The Great Recession, Household Income, and Children's Test Scores *

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Abstract

The Great Recession had a major impact on the economic welfare of households worldwide. We examine how income changes during the recession were associated with children's educational performance in Ireland, one of the most affected countries. Using longitudinal data on standardised numerical and verbal test scores, collected before and after the height of the recession when cohort members were aged 9 and 13, we compare regression results from random effects and fixed effects models. The latter account for time invariant omitted variables that are potential common causes of both household income and academic performance. We also investigate non-linearities and effect heterogeneity using quantile regression. Log household income is correlated with reading and maths test scores in the random effects models for both girls and boys. Quantile results suggest that, for boys, those with high ability are less affected. However, in the fixed effects models the coefficients are attenuated by more than 50%. We find similar results using subjective perception of exposure to financial losses in place of household income. Overall, there is little evidence of short-run negative effects of income losses during the Great Recession on children's educational performance. In this paper we estimate the effect of transitory shocks; further data are required to isolate the impact of permanent income and any long-run impacts.

JEL Classification: *I24, I30, J10*

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1 Introduction

The Great Recession is the major economic event of recent decades. The effects of the financial crisis were widespread and included large declines in GDP and household income in many countries. These impacts 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 2007-2012 depending on the country). The impact on early life environment is an important aspect of the recession for a number of reasons, not least because of potential impacts on educational attainment. The economic costs of failure to reach developmental potential are enormous (Heckman et al., 2013), and a complete description of how the Great Recession affected household resources and wellbeing should take account of this.

There are several ways in 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 investment such as time use (Altintas, 2016; Bono et al., 2016; Kalil et al., 2012; McGovern and Rokicki, 2017; Putnam, 2016). For example, in 2010, US households in the highest income quintile spent $9,000 per young child on childcare and enrichment spending over the previous 3 months, around 9 times more than the households in the lowest income quintiles (Kornrich, 2016). Therefore, if the Great Recession resulted in lower household incomes, this could have reduced human capital investments and accumulation for affected childhood cohorts, and thus their educational performance. These differences in family background are also apparent when examining differences in child development outcomes (Anger and Schnitzlein, 2017; McCulloch and Joshi, 2002; McIntosh and Munk, 2007).

As well as direct effects on resources available for human capital investments, other mechanisms through which children are likely to have been affected by the recession include increased stress associated with financial insecurity (Aber et al., 1997; Deaton, 2012; McLoyd, 1990) and resulting psychological distress associated with increased levels of negative affect (Haushofer and Fehr, 2014). 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 has found that the recession increased behavioural problems among school children whose households were most affected

(Smyth, 2015) and negatively impacted the health of young children (Reinhard et al., 2018). Mother's psychological distress may be one of the mediators in the relationship between family income and child socio-emotional behaviour (Noonan et al., 2018).

Overall, literature reviews have suggested that the magnitude of income effects on children's cognitive development is important (Blanden and Gregg, 2004; Blow et al., 2004; Cooper and Stewart, 2017; Duncan et al., 2014). Based on these results and the evidence we have supporting the proposed mechanisms, the main research hypothesis we consider in this paper is that reductions in family income driven by the recession negatively impacted children's educational performance. The relationship between economic resources and child development is of particular policy interest given that a number of recent papers have found positive effects of welfare and transfer programmes, which operate mainly through raising household income, on children's development. These include the Earned Income Tax Credit (EITC) (Bastian and Michelmore, 2018; Dahl and Lochner, 2012), the Mothers' Pension program (Aizer et al., 2016), and a cash transfer intervention in the US (Akee et al., 2010), as well as the expansion of child tax benefits in Canada (Milligan and Stabile, 2011). However, the evidence on transitory or wealth shocks is more mixed (Aughinbaugh and Gittleman, 2003; Cesarini et al., 2016; Heckman and Mosso, 2014; Rothstein and Wozny, 2013), which is why it is important to provide further evidence on the impact of the recession.

Importantly, the effects of the Great Recession may have been heterogeneous, 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 SES 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 and persist in the long-run (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). Dynamic complementarities mean that capacity to learn at an early age can influence future trajectories (Cunha and Heckman, 2007, 2008). Inequality in early academic ability may therefore have long term consequences not just for those individuals who are affected by disadvantage, but for society as a whole because these initial differences contribute to widening the socioeconomic gradient across the life cycle (Doyle et al., 2009). Initial differences in human capital can perpetuate disadvantage through intergenerational transmission and restricted social mobility, that is, children of disadvantaged children also tend to have lower levels of human capital. As advantages accumulate for those from higher SES households, it becomes increasingly difficult for those children who grew up in households experiencing disadvantage to achieve their full developmental potential and escape from economic and social poverty (Duncan and Sojourner, 2013). In the UK, early life cognitive ability accounts for around 20% of intergenerational persistence in income (Blanden et al., 2010). Recent data support the hypothesis that recession effects were heterogeneous because human capital investments by families during this period were most affected for the least well-off; in the US the gap in spending on education between high and low income households increased by 20% over this time (Lunn and Kornrich, 2018). Therefore it is important to establish whether the Great Recession further exacerbated the already substantial SES differences in test scores (Heckman and Masterov, 2007), as this could have important effects on equality of opportunity among future generations. Based on the potential for heterogeneous recession impacts, the second research hypothesis we consider is that children living in families with the least resources were most affected by reductions in household income.

In this paper, we contribute to the literature on the effects of the crisis and determinants of human capital accumulation by examining the effect of the Great Recession and household income on educational performance. We use survey data on individual children and households to link changes in household income to performance on school tests over time, before and after the height of the recession. The Growing Up in Ireland (GUI) survey is a nationally representative longitudinal cohort study. The GUI Child Cohort recruited families of 9 year old school children in 2007/8 and interviewed them again in 2011/12 when the children were 13 years old. The data include a wide range of information collected from children, primary care-givers, and schools. Importantly for the purposes of this paper, the data are longitudinal, span the main part of the recession, contain data on the financial impact of the economic downturn (Whelan et al., 2015), and include standardised tests on reading and maths. Therefore, we are able to add to the existing literature in a number of respects. First, we examine a particularly relevant context given that the recession in Ireland represented a severe income shock observed on a mass scale over a relatively short period of time. The richness of the data, coupled with the magnitude of the recession, provides an ideal opportunity to examine research hypotheses regarding the relationship between income and children's test scores. Second, we examine these effects in nationally representative data which contain detailed information on family characteristics, including financial circumstances. Because the data contain information on the same children over time, we can account for time-invariant omitted variable bias and fixed family background characteristics, of which many are likely to be difficult to measure (Anger and Heineck, 2010; Cobb-Clark et al., 2018; Lundborg et al., 2018). While the recession was severe, it was also relatively short, meaning that we are able to evaluate the impact of a short-run shock rather than a permanent change in, say, income expectations or earning potential. Finally, the scope of our data allow us to examine potential heterogeneous recession effects, including a comparison of objective and subjective recession impacts.

