Parental job loss and early child development in the Great Recession

Gabriele Mari*

Erasmus University Rotterdam

Renske Keizer

Erasmus University Rotterdam

A more recent version has been published in Child Development (open access):
https://srcd.onlinelibrary.wiley.com/doi/10.1111/cdev.13517

Abstract

Parental job loss may stifle early child development, and this might help explain why children of displaced parents fare worse later in life. To investigate this, the study relies on Irish cohort data (N = 6,303) collected around the Great Recession. A novel approach to mediation analysis is deployed, assessing predictions derived from models of family investment and family stress.

Parental job loss is found to exacerbate problem behaviour at age 3 and 5, via the channels of parental income and maternal negative parenting. By depressing parental income, job loss also hampers children's verbal ability at age 3. This is tied to reduced affordability of formal childcare, highlighting a policy lever that might tame the intergenerational toll of job loss

*Correspondence at: mari@essb.eur.nl. The present study was supported by a grant from the Netherlands Organization for Scientific Research (NWO MaGW VIDI grant no. 452-17-005 to R.K.) and by a grant from the European Research Council (ERC StG grant no. 757210 to R.K.). Data from Growing Up in Ireland were accessed via the Irish Social Science Data Archive - www.ucd.ie/issda. The authors wish to thank Geoffrey Wodtke, Katrien Helmerhorst, and Lisa van der Storm for their feedback and technical support, as well as participants in the 2019 Nederlandse Demografiedagen. Any errors or omissions are the authors' own.

Widespread job loss has been a prominent feature of the Great Recession and, within households, the consequences of job loss likely extend across generations. Previous research has either looked at the personal repercussions of job loss or at the long-term outcomes of children whose parents were displaced. These children typically under-perform their peers, at school (e.g. Rege et al., 2011; Stevens & Schaller, 2011) or in the labour market (e.g. Oreopoulos et al., 2008; Gregg et al., 2012). Yet most studies have linked parental job loss experienced during infancy to outcomes measured when offspring have reached adolescence or adulthood. What goes on during infancy itself has remained untapped, despite the fact that childhood might be a more malleable life stage for interventions aimed at the equalisation of life chances (e.g. Heckman et al., 2006; Duncan & Magnuson, 2013).

Hence we focus on how parental job loss may affect children's early development, focusing on pre-school age. Job displacement may affect parental income and parenting inputs, and both are central to family processes and child outcomes (Yeung et al., 2002; Gershoff et al., 2007; Cabrera et al., 2011; Washbrook et al., 2014; Khanam & Nghiem, 2016; Layte, 2017). Income losses may impinge on parental investments that could foster children's cognitive development. Parenting in family environments burdened by stress, economic and psychological, may hamper behavioural adjustment in children. Cognitive and behavioural development at an early age, in turn, predict success in school and the labour market (Heckman et al., 2006; Conti & Heckman, 2014). The contribution of parental job loss to child outcomes, via investment and parenting channels, might thus shed light on why children of displaced parents are worse off later in life.

We combine three waves of Irish cohort data collected around the time of the Great Recession (Growing Up in Ireland [GUI], 2008-2013). Hit the hardest in OECD comparison, Ireland saw unemployment rates roughly treble for men and double for women during that period (Nolan & Maître, 2017; Savage et al., 2019). The rise in unemployment was concentrated in the population under 35, and thus around the age of first parenthood and union formation in Ireland (Billari & Liefbroer, 2010). Not surprisingly then, the chances for a dependent child to live below the poverty line *and* with a jobless parent increased by around half in the period (Nolan & Maître, 2017).

