are correlated over time and the proportion of the error term which can be explained by the time varying omitted variables as compared to the time invariant omitted variables (which would be accounted for as part of the FE model). Previous studies found that measurement error has an important impact on estimates of intergenerational mobility (Nyblom and Stuhler, 2016), and that a substantial proportion of the difference between twin estimates of the return to schooling and estimates in the general population can be accounted for by measurement error as opposed to omitted variable bias (Kohler et al., 2011). A similar issue could be arising here.

We can assess how much measurement error would be required by returning to Equation (1)—abstracting from other control variables:

$$\text{Test } z\text{-Score}_{it} = \alpha_1 \text{Log Household Income}_{it} + \varepsilon_{it}$$

when income is mismeasured and assuming errors are independent within households over time:

$$\text{Log Household Income}_{it} = \text{Log Household Income}_{it}^* + v_{ij}$$

It can be shown (e.g. Griliches, 1979; Kohler et al., 2011) that the probability limit of the FE coefficient estimate for household income (with two time periods) is given by:

$$\text{plim } \alpha_1^{FE} = \alpha_1^{1-\sigma^2(v_{ij})/\sigma^2(\text{Log Household Income}_{it}^*)(1-\rho_x)}$$

where ρ_x is the within household correlation for income for wave 1 and wave 2. Therefore, the more persistent household income is over time, the worse the measurement error problem becomes for estimating the relationship between income and test scores in a fixed effect model. In our results the coefficients are substantially smaller in the FE models than the RE models, for example, for boys maths they are around 30 percent of the RE coefficients. Assuming $\rho_x = 0.75$, this would imply a signal to noise ratio ($\frac{\sigma^2(v_{ij})}{\sigma^2(\text{Log Household Income}_{it}^*)}$) of around 0.19.

Some validation studies have been conducted for the US. For example in a widely cited paper, Bound and Krueger (1991) report reliability ratios of between 0.65 and 0.81 in first difference income data based on comparing the Current Population Survey to tax records. Without external validation data for Ireland, it is difficult to assess how much of a factor attenuation bias plays. It is also possible that the correlation in income might not be uniform across households, leading to non-random measurement error that would likely bias results in the FE models. The impact of group-specific shocks, particularly for households at the lower end of the income distribution, and how this affects the measurement error problem and self-reporting of economic status, is another important direction for research on income impacts of the recession.

However, given that we reach a similar conclusion with our alternative measure of household economic status (the reported recession impact in Table 3), it seems reasonable that measurement error may not be the only factor in explaining what are generally precisely measured negligible estimates.

Third, and finally, an alternative possibility is that negative impacts of short-run changes in income may be compensated for by positive impacts, for example, by parents spending more time at home with their children. 67 percent of households reported having had their working hours reduced because of the recession. While there was little overall difference in mother's employment from wave 1 to wave 2, father's employment dropped from 92 percent to 84 percent. However, the potential stress associated with unemployment or even reduced hours could negate any positive impacts of additional time spent with children.

Given the nature of potential omitted variable bias we are unable to definitively distinguish between these explanations for why the RE and FE results differ, but it is possible that all are operating to some extent. Overall, our results contribute to the growing literature on how and why economic deprivation and financial insecurity affect child wellbeing and educational achievement. Permanent income may be a much more important influence than transitory shocks in income, a result supported by recent literature (Aizer et al., 2016; Akee et al., 2018; Bastian and Micheltore, 2018). Recent research has emphasized that relative social position may be important for children's academic outcomes (Jerrim et al., 2021).