1.1 Magnitude of Household Income Losses in Ireland During the Recession

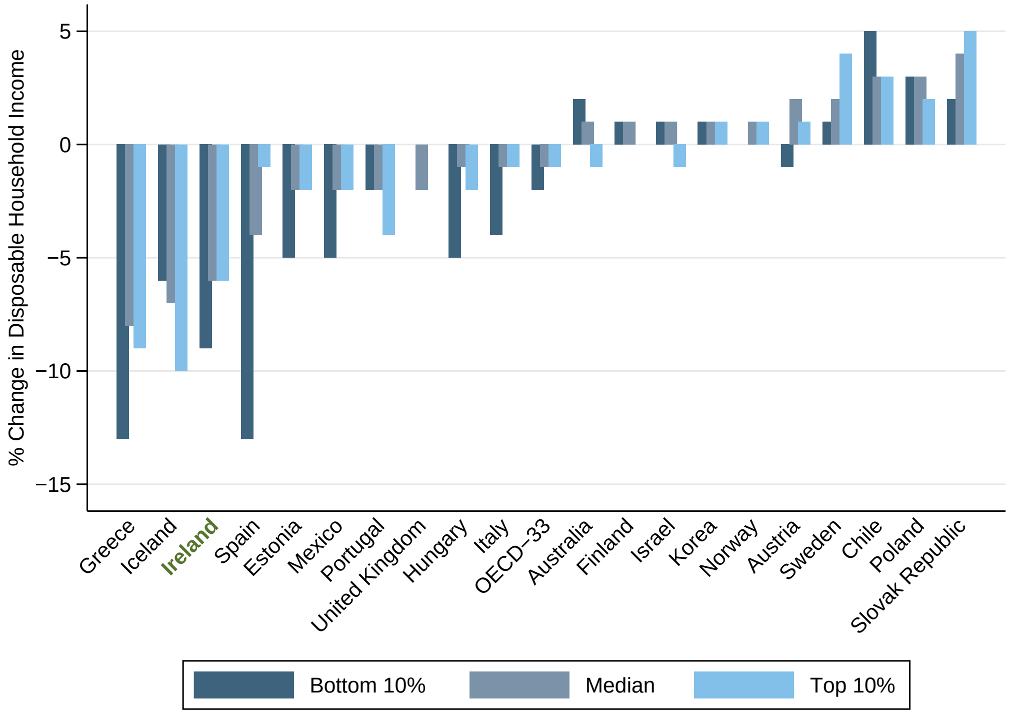
While the Great Recession had a substantial effect on many countries around the world, its impact was quite different depending on the context. For example, Canada and Australia did not experience a major change in GDP, while Ireland was one of the most affected high-income countries that experienced substantial declines in national income (a reduction of more than 30% during the period).

The magnitude of the impact of the recession in Ireland compared to other countries in the OECD group of developed countries is demonstrated in Figure 1. It shows the change in household income over the period 2007-2011. Ireland was the third most affected country after Greece and Iceland, with average declines of around 6% in income. In contrast, countries in Western Europe such as France and Germany 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 income changes at different points in the income distribution; in Ireland low 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 Figures 2 and 3, which shows the change in (log) income reported by each household between the first two waves of the GUI survey (2007/8 and 2011/12). These households are the families of the nationally representative cohort of children who were aged 9 in 2007/8. 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 3 tertiles based on their baseline (log) household income in 2007/8, and in Figure 2 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 lower tertile experienced a substantial decline in income during this period.

We also calculated the change in (log) income from wave 1 to wave 2 categorised into 3 quartiles based on whether the household experienced a large loss, little to no change, or a large gain. Figure 3 shows that

Figure 1: Change in Equivalised Disposable Household Income in a sample of OECD Countries 2007-2011

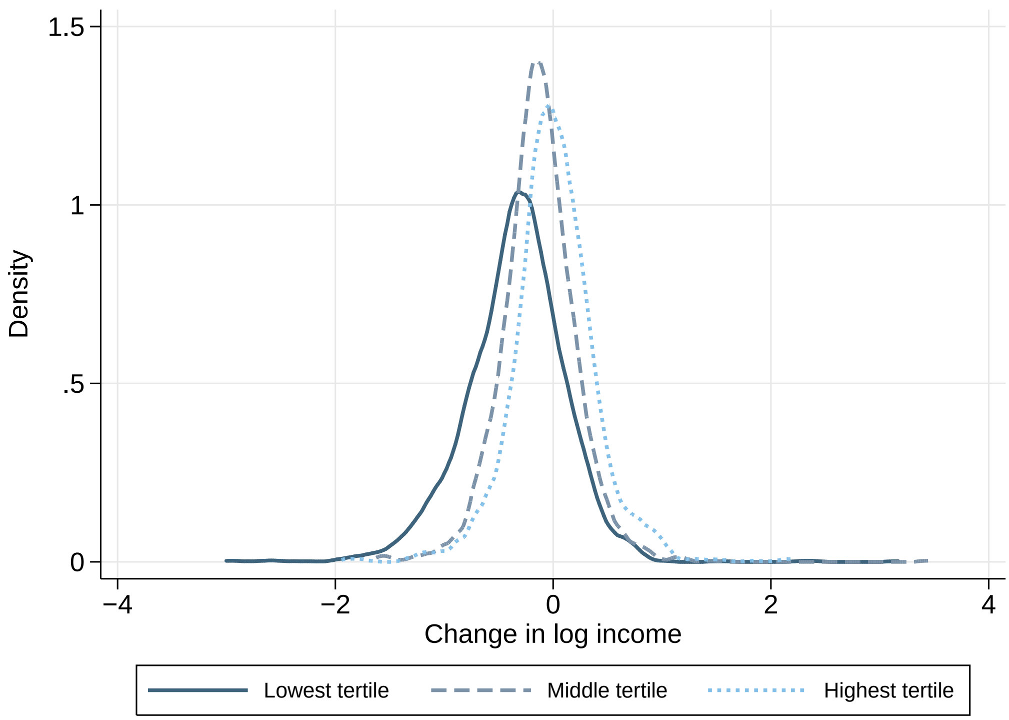


Note: Data are from OECD (2014). Selected OECD countries are the top 10 and bottom 10 in terms of average percentage change, and the OECD average. Countries are sorted by average loss, but also show the change among the top ten percent and bottom ten percent of households.

amongst the least well-off tertile at baseline, 50% experienced a large loss in income. Amongst the most well-off tertile, only 15% experienced a large loss in income. Interestingly, a substantial proportion of households still experienced a large increase over the time period, particularly among the most well-off group (53%). This again highlights the importance of taking potentially heterogeneous effects into account in the analysis.

Finally, in Figure 4, the recession impact is also evident in additional (non-income based) measures. We show, again by baseline household income tertile, the reported experience of adverse economic events between waves 1 and 2 of the GUI 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 basics, 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% of those in the lowest income tertile at baseline reported a redundancy, compared to 12% in the highest income tertile. However, those in the middle and highest income group were more likely to report that their hours were reduced compared to the lowest income group. Overall, both the 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.