Investigating widespread job loss and its consequences in a recent Irish cohort, our main contribution is thus twofold. First, we show that parental job loss is detrimental to early child development, expanding our current understanding of intergenerational dynamics tied to labour market turmoil (cf. Gregg et al., 2012). With respect to the few studies on early childhood (Peter, 2016), we provide a more comprehensive account, one that disentangles the influence of both paternal and maternal job loss, on both cognitive and behavioural outcomes, and at different time points during pre-school age. Second, we assess multiple paths via which parental job loss might have an impact on child outcomes. Complementing previous studies, we investigate the role of parental investments and family stress by implementing a novel approach to mediation analysis (e.g. G. T. Wodtke, 2018). This allows us to contribute to long-standing debates on family processes (Conger & Donnellan, 2007), and also highlight levers at the disposal of policy-makers to mitigate the toll of job loss across generations.

1. Background: job loss from parents to children

Many have examined whether children fare worse during adolescence and early adulthood if their parents were previously displaced or laid off. Most have found that paternal, but not maternal, job loss adversely affects children in the long term. Looking at plant closures in Norway, Rege and colleagues (2011) found that children of displaced fathers attain lower grade point averages in 10th grade. Similar results have been found in other contexts (Gregg et al., 2012; Coelli, 2011) and for other aspects of school performance such as grade retention (Stevens & Schaller, 2011). On college enrolment, evidence also pointed to small negative effects of paternal job loss (Hilger, 2016), whereas findings for adult-life earnings have been more mixed (Oreopoulos et al., 2008; Bratberg et al., 2008; Gregg et al., 2012; Hilger, 2016) – hinting perhaps at a dilution of the influence of parental job loss over children's lifetime (but see Schmidpeter, 2020).

However small or diluted though, these effects later in life might precipitate from responses to parental job loss during childhood itself. Recent research (Peter, 2016) supported the idea that job loss indeed obstacles early development, as German children of a displaced mother show more behavioural problems at age 5-6 compared to their peers in observationally similar households where maternal job loss did not occur. Paternal job loss may lead, according to a number of longitudinal studies, to a higher incidence of low birth weight and worse health across the board in young children (Lindo, 2011; Schaller & Zerpa, 2019), which in turn are well-known correlates of cognitive and behavioural development (e.g. Currie, 2009).

These few studies prompt asking not just if, but also why parental job loss may hinder children's development. Mechanisms can be analytically distinguished based on two theoretical models, namely that of Family Investment (e.g. Leibowitz, 1974) and of Family Stress (e.g. Conger & Donnellan, 2007). In accordance with the first, parental investments of time and money are crucial inputs in the production of child outcomes, particularly cognitive ones (e.g. Washbrook et al., 2014; Khanam & Nghiem, 2016). These investments may be impaired or halted by job loss. Focusing on money, job loss depresses long-term earnings, particularly during recessions (e.g. Davis & Von Wachter, 2011), and may thereby reduce a household's permanent income. Studies have consistently found evidence for substantial income losses, and yet, surprisingly, such losses seem to play little to no role in explaining the intergenerational effects of job loss (Bratberg et al., 2008; Rege et al., 2011; Peter, 2016; Hilger, 2016).

It could be though that much depends on the timing of job loss. Job losses around specific stages of children's educational trajectories might have a stronger impact. Schmidpeter (2020) found that parental unemployment, occurring around the time of early tracking in the Austrian school system (age 10), is most harmful for children's university completion chances and future earnings (see also Coelli, 2011; Lehti et al., 2019). Focusing on pre-school age in our paper, the relevant educational investment decision likely involves formal childcare. This investment has been shown to generate developmental benefits for children, particularly in low-income households (e.g. Duncan & Magnuson, 2013; Felfe & Lalive, 2018). Yet, similar to other Anglophone countries, net childcare costs can exceed 20% of disposable income for low-income households in Ireland (Browne & Neumann, 2017: 18-19). The Early Childcare Supplement, a yearly transfer introduced in 2006 to ease childcare costs, was first subject to cuts and then abolished by the end of 2009 (Nolan & Maître, 2017).