Caution is warranted, however, because there are limitations to this study. First, although the reading and maths scores in both waves are designed to be comparable, there may be some measurement error due to changes in how the underlying tests are designed. This should be mitigated to a certain extent because we focus on the child's rank rather than their raw score, but if there is random measurement error leading to children being assigned the incorrect ranking because of changes in the test, this will tend to increase the magnitude of standard errors (since the measurement error is then in the dependent variable), but not affect coefficients (Hausman, 2001). Second, there is attrition in this study, as not all those present in wave 1 were re-interviewed in wave 2. It is possible to account for selection on observed characteristics using multiple imputation or weighting (Solon et al., 2015), and when we estimated weighted regressions that ensure the sample remains nationally representative in both waves and allow us to adjust for data which are missing at random conditional on covariates, we found results that were almost identical to those presented above. This suggests that attrition based on observed characteristics does not affect our estimates. Unfortunately, accounting for selection based on unobservables is more problematic, and credible adjustment for this type of non-ignorable missing data generally requires the availability of a selection variable that predicts participation but is unrelated to the treatment of interest (Madden, 2008), something that is not available here. It is important to note that our heterogeneity analysis does not suggest the relationship between income and test scores varies by socioeconomic status. Nevertheless, we cannot rule out selective attrition. For example, it could be that those families whose children were most impacted by the recession were least likely to participate in the second wave, although this would likely imply that our results are underestimates. While it seems less probable that those families with children who were least affected were less likely to participate, it is a possibility. Methodological development aimed at addressing this issue, and availability of additional information on, e.g. survey metadata (McGovern et al., 2018), would be very helpful in this and other cohort studies. Third, although the FE model accounts for time-invariant unmeasured

variables, we cannot definitively rule out time-varying factors. Further data and alternative identification strategies would be required to assess whether this affects our results. Finally, some of the families interviewed toward the end of the interview period of wave 1 may have already been impacted by the recession, though this number is likely to be very small as the main impact of the recession has been documented to have started in the last quarter of 2008, at which point interviews were already completed. Unfortunately we do not have access to date of interview. Nevertheless, our subjective measure of the recession can be used to explore this to a certain extent. Households were asked to report the overall impact of the recession on them in wave 2, so we are not relying on them having been interviewed at any particular time in wave 1. In the unlikely event that a household experienced a recession shock before being interviewed in wave 1 that did not appear in the income data, we would still expect them to be correctly classified according to this subjective measure. As shown in Figure A5 in the Appendix, this subjective measure is highly predictive of experience of redundancy and changes in log income. In addition, a sensitivity analysis which removed households with inconsistent objective and subjective assessments of the recession found no difference in results.

Future work should further examine employment changes through which income shocks affect child development, such as by using the household's self-reported information and the aggregate impact by employment industry or occupation (Bono and Morando, 2021; Briody et al., 2020). This analysis would be useful for better understanding which types of economic shocks are most harmful for child development, and which families are most affected. In addition, economic shocks may have a longer time horizon than we were able to measure in these data, and future work could examine the longer-run impacts of the recession throughout adolescence.

7. CONCLUSIONS

Ireland was one of the countries most affected by the Great Recession, with falls in median household income of around 6 percent over the period 2007–2011. While fixed effect models suggest these changes in income did not affect children's test scores in the short-run, this does not rule out income being an important determinant of human capital accumulation over a longer time horizon. Although we cannot address the causal question directly in our own data because we cannot implement a strategy to estimate the impact of wealth (permanent family income), there is clear evidence that children from less well-off households do worse on measures of academic performance. This finding of an association between measures of SES and children's academic outcomes is consistent across the literature. Findings that changes in income are less important than other components of SES could potentially reflect the context studied. For example, social welfare policies in Ireland may have been successful in helping households that experienced the effects of the recession. Our results imply that responding to short-run income shocks is unlikely to be sufficient in and of itself for policy makers to address socioeconomic gradients in educational outcomes. Instead this may require directing focus to addressing the lasting effects of disadvantage throughout childhood.

COMPETING INTERESTS STATEMENT

The authors have no competing interests to declare.

ROLE OF THE FUNDING SOURCE

There was no funding source for this research.

DATA AVAILABILITY STATEMENT

The Growing Up in Ireland data is publicly available and may be requested from the Irish Social Science Data Archive: <http://www.ucd.ie/issda/data/growingupinirelandgui/>.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article at the publisher's web site:

Figure A1: Change in Equivalised Disposable Household Income in a sample of OECD Countries 2007-2011

Figure A2: Mean test scores in waves 1 and 2 by household income at baseline (categorized into higher and lower income)

Figure A3: Mean test scores in waves 1 and 2 by mother's education at baseline (categorized into higher and lower education groups)

Figure A4: Mean test scores in wave 2 by whether the household experienced a large income shock or a low/no income shock between waves

Figure A5: Changes in log income and the probability of experiencing a redundancy by subjective recession impact

Table A1: Full Results for Panel Models

Table A2: Full Results for Subjective Models