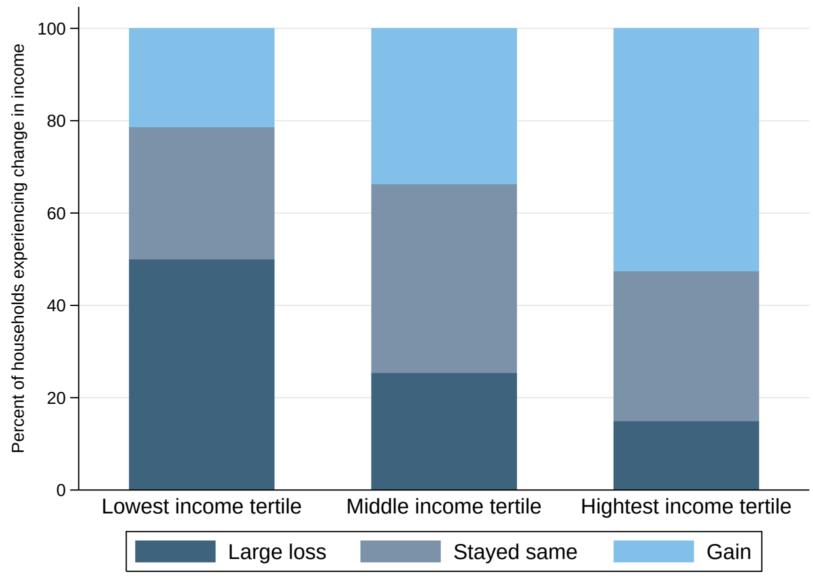
Figure 2: Distribution of Changes in Log Equivalised Household Income Stratified by Baseline Log Equivalised Household Income Tertile



Note: Data are from the Growing up in Ireland child cohort waves 1 (2007/8) and 2 (2011/12).

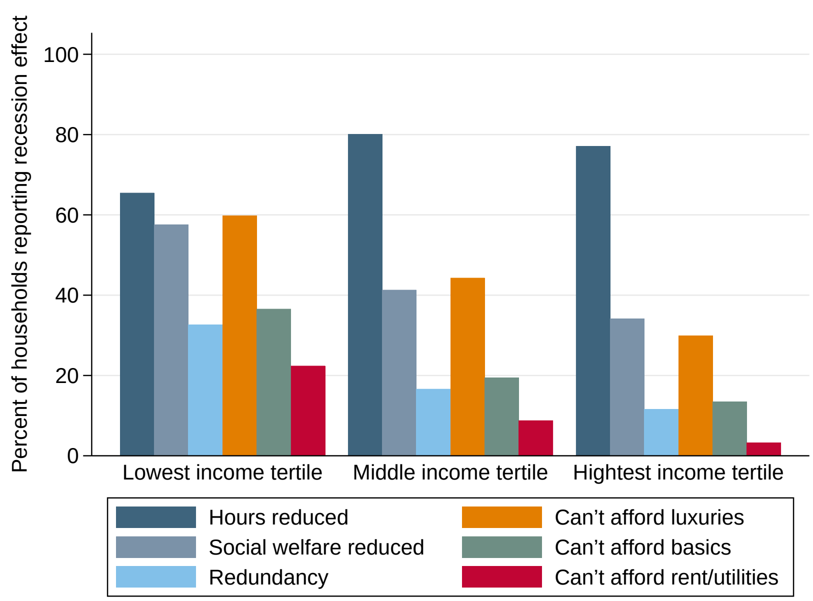
The rest of this paper is structured as follows. In the next section we provide a brief summary of the existing literature. In Section 3, we describe the data and methods we adopt, and in particular our approach to accounting for both observed and unobserved heterogeneity. The main comparison will be between random and fixed effects panel models, using both linear and quantile regression. Our main exposure will be changes in household income over time, but we also compare these results to the impact of subjective reports of exposure to recession effects. We present our results in Section 4 and discuss their interpretation in Section 5, while Section 6 concludes with an overview of potential policy implications of this research.

Figure 3: Categories of Changes in Log Equivalised Household Income Stratified by Baseline Log Equivalised Household Income Tertile



Note: Data are from the Growing up in Ireland child cohort waves 1 (2007/8) and 2 (2011/12).

Figure 4: Additional Recession Effects Stratified by Baseline Log Equivalised Household Income Tertile



Note: Data are from the Growing up in Ireland child cohort wave 2 (2011/12).

2 Literature review

A large literature in public health, education, psychology and economics has explored the relationship between income and financial security and measures of child behaviour, 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, 2018), within family comparisons (Blau, 1999), randomisation in the form of lotteries (Lindahl, 2005), and natural experiments (Duncan and Sojourner, 2013). Much of this literature is US-focused.

Studies tend to explore two mechanisms through which income affects children's cognitive and health outcomes. The first is the family stress model, the idea that economically disadvantaged households experience psychological distress as a result of the economic pressures they face, which may lead to depressive and hostile feelings and adversely affect parenting behaviour (Duncan et al., 2014). Neurologically, prolonged stress may interfere with children's executive functioning and development (Thompson, 2014). Aber et al. (1997) conducted a literature review on the effects of poverty and financial stress on children's health and cognitive outcomes; they find that poverty affects child development through increased emotional stress, poor parental behaviours (a tendency to be less nurturing and more punitive in the face of stress), and family processes such as divorce.

The second mechanism is through resource constraints, which reduce capacity for parental investments (such as educational, nutritional, and time investments) in children. Levy and Duncan (2000) use a sibling model to eliminate omitted variable bias caused by fixed family differences; they find that family income during childhood has positive effects on children's educational attainment, particularly for children ages 0-4. Children from farming households and those with more access to nutrition programs were more protected, lending credibility to the theory of nutrition as a mechanism. Other studies provide more evidence of the importance of nutrition. Hoynes et al. (2016) exploit the staggered roll out of the Food Stamp program to examine how increases in household income in early childhood affect adult health and economic outcomes, finding that access to food stamps in childhood leads to significant reductions in adult health conditions including obesity, high blood pressure, heart disease, and diabetes, and increases in women's economic self-sufficiency. In a systematic review on the impacts of the Great Recession, Rajmil et al. (2014) find an adverse effect of the crisis on food intake by children, including less fruit and vegetables, fewer and lower quality meals, and intake of cheaper food. Finally, Aughinbaugh and Gittleman (2003) use data from both the US and the UK to examine differences in the relationship between income and child outcomes in varying economic policy contexts; they find that for both nations the results are very similar a small, but significant association with test scores and behavioral problems and they find evidence that financial resources may be the more important pathway compared to family stress.

A number of studies in the economics literature have attempted to identify causal effects of permanent versus transitory income shocks on child outcomes. Bastian and Michelmore (2018) exploit expansions in the US Earned Income Tax Credit over four decades and find that an additional \$1000 in tax credits when a child is 13-18 years old increases the likelihood of completing high school and college, being employed as a young adult, and increases earnings. They attribute these effects to an increase in maternal labour supply, a contributor to permanent income. Duncan et al. (2011) analyse a set of welfare and antipoverty experiments conducted in the 1990s, applying an instrumental variables approach to leverage variation in income on child achievement. They find that a \$1000 increase in annual income increases young children's achievement scores by 5-6% of a standard deviation. Duflo (2000) uses a difference-in-differences design to estimate the effect of an increase in the old age pension to black South Africans on grandchildren's height-for-age, finding a large effect for income 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).

Other results on transitory income are mixed. Akee et al. (2010) use quasi-experimental methods by exploiting the 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 players, and find no effects for most outcomes. As with Humlum (2011), they attribute these findings to Sweden's extensive social safety net. 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. Blau (1999) uses longitudinal data from the US and applies fixed-effect and random-effects models to estimate the impact of income on cognitive and development outcomes, finding that the effect of current income is small, while the effect of permanent income is substantially larger.

Finally, the literature has found evidence of non-linearity in the impact of income on children's outcomes.