Irish households hit by job loss might have thus forgone investments in formal childcare and, via this channel, children exposed to parental job loss might lag behind in their development. This might go to the special detriment of the least well-off, although predictions are ambiguous. Parents with more resources, such as higher education, might be better poised to substitute formal childcare with educational inputs of their own (e.g. Fort et al., 2020). Despite their advantage "at the baseline", though, households with better-educated parents also had to bear the brunt of job loss in Ireland, with significant numbers sliding into joblessness and poverty during the recession (Nolan & Maître, 2017). On the other hand, lower educated parents typically face more constraints combining their work schedules and child stimulation (e.g. Hsin & Felfe, 2014). Job loss might make formal childcare unaffordable particularly in these households, but free up time for parent-child interactions. Job loss may thus simultaneously deplete economic investments and free up time investments in children, but how and to what avail across households merits a separate investigation.

Job loss may also affect families beyond parental investments and more in line with the pathways of Family Stress. It is well-established, for example, that mental health deteriorates following job loss, and displaced spouses may adversely affect each other (Marcus, 2013; Mendolia, 2014). Poorer parental mental health has in turn been associated with a kind of parenting that is lower in warmth, less consistent, and more hostile – leading then to heightened behavioural problems among children (e.g. Yeung et al., 2002; Washbrook et al., 2014; Khanam & Nghiem, 2016; Peter, 2016). Such "negative" parenting (e.g., Grant et al., 2003) might thus flow from parental job loss and hamper behavioural development among children. We expect this to hold especially for maternal job loss, as mothers more than fathers have been found to respond to poor economic circumstances with more negative forms of parenting (e.g. P. W. Jansen et al., 2012).

2. Empirical approach

2.1. Growing Up in Ireland and the study sample

Data were collected as part of Growing Up in Ireland (GUI), a longitudinal study focused on children's developmental trajectories as well as on parental health, socio-economic circumstances, and child-rearing practices (e.g. McCrory et al., 2013). The child's mother is the primary respondent in most cases; fathers, if present, are also interviewed in each wave. Children in the study were sampled from the Child Benefit register, covering all habitual residents in Ireland. Study children were born between 1 December 2007 and 30 June 2008. Conception and birth thus predate the Great Recession and especially precede the peak of unemployment recorded only later in Ireland, in 2011. Study children were 9 months old at the time of the first interview (Wave 1, 2008/9) and we follow them at age 3 (Wave 2, 2011) and 5 (Wave 3, 2013). Effectively, we can thus count on one observation prior, one during, and one after the peak of the Great Recession (see also Reinhard et al., 2018).

A total of 11,134 households participated in Wave 1 of GUI, corresponding to a 70.2% valid contact response rate. Such sample numbers further amount to roughly one third of all births in the December 2007-June 2008 period. Over Wave 2 and Wave 3, however, around 22% of the original sample was lost to follow-up. We restrict our analyses to households followed up to and including Wave 3, and are thus left with 8,712 households. As noted by McCrory and others (2013: 14), loss to follow-up is "higher among more socially disadvantaged groups and one-parent families". To correct for this, we construct probability weights following procedures detailed in Section S1 of the Supplementary material.

We perform a number of further sample exclusions. To account for these, we devise another probability weight (e.g. Seaman & White, 2013) and combine it by multiplication with weights tackling loss to follow-up. First, an additional 1,649 observations had incomplete records on one or more measures deployed in this study and we perform listwise deletion. Out of the remaining 7,063 complete records we further excluded 406 households in which either the mother or father of the study child never held a full-time job. We follow here previous studies on the (intergenerational) effects of job loss (e.g. Jacobson et al., 1993; Schmidpeter, 2020) and limit our analysis to households with a minimum attachment to the labour market.

In line with previous studies using GUI (Reinhard et al., 2018), we also restrict our sample to families in which the mother of the study child remained the primary respondent across all waves. This is to ensure continuity in the assessments of the study child and avoid, vice versa, picking up differences over time that are due to inconsistencies across parental reports. As a result, 170 records were dropped, as they either listed the study child's father as the primary respondent in Wave 1 (17) or registered a change in the primary respondent in Wave 2 or 3 (153). Finally, we dropped 184 two-parent households in which both parents reported losing their job between Wave 1 and Wave 2. The small cell number prevents, regrettably, credible analysis of children's outcomes in this particular type of households. All our findings are substantially unchanged when including these households.

Our final sample comprises 6,303 households, around 72% of the GUI sample followed from Wave 1 to Wave 3. Table 1 displays baseline characteristics for the analytical sample, as measured in Wave 1. Our sample predominantly features two-parent households, of Irish descent, in which the mother has tertiary education and was employed full-time prior to birth, not receiving any welfare payments, and belonging to more affluent income-quintile groups. With respect to the original cohort, as expected (McCrory et al., 2013), our sample has a skew towards more advantaged social strata. The aforementioned weights counter this skew though: as displayed in Section S1 of the Supplementary material, minor differences between weighted and unweighted analyses, when present at all, do not alter our main conclusions. In the remainder, we will therefore stick to unweighted analyses.

(Table 1 around here)

2.2. Main measures: exposure, outcomes, and mediators

In our study, we leverage the longitudinal nature of GUI by staggering our measures of exposure to parental job loss, of child outcomes, and of mediators of their relationship. Specifically, we consider the effects of parental job loss, occurred between Wave 1 and Wave 2, on children's cognitive and behavioural outcomes measured in Wave 2 and Wave 3, i.e. when the child is 3 and 5 respectively. Mediators are measured at Wave 2 and we thus assume their value is responsive to prior job loss and also not inversely affected by child outcomes.

Building on previous research using GUI (Layte & McCrory, 2018; Reinhard et al., 2018), we exploit survey items asking the primary respondent to indicate whether any of a series of changes "due to the recession" occurred since the previous interview (McCrory et al., 2013). Among them, respondents were asked whether they or their partner "were made redundant or lost their job due to the recession". We use info collected in Wave 2 to distinguish children exposed to one of three conditions between Wave 1 and Wave 2, namely 1) paternal job loss (16.3%), 2) maternal job loss (8.1%), and 3) no job loss (75.6%, the reference group). Similar to other studies based on survey data (Stevens & Schaller, 2011; Peter, 2016), our measure of parental job loss is thus a self-report and much relies on respondents' ability to correctly assess the reasons underlying job loss.

Despite this limitation as compared to, say, register data on plant closures (e.g. Rege et al., 2011), our data is rich on early developmental outcomes rarely available outside of surveys. Further, the availability of two measurements, at age 3 and 5, may allow us to uncover effects that mature over time or, vice versa, wane already during pre-school age.

We first track children's cognitive development in terms of verbal ability, as assessed via the Naming Vocabulary subtest of the British Ability Scales, 2nd ed. (BAS, e.g. Hill, 2005). In this subtest, the child is tasked with identifying and naming different objects in a coloured booklet. Test scores measure children's expressive (English) vocabulary and knowledge of nouns, which in turn are components of General Conceptual Ability (*ibidem*). Considering verbal ability allows us to compare our findings to previous research linking vocabulary test scores to parental resources and, especially, to parental income (e.g. Washbrook et al., 2014; Khanam & Nghiem, 2016). Similar to previous research also relying on BAS (e.g. Kühhirt & Klein, 2018), we take the ability scale which corrects for differences in item difficulty. We standardise ability scores to express our findings in terms of z-scores.

In terms of behavioural development, we employ measures from the Strengths and Difficulties Questionnaire (SDQ, e.g. Goodman & Goodman, 2009), an extensively validated screening tool for psychopathology in children and adolescents. SDQ measures have also been shown to generate returns in school and the labour market (Currie, 2009; Conti & Heckman, 2014) and to be responsive to parental resources and parenting practices (e.g. Washbrook et al., 2014; Khanam & Nghiem, 2016; Layte & McCrory, 2018). Five subscales can be derived from the questionnaire, administered here to the mother of the study child. The subscales tap emotional symptoms, hyperactivity/inattention, conduct problems, peer problems, and prosocial behaviour. For our analyses, we combined measures for emotional symptoms and peer problems into a single score for *internalizing problems* and, conversely, we summed up conduct problems and hyperactivity/inattention scores to obtain a measure of *externalizing problems*. We follow here previous studies (Goodman et al., 2010) showing how the five separate SDQ subscales might be more appropriate in high-risk samples and when studies aim at deploying the SDQ to screen for clinical disorders. Our study does not fit such profile and we thus opt for two composite measures, with the further aim of reducing measurement error and increasing statistical power. Composite internalizing and externalizing scores have also been frequently featured in previous studies on family investment and family stress (e.g. Yeung et al., 2002; Gershoff et al., 2007; Kiernan & Huerta, 2008), helping us comparing our findings to previous ones.