Recent work examines the impact of the Mother's Pension program, comparing the adult children of mothers who received cash transfers from the program to adult children of mothers who applied but were rejected, finding that the cash transfers increased children's longevity by about 1 year, and children obtained a third more years of schooling, were less likely to be underweight, and had higher incomes in adulthood. Moreover, they find that the program had 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 effects of income on test scores, maternal health, and mental health. In particular, they find effects differ by gender, and that benefits to the least educated families drive the results. Using longitudinal data and a quasi-experimental design, Akee et al. (2018) also find large beneficial effects of income transfers on children's emotional and behaviour health and on parental relationships, which are most pronounced for the poorest children.

Two reviews of early literature concluded that while there appear to be small causal effects of permanent income over a range of child outcomes, the effects are probably too small to make income transfers to low-income households a sensible approach to generating large changes in outcomes for children (Blanden and Gregg, 2004; Blow et al., 2004). Another review of theory and literature by Heckman and Mosso (2014) concludes that the role of income in reducing credit constraints and shaping child development are not as important as parenting and mentoring. However, a more recent report published in 2017, which covered 61 studies using causal inference methods, including 6 randomised controlled trials, 33 quasi-experiments, and 22 observational studies, finds positive effects of income on children's cognitive and socio-behavioural outcomes (Cooper and Stewart, 2017). The effects are small, though non-negligible, and are comparable to effect sizes from other types of interventions. They also find further support for both mechanisms of nutrition and financial stress, as well as new evidence that income may reduce child abuse and neglect. Finally, they find that income effects are likely to be non-linear, with greater effects at the bottom of the income distribution.

Our analysis fits into this literature in the sense that we are able to compare estimates of short-run associations with both permanent income and transitory income changes, as well as the importance of transitory changes across the permanent income distribution.

3 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 (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 2007/8. Both cohorts were then subsequently followed up on longitudinally. We focus on the 1998 cohort, as these children participated in standardised 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 major shocks of the recession hit in Ireland in 2008, and the second wave corresponding to after the deepest point of the recession, before any growth in employment was evident (Watson et al., 2014; Whelan et al., 2015).

In addition to standardised tests conducted in both waves, the 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, but information was also collected on the subjective impact of the recession on families. Therefore, we are able to compare both objective and subjective recession effects. In addition, when we investigate how the recession affected children's educational attainment, we are able to adjust for a wide range of background characteristics which might otherwise be a common cause of both our outcome and our exposure.

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 causal effects (Deaton, 1997; Solon et al., 2015). Nevertheless, we have verified that results are not sensitive to including weights in the regression analysis.

Table 1: Descriptive Statistics for Waves 1 and 2

	Wave 1 (2007/8)	**Wave 2 (2011/12)**
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

Note: Data are from the Growing up in Ireland child cohort waves 1 (2007/8) and 2 (2011/12). Father's employment is only known for fathers in the household. Descriptive statistics are weighted.

As shown in Table 1, mean equivalised (adjusted for composition) household income was €19,352, or 9.7 in logs (corresponding medians were €14,000 and or 9.5). These data refer to 2007/8, before the main impact of the recession. Collected demographic characteristics include parental marital status, education, age, and employment, as well as household size, and place of residence (urban or rural). Overall, 41% of children have mothers with more than secondary qualifications, 31% have fathers with more than secondary qualifications, 50% have mothers aged 39 or less, and 56% live in rural areas. 61% of families reported that the recession had a significant or very significant impact on them. This supports our view that Ireland is an ideal location to study these income and recession effects on children.

The data also contain information on assessments of maths and reading ability. These tests were administered to study children in both waves as part of the interviews, under controlled conditions (Thornton et al., 2016). Therefore, they represent objective 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, standardised 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. In fact, the outcomes reported in the data are already standardised 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.

There are important features of income as a main independent variable. It can be objectively measured 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 can operate through a number of 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 an alternative measure; 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.

To summarise 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 and also stratify all our models by gender, allowing for differential impacts on girls and boys, as previous research (Cobb-Clark and Moschion, 2017; Humlum et al., 2018), including using the GUI survey (McGovern, 2013), suggests potentially different human capital formation processes for each. We consider two measures of exposure, household income and subjective reports of how the recession impacted on the family. Throughout this part of the analysis, we use log equivalised household income to allow for diminishing returns but consider additional non-linearities as part of sensitivity analyses. We model test scores as a function of these two sets of predictors (objective and subjective), while adjusting for the other demographic characteristics shown in Table 1. With household income as the exposure, our main regression model is then as follows:

$$\text{Test z-score}_{it} = \alpha_1 \text{Log Household Income}_{it} + X_{it}\beta_1 + Z_i\delta_1 + \epsilon_{it} \tag{1}$$

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 (mother's age, mother's employment, and region) for which we do not include the values at time $t = 2$ as they may be outcomes of income. β_1 and δ_1 are the relevant parameter vectors. ϵ_{it} is an idiosyncratic error term, which in the RE model is assumed to be normally distributed. The FE model is based on first differences (which with $t = 2$ is equivalent to the de-meaning transformation). α_1 is the coefficient of interest.

For the models that use subjective recession experience as the exposure ("What effect did the recession have on your family?" with the responses ranging from "No effect at all" to "A very significant effect"), we need to modify our empirical strategy slightly because the question of interest was only asked in wave 2 of the survey. For the FE specification shown in Equation 1, we can estimate a comparable model by taking 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):

$$\Delta\text{Test z score}_i = \alpha_2 \text{RessionExp}_i + X_{i,t=2007/8}\beta_2 + Z_i\delta_2 + \eta_i \tag{2}$$

α_2 is the coefficient of interest. For the equivalent of the RE approach in Equation 1, we can estimate a comparable model by using the outcome in wave 2 ($t = 2011/12$) and all control variables at baseline ($t = 2007/8$). This model can be summarised as follows:

$$\text{Test z score}_{i,t=2011/12} = \alpha_3 \text{RessionExp}_i + X_{i,t=2007/8}\beta_3 + Z_i\delta_3 + \mu_i \tag{3}$$

For the heterogeneity analysis, we consider two extensions. First, we examine non-linearity in the impact of income. For example, it is reasonable to imagine 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. To this end, we implement models where the outcome is test z-scores in 2011/12 in which we interact the change in income (from wave 1 to wave 2) with tertiles of baseline income (in wave 1):

$$\Delta\text{Test z score}_i = \alpha_4 \text{RessionExp}_i + X_{i,t=2007/8}\beta_4 + Z_i\delta_4 + e_{it} \tag{4}$$

Second, we consider whether the income effects 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 which allow us to examine income effects 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, 2016), which allows us to account for unobserved heterogeneity while still focusing on the unconditional quantiles. The structural quantile function (SQF) for this model can be summarised as follows:

$$\text{Test z-score}_{it} = \phi_i(\tau) + \alpha_5(\tau)\text{Log Household Income}_{it} + X_{it}\beta_5(\tau) + Z_i\delta_4(\tau) + u_{it} \tag{5}$$

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.

The results of these analyses are presented in the next Section 4.

4 Results

4.1 Panel Results for Income

We begin in Table 2 by presenting results for maths and reading scores from panel models based on the regression specification in Equation 1, with log household income as the recession measure. The first panel is for reading, while the second panel is for maths. Columns 1 and 2 show results for girls, while columns 3 and 4 are for boys. In terms of the empirical approach, columns 1 and 3 show results from random effects models, while columns 2 and 4 implement fixed effects 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 effect 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% increase in household income raises test scores by 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.