We further rely on one main measure for each channel via which parental job loss might affect child outcomes. We first consider parental economic inputs in the form of gross annual household income, reported by the primary respondent at Wave 2. Following common practices, we then take the logarithm of this measure. As noted elsewhere (Khanam & Nghiem, 2016), taking the log well reflects the assumption that child outcomes might linearly co-evolve with parental income but only up to a point, after which additional income might produce diminishing returns for children.

Finally, we consider the z-scores of a composite measure of maternal negative parenting, tapping this input also at Wave 2. Parenting measures in GUI are self-reported and derived from 17 items adopted from the Longitudinal Study of Australian Children (LSAC, Zubrick et al., 2013). These items sum up to three parenting dimensions (E. Jansen et al., 2012), namely hostility, warmth, and consistency. To build an overall measure of negative parenting, we reverse code warmth and consistency and combine it with hostility in a single measure, using the score predicted by Principal Component Analysis. We focus on maternal reports as the father may not always be present, for example in lone-parent households. In two-parent households, we thus proceed on the assumption that paternal job loss may have spillover effects on the partner and be reflected in her parenting (Marcus, 2013; Mendolia, 2014).

2.3. Model specifications

In our analyses, we aim, first, at estimating the total effects of parental job loss on child outcomes via the following regression specifications:

$$D_{ijw} = \alpha_{ijw} + \beta_1 PJL_i + \beta_2 MJL_i + \delta \mathbf{C}_i + \epsilon_{ijw} \quad (1)$$

$$D_{ijw} = \alpha_{ijw} + \beta_1 PJL_i + \beta_2 MJL_i + \delta \mathbf{C}_i + \gamma \mathbf{B}_i + \epsilon_{ijw} \quad (2)$$

where D_{ijw} stands for one of j developmental outcomes, as measured for a given child i in waves w = 2, 3. Both specifications include our main coefficients of interest, β_1 and β_2, respectively associated with paternal job loss (PJL_i) and maternal job loss (MJL_i). Households with no job loss registered between Wave 1 and Wave 2 are part of the comparison group, and thus the omitted reference category for this polytomous exposure. Equations 1 and 2 then differ in terms of the additional covariates. In Equation 1, we only include a vector of child characteristics $\mathbf{C}_i$ recorded at Wave 1. These are sex of the child, dummies for birth order, a counter for the number of siblings, and low birth weight ($<$ 2500 g). We also add scores for three domains – communication, problem solving, and personal/social – of the Ages and Stages Questionnaire (e.g. Squires et al., 1997) to adjust for children's cognitive abilities at the baseline (e.g. Charkaluk et al., 2017), and four scales for child temperament ("fussy/difficult", "unadptable", "unpredictable", and "dull") based on the Infant Characteristics Questionnaire (Bates et al., 1979) to tap into precursors of problem behaviour at the baseline. We expect all these child features $\mathbf{C}_i$ to only affect child outcomes, and not to influence the odds of parental job loss. Their inclusion may enhance the precision of estimates of β_1 and β_2 in Equation 1. This first specification thus provides a benchmark of the total association between parental job loss and child outcomes.