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***	0.0349	0.157***	0.00727
	(0.0228)	(0.0296)	(0.0249)	(0.0350)
	Panel B: Maths Test Score			
Log Income	0.101***	-0.0625*	0.174***	0.0505
	(0.0232)	(0.0363)	(0.0258)	(0.0381)
Control variables	Y	Y	Y	Y
Observations	7,351	7,351	6,942	6,942

Clustered standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: All regressions include control variables, although only the coefficient on the main independent variable is shown. 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 in parentheses.

Although the coefficient for girls' maths score is negative and marginally significant, at .06 standard deviations, it does not provide evidence of a strong income effect. 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 educational achievement. Coefficients on control variables shown in the Appendix are in line with expectations and previous research.

Table 3: Subjective Recession Impact and Children's Test Scores

	Girls		Boys	
	OLS Levels	OLS Changes	OLS Levels	OLS Changes
	Panel A: Reading Test Score			
Very significant effect	-0.164**	0.0169	-0.139**	-0.0658
	(0.0688)	(0.0561)	(0.0656)	(0.0672)
Significant effect	0.00467	0.0241	-0.0684	-0.0140
	(0.0644)	(0.0526)	(0.0619)	(0.0636)
Small effect	0.00195	0.000559	-0.114*	-0.0450
	(0.0650)	(0.0531)	(0.0626)	(0.0644)
No effect (omitted)	–	–	–	–
	Panel B: Maths Test Score			
Very significant effect	-0.111*	0.0848	-0.218***	-0.00981
	(0.0667)	(0.0686)	(0.0714)	(0.0676)
Significant effect	-0.0191	0.0477	-0.112*	0.00947
	(0.0637)	(0.0633)	(0.0671)	(0.0634)
Small effect	0.0395	0.0521	-0.0662	0.0460
	(0.0647)	(0.0645)	(0.0677)	(0.0643)
No effect (omitted)	–	–	–	–
Control variables	Y	Y	Y	Y
Observations	3,352	3,118	3,210	2,965

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Levels and changes refers to covariates and outcomes in models. A summary of the regression specification is shown in Equation 2 (Changes) and Equation 3 (Levels). All regressions include control variables, although only the coefficient on the main independent variable is shown. The full table is presented in the Appendix. Standard errors are clustered at the child level and shown in parentheses.

4.2 Panel Results for Subjective Recession Impact

Table 3 presents results from corresponding models with subjective measures of recession impact as the main independent variable. The omitted category is that the recession had no impact on the household. Estimates are comparable to those in Table 2 in that the models in levels (which correspond to the RE specification in the income analysis) suggest substantial recession impacts for both reading and maths, and for both boys and girls. For example, girls from families who reported a very significant recession effect scored .164 standard deviations less on reading scores than families who reported no recession effects. Also as with Table 2, the models in changes (which correspond to the FE specification in the income analysis) do not suggest the recession had a substantial effect.

4.3 Results for Heterogeneous Income Impacts

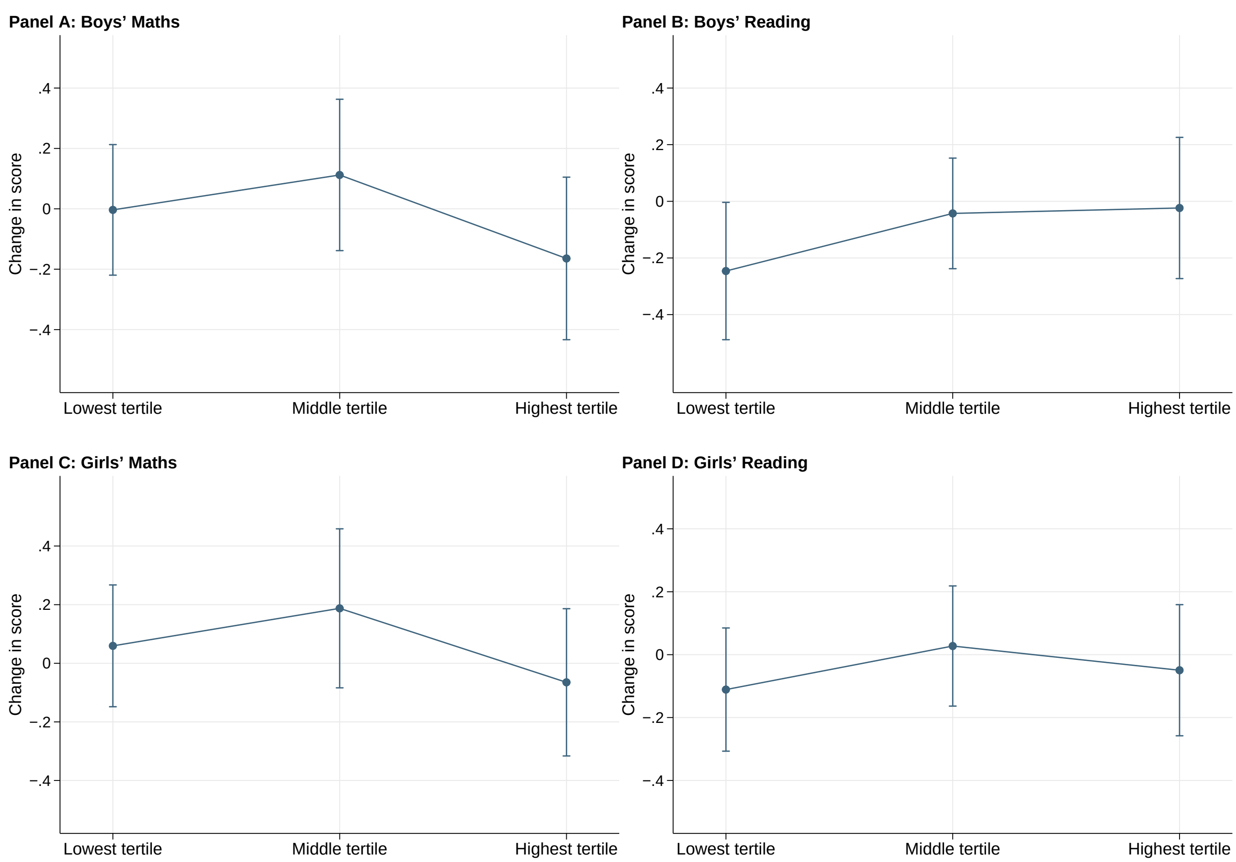
Next, we consider heterogeneity in the recession impact. First, we examine whether there is a non-linear relationship between income and test scores. Our models thus far have considered log income, which acknowledges diminishing returns, but nevertheless imposes log-linearity, assuming constant proportional effects. We investigated whether there were asymmetries (income losses being different from income gains) or polynomial-type income effects, but were unable to identify evidence that these were present. Therefore, in the following analysis we focus on establishing whether income effects may have differed by family. We implemented models where we interacted subjective assessments of how the recession impacted on households with baseline income. This allows us to investigate whether, for example, a negative income shock had a more detrimental effect on families who were already struggling financially.

Better-off households could 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% of their income came from social welfare increased from 13% to 19% over the two waves. Beliefs about how best to invest in response to shocks could also differ by family background (Restrepo, 2016). We consider the change in maths and reading test scores for three tertiles of household income at baseline (in wave 1 at $t = 2007/8$), 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 effects in Figure 5. 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% level). The magnitude 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.

Next we turn to examine whether there is heterogeneity by child, specifically whether children of varying ability are differentially affected by the recession. This could arise, if, for example, children with lower ability required a higher level of investment to attain the same achievement level, and were 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).

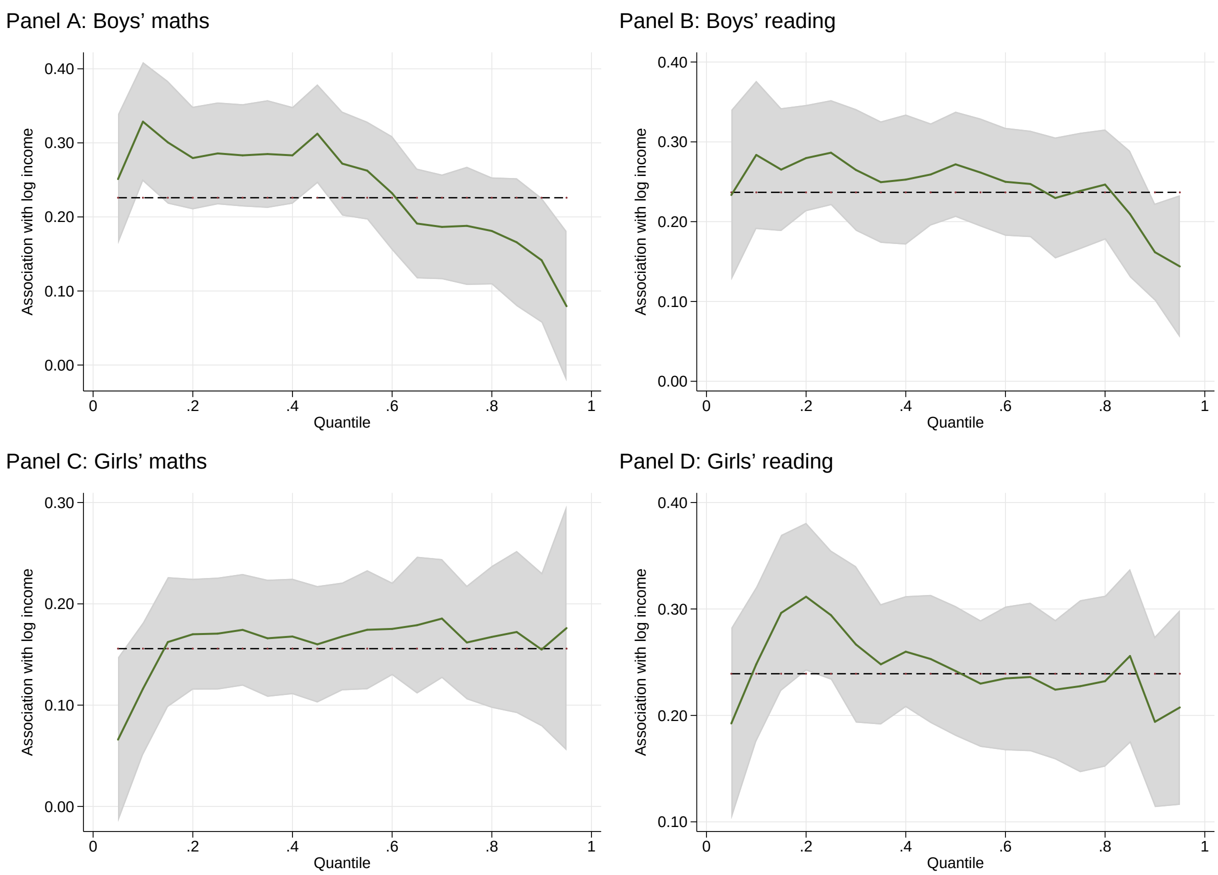
Figure 5: Subjective Recession Effects by Baseline Income for Boys' and Girls' Reading and Maths Scores



Note: 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.

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. The pooled quantile estimates (with standard errors clustered by child (Parente and Santos Silva, 2016)) are shown in Figure 6. 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 high ability, especially for maths.

Figure 6: Pooled Quantile Results



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 effects are included in the model. Therefore, we implement the approach suggested by Powell (2014, 2016), 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.

Table 4: Quantile Fixed Effects Regression Results

Variable	Girls 25th Percentile	Girls Median	Girls 75th Percentile	Boys 25th Percentile	Boys Median	Boys 75th Percentile
	Reading					
Log Household Income	0.0158	0.0519	0.0991	0.0454	0.0740	0.0453
	(0.0650)	(0.0583)	(0.0633)	(0.0685)	(0.0840)	(0.213)
	Maths					
Log Household Income	-0.0217	-0.00971	-0.0211	0.0538	0.0895	0.0152
	(0.0655)	(0.0989)	(0.0813)	(0.0756)	(2.193)	(0.0776)
Control variables	Y	Y	Y	Y	Y	Y
Observations	7,351	7,351	7,351	6,942	6,942	6,942

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All regressions include control variables, although only the coefficient on the main independent variable is shown. A summary of the regression specification is shown in Equation 5. Estimates are based on non-additive fixed effect quantile panel models (Powell 2014, 2016). Standard errors are clustered at the child level and shown in in parentheses.

These (non-additive) FE quantile panel results are shown in Table 4.There is no evidence of an income effect at any point in the ability distribution, neither for boys nor girls, and neither for reading nor maths The magnitude of the coefficients is relatively small compared to pooled effect sizes of up to 0.3 standard deviations, and are not statistically significant at any quantile in the distribution. As with the OLS panel models, there is a clear discrepancy between pooled and FE estimates. We consider the interpretation of these differences in the following Section 5.

5 Discussion

Overall, our results suggest a clear pattern. For boys and girls, and for maths and reading, pooled and RE models indicate a significant and relatively large association between both income changes and subjective assessment of recession impact and children's test scores. There is little evidence of non-linearities or heterogeneity by ability, except perhaps some indication that boys from low income households are most affected by the recession (in terms of reading), and some indication that boys with high ability are least affected. However, further data would be required to assess this heterogeneity conclusively. The RE and pooled models would therefore suggest that household income has an important effect on children's human capital accumulation. In contrast, FE models consistently show negligible and non-significant effect sizes for income and subjective recession effects. Analysis of changes in income 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 and time-invariant omitted variable bias. It is reasonable to suspect there may be factors that affect both human capital accumulation and household income. 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 effect sizes in the different models).

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 expected coefficient estimates to be attenuated when the independent variable is affected (Hausman, 2001). It could seem that the reduction in the coefficient is too large to have been caused by measurement error, however in fact this attenuation can be substantial in fixed effect models (McGovern, 2018). 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 (Nybom and Stuhler, 2016), and that much of the difference between estimates of the return to schooling among twins could have been driven 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:

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

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:

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

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% of the RE coefficients. Assuming $\rho_x = 0.75$, this would imply a signal to noise ratio $\frac{1-\sigma^2_{v_{ij}}}{\sigma^2_{\text{Log Household Income}^*_{ij}}}$ 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. However, given that we reach a similar conclusion with our alternative measure of household economic status (the reported recession effect 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, coefficient estimates could reflect differences in the underlying quantities the two models are estimating. The pooled RE model involves the level of (log) income, whereas in a two period model the FE estimates are equivalent to a regression with changes in income (this will not hold with more than two periods).

Therefore they are capturing two very different processes, one short-run and the other long-run. The RE model is more likely to capture permanent income (seeing as we expect the level of income to be serially correlated over time), whereas the FE model relies on transitory shocks to income as measured by income changes. Therefore, the two models can also be seen in terms of permanent income versus transitory income shocks. From this perspective, and in the absence of omitted variable bias affecting the former, our results suggest that long run family income matters greatly for children's human capital, and it is this process that drives differences in children's test scores, rather than temporary income shocks which do not appear to have important effects, at least in the context which we examine. However, the similarity between objective and subjective results would again suggest this may not be the only explanation.

Fourth, and finally, an alternative possibility is that negative effects of short-run changes in income may be compensated for by positive effects, for example, by parents spending more time at home with their children (Felfe et al., 2015; Hallberg and Klevmarken, 2003; Verropoulou and Joshi, 2009). 67% of households reported having had their 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% to 84%. However, it seems likely that the potential stress associated with unemployment or even reduced hours could negate any positive effects 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 likely 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 Michelmore, 2018).

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 some attrition in this study, as not all those present in wave 1 were re-interviewed in wave 2. We assessed this possibility using survey weights, and results were not affected. However, weighting generally cannot account for data which are not missing at random. Finally, although the FE model accounts for time-invariant unmeasured variables, we cannot definitively rule out time-varying factors. Further data would be required to assess whether this affects our results.

6 Conclusions

Ireland was one of the countries most affected by the Great Recession, with falls in median household income of around 6% 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 effect of permanent family income, there is clear evidence that children from less well-off households do worse on measures of academic performance. This is a consistent finding across the literature. In the Irish context, we found evidence that changes in income are much less important than measures of permanent income, although the lack of short-run impact could potentially reflect the context studied. For example, because social welfare policies in Ireland may have been successful in helping households which experienced the effects of the recession. Our results imply that governments and policy makers should direct their focus to combatting the lasting effects of disadvantage throughout childhood. Responding to specific income shocks is unlikely to be sufficient in and of itself to address socioeconomic gradients in educational outcomes.

Compliance with Ethical Standards

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Appendix

Table A1: Full Results for Panel Models

Variables	Panel Random Effects	Panel Fixed Effects	Panel Random Effects	Panel Fixed Effects	Panel Random Effects	Panel Fixed Effects	Panel Random Effects	Panel Fixed Effects
	Reading Test Score				Maths Test Score			
	Females	Females	Males	Males	Females	Females	Males	Males
Log Household Income	0.164***	0.0349	0.157***	0.00727	0.101***	-0.0625*	0.174***	0.0505
	(0.0228)	(0.0296)	(0.0249)	(0.0350)	(0.0232)	(0.0363)	(0.0258)	(0.0381)
Wave 2	-0.295***	-0.300***	-0.0910***	-0.113***	0.526***	0.513***	0.670***	0.662***
	(0.0138)	(0.0150)	(0.0153)	(0.0170)	(0.0160)	(0.0184)	(0.0161)	(0.0180)
Mother's Marital Status (Omitted=Not Married)								
Married	-0.406	-0.295	0.250***	0.802***	0.453	0.821***	0.259***	0.850***
	(0.272)	(0.419)	(0.0728)	(0.0845)	(0.289)	(0.109)	(0.0803)	(0.0889)
Not in household	-0.168	-0.235	0.407**	0.838***	0.700*	0.883***	0.763***	1.123***
	(0.334)	(0.460)	(0.173)	(0.240)	(0.367)	(0.236)	(0.245)	(0.334)
Mother's Education (Omitted=Less than Secondary)								
Secondary	0.206***	0.00180	0.165***	0.132*	0.248***	0.0711	0.241***	0.0485
	(0.0351)	(0.0600)	(0.0399)	(0.0696)	(0.0331)	(0.0713)	(0.0391)	(0.0730)
More than secondary	0.382***	0.00588	0.349***	0.0321	0.385***	0.00130	0.371***	-0.00905
	(0.0372)	(0.0767)	(0.0417)	(0.0911)	(0.0347)	(0.0981)	(0.0411)	(0.0991)
Missing	0.224	-0.152	0.163	0.159	0.0705	0.0351	0.0686	0.0492
	(0.199)	(0.241)	(0.154)	(0.224)	(0.174)	(0.299)	(0.302)	(0.401)
Father's Education (Omitted=Less than Secondary)								
Secondary	0.198***	0.0722	0.172***	0.00924	0.115***	-0.0681	0.187***	-0.00153
	(0.0319)	(0.0480)	(0.0363)	(0.0582)	(0.0313)	(0.0551)	(0.0367)	(0.0612)
More than secondary	0.258***	0.0269	0.275***	0.0294	0.175***	0.0358	0.261***	-0.0434
	(0.0331)	(0.0570)	(0.0376)	(0.0758)	(0.0320)	(0.0683)	(0.0367)	(0.0755)
Not in household	-0.368	-0.320	0.387***	0.803***	0.498*	0.840***	0.406***	0.860***
	(0.267)	(0.415)	(0.0555)	(0.0787)	(0.285)	(0.0860)	(0.0552)	(0.0726)
Missing	0.0290	-0.0328	0.160***	0.0571	-0.0112	-0.0496	0.126***	-0.00293
	(0.0367)	(0.0481)	(0.0482)	(0.0721)	(0.0403)	(0.0624)	(0.0463)	(0.0668)
Mother's Employment at Baseline (Omitted=Not Employed)								
Employed	0.00406		0.0226		0.0123		0.0565**	
	(0.0275)		(0.0279)		(0.0244)		(0.0279)	
Not in household	-0.0312		-0.138		0.152		-0.259	
	(0.258)		(0.243)		(0.260)		(0.309)	
Father's Employment at Baseline (Omitted=Not Employed)								
Employed	0.126**		0.0728		0.104**		0.112**	
	(0.0548)		(0.0553)		(0.0479)		(0.0515)	
Not in household	0.0801		-0.0362		-0.0205		-0.0635	
	(0.0809)		(0.0808)		(0.0726)		(0.0859)	
Mother's Age at Baseline (Omitted=<40)								
40-49	0.213***		0.238***		0.179***		0.196***	
	(0.0262)		(0.0270)		(0.0230)		(0.0269)	
50 and over	0.427***		0.232***		0.186**		0.163**	
	(0.0871)		(0.0802)		(0.0850)		(0.0718)	
Missing	0.313				0.608***			
	(0.203)				(0.174)			
Household Size (Omitted=2)								
3	-0.163**	-0.0498	-0.102	-0.200*	-0.129	-0.0246	-0.0588	-0.145
	(0.0798)	(0.118)	(0.0794)	(0.120)	(0.0795)	(0.136)	(0.0831)	(0.147)
4	-0.137*	-0.0176	-0.120	-0.195	-0.0490	0.121	-0.0458	-0.124
	(0.0823)	(0.131)	(0.0826)	(0.132)	(0.0794)	(0.152)	(0.0834)	(0.146)
5	-0.155*	-0.108	-0.123	-0.231	-0.0438	0.0818	0.0114	-0.0404
	(0.0846)	(0.141)	(0.0857)	(0.143)	(0.0812)	(0.165)	(0.0852)	(0.151)
6	-0.227***	-0.146	-0.166*	-0.269*	-0.0483	0.122	0.0971	0.147
	(0.0880)	(0.149)	(0.0890)	(0.152)	(0.0837)	(0.171)	(0.0885)	(0.162)
7	-0.258***	-0.0115	-0.260***	-0.223	-0.0697	0.198	0.00371	0.0949
	(0.0938)	(0.164)	(0.0957)	(0.173)	(0.0906)	(0.196)	(0.0949)	(0.178)
Rural Region	-0.0130		-0.0655**		0.0103		-0.0309	
	(0.0259)		(0.0265)		(0.0228)		(0.0266)	
Constant	-1.491***	0.183	-2.099***	-0.570	-2.646***	-1.014**	-3.198***	-1.867***
	(0.367)	(0.531)	(0.266)	(0.390)	(0.371)	(0.401)	(0.275)	(0.416)
Observations	7,351	7,351	6,942	6,942	7,351	7,351	6,942	6,942
R-squared		0.155		0.023		0.265		0.376

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2: Full Results for Subjective Models

	OLS Levels	OLS Changes	OLS Levels	OLS Changes	OLS Levels	OLS Changes	OLS Levels	OLS Changes
	Reading Test Score				Maths Test Score			
Variables	Girls	Girls	Boys	Boys	Girls	Girls	Boys	Boys
Subjective Effect of Recession (Omitted=No Effect)								
Very significant effect on family	-0.164**	0.0169	-0.139**	-0.0658	-0.111*	0.0848	-0.218***	-0.00981
	(0.0688)	(0.0561)	(0.0656)	(0.0672)	(0.0667)	(0.0686)	(0.0714)	(0.0676)
Significant effect on family	0.00467	0.0241	-0.0684	-0.0140	-0.0191	0.0477	-0.112*	0.00947
	(0.0644)	(0.0526)	(0.0619)	(0.0636)	(0.0637)	(0.0633)	(0.0671)	(0.0634)
Small effect on family	0.00195	0.000559	-0.114*	-0.0450	0.0395	0.0521	-0.0662	0.0460
	(0.0650)	(0.0531)	(0.0626)	(0.0644)	(0.0647)	(0.0645)	(0.0677)	(0.0643)
Mother's Marital Status (Omitted=Not Married)								
Married	-0.443*	0.000441	-0.520***	0.00529	0.251	0.0602	-0.241*	0.0556
	(0.238)	(0.0582)	(0.134)	(0.0687)	(0.439)	(0.0662)	(0.136)	(0.0773)
Not in household	-0.411	0.0886	-0.563**	0.0561	0.454	0.315	0.224	0.0434
	(0.329)	(0.171)	(0.243)	(0.202)	(0.488)	(0.241)	(0.242)	(0.245)
Mother's Education (Omitted=Less than Secondary)								
Secondary	0.285***	-0.000325	0.131**	-0.0626	0.234***	-0.0284	0.262***	-0.0569
	(0.0513)	(0.0410)	(0.0524)	(0.0487)	(0.0464)	(0.0478)	(0.0573)	(0.0524)
More than secondary	0.569***	0.0714*	0.350***	-0.0635	0.457***	0.0641	0.459***	0.0112
	(0.0514)	(0.0418)	(0.0519)	(0.0488)	(0.0462)	(0.0491)	(0.0570)	(0.0515)
Missing	0.275	0.0821	-0.366	-0.375	0.130	0.491**	-0.375	-0.400**
	(0.229)	(0.306)	(0.229)	(0.238)	(0.207)	(0.243)	(0.321)	(0.202)
Father's Education (Omitted=Less than Secondary)								
Secondary	0.210***	-0.0197	0.184***	-0.0517	0.129***	0.0327	0.168***	-0.0606
	(0.0494)	(0.0392)	(0.0481)	(0.0443)	(0.0472)	(0.0454)	(0.0529)	(0.0482)
More than secondary	0.346***	0.0234	0.356***	-0.0219	0.191***	0.0146	0.349***	0.0356
	(0.0468)	(0.0384)	(0.0463)	(0.0429)	(0.0457)	(0.0457)	(0.0507)	(0.0457)
Not in household	-0.519**		-0.515***		0.230		-0.215*	
	(0.231)		(0.122)		(0.436)		(0.119)	
Missing	0.0106	0.0594	0.103*	-0.0302	-0.0459	0.0232	0.0887	-0.0391
	(0.0590)	(0.0660)	(0.0623)	(0.0898)	(0.0578)	(0.0815)	(0.0675)	(0.0858)
Mother's Employment at Baseline (Omitted=Not Employed)								
Employed	-0.0151	0.00923	0.0111	-0.0192	0.0120	0.00456	0.0986***	0.0435
	(0.0321)	(0.0284)	(0.0302)	(0.0306)	(0.0305)	(0.0339)	(0.0330)	(0.0334)
Not in household	0.0360		0.0253		0.194		-0.229	
	(0.258)		(0.275)		(0.263)		(0.329)	
Father's Employment at Baseline (Omitted=Not Employed)								
Employed	0.0795		0.0577		0.111*		0.168***	
	(0.0648)		(0.0596)		(0.0612)		(0.0637)	
Not in household	0.0660		-0.00156		-0.0139		0.00113	
	(0.0933)		(0.0891)		(0.0835)		(0.1000)	
Mother's Age at Baseline (Omitted=<40)								
40-49	0.182***	-0.0129	0.195***	-0.0632**	0.185***	0.0330	0.176***	-0.0667**
	(0.0308)	(0.0272)	(0.0295)	(0.0296)	(0.0290)	(0.0330)	(0.0319)	(0.0322)
50 and over	0.519***	0.0602	0.169*	-0.0353	0.324***	0.157*	0.00294	-0.260**
	(0.0940)	(0.0886)	(0.0892)	(0.0955)	(0.0974)	(0.0932)	(0.0822)	(0.104)
Household Size (Omitted=2)								
3	-0.120	0.210**	-0.00517	0.0628	-0.157*	0.0984	-0.00852	0.0775
	(0.110)	(0.0981)	(0.0944)	(0.111)	(0.0945)	(0.114)	(0.107)	(0.111)
4	-0.122	0.159*	-0.163*	0.0136	-0.0850	0.0270	-0.135	0.0211
	(0.110)	(0.0945)	(0.0955)	(0.113)	(0.0923)	(0.109)	(0.108)	(0.114)
5	-0.163	0.185*	-0.160	0.0159	-0.0852	0.0717	-0.0685	0.0472
	(0.112)	(0.0965)	(0.0971)	(0.116)	(0.0942)	(0.111)	(0.110)	(0.116)
6	-0.261**	0.177*	-0.255**	-0.0136	-0.0758	0.0799	-0.0105	-0.0199
	(0.116)	(0.0999)	(0.102)	(0.118)	(0.0982)	(0.116)	(0.114)	(0.120)
7	-0.354***	0.0963	-0.413***	-0.0268	-0.136	0.0681	-0.196	-0.00876
	(0.123)	(0.106)	(0.109)	(0.125)	(0.107)	(0.124)	(0.121)	(0.128)
Rural Region	-0.00608	0.0869***	-0.0224	0.0880***	0.0404	0.106***	0.0270	0.113***
	(0.0305)	(0.0269)	(0.0288)	(0.0292)	(0.0287)	(0.0318)	(0.0313)	(0.0313)
Constant	-0.204	-0.579***	0.271	-0.0148	-0.946**	0.233**	-0.311	0.526***
	(0.279)	(0.0985)	(0.201)	(0.119)	(0.456)	(0.113)	(0.211)	(0.116)
Observations	3,352	3,118	3,210	2,965	3,352	3,118	3,210	2,965
R-squared	0.142	0.011	0.106	0.009	0.102	0.011	0.115	0.014

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1