Next, with Equation 2, we probe these associations to the inclusion of $\mathbf{B}_i$. This vector comprises a set of maternal and household characteristics that may affect child outcomes *and* the odds of experiencing parental job loss (see also Watson et al., 2015). Despite bringing about widespread job loss, the Great Recession did not increase the odds of job loss at random. Job and income losses were concentrated, for example, among workers below 35 and among the middle and lower end of the income distribution (Nolan & Maître, 2017; Savage et al., 2019). The vector $\mathbf{B}_i$ thus includes the following set of covariates, all measured at Wave 1 and thus prior to job loss: a quadratic for maternal age at birth, dummies for maternal education, maternal work status prior to birth, whether the mother lives and/or is married to her partner, whether the mother is of Irish descent, whether anyone in the household receives welfare payments, equivalised household income (dummies based on quintiles), self-reported scores for maternal depression (CES-D, Radloff, 1977) and maternal attachment (Condon & Corkindale, 1998).

These variables are aimed at curbing confounding bias from our estimates. To grant a causal interpretation to our estimates, we thus rely on a *selection on observables* assumption in line with previous observational literature (e.g. Peter, 2016). In short, our estimates approximate the causal effect of parental job loss on child outcomes if and to the extent that $\mathbf{B}_i$ incorporates a sufficient set of variables to block all spurious paths between exposure and outcome.

2.4. Mediation analyses

On top of the total effect of job loss, our concern lies with the mediating paths linking parental job loss to early child development, either via income or parenting inputs. We therefore set up a formal mediation analysis (Pearl, 2012; VanderWeele, 2015) to identify direct and indirect effects of job loss under a set of assumptions. Specifically, we identify causal direct and indirect effects only by blocking all spurious paths not just between exposure and outcome, as per Equation 2, but also between the exposure and the mediator of interest, as well as between the latter and the outcome. Several of the variables predating job loss and included in both $\mathbf{C}_i$ and $\mathbf{B}_i$, for example, can serve these purposes. For one, both child temperament and maternal depression (attachment) at the baseline might confound the relationship between maternal negative parenting and child outcomes in later waves.

Other sources of mediator-outcome confounding, however, could take their value "post exposure", and be affected by the exposure in the first place. If we were to adjust for such post-exposure variables in our regressions, though, we would bias the effects of job loss by a) "controlling away" some of the paths via which these effects operate in the first place, and by b) possibly inducing collider stratification bias (e.g. VanderWeele, 2015: 342). To move past these hurdles, we follow a regression-with-residuals (RWR) approach (G. Wodtke & Zhou, 2019; G. T. Wodtke et al., 2020). This novel approach allows, in short, to purge the problematic association between exposure and some candidate confounders via simple regression residualization, so that these variables can then be safely included when investigating mediation.

We specifically consider parental separation, the birth of a sibling, and whether the household moved as events that may have been influenced by parental job loss (e.g. Huttunen et al., 2018) and that might induce mediator-outcome confounding. For child outcomes at Wave 2, we consider these variables as measured at Wave 2, whereas for outcomes at Wave 3 we also incorporate the birth of an additional sibling and parental separation as measured at Wave 3. Differently from Wave 2, we have no information on family moves in Wave 3 and this post-treatment variable could not be added to our models.

In practice, RWR involves four steps. First, we centre pre-exposure variables around their unconditional sample mean, thus obtaining mean-centred vectors $\hat{\mathbf{C}}_i^{\perp}$ and $\hat{\mathbf{B}}_i^{\perp}$ from the original $\mathbf{C}_i$ and $\mathbf{B}_i$. Variables in these sets take their value prior to parental job loss and thus we do not need to purge their association with it. Second, for each candidate post-exposure confounder we fit a model with all pre-exposure variables and the exposure as covariates, and then extract the residuals. Throughout we fit linear probability models for our post-exposure variables and enclose their residualised counterpart in the vector $\hat{\mathbf{L}}_i^{\perp}$.

Step three involves fitting two models, one for the mediator of interest and one for the outcome. These are as follows:

$$M_{im} = \alpha_{im} + \theta_1 \hat{\mathbf{C}}_i^{\perp} + \theta_2 PJL_i + \theta_3 MJL_i + \epsilon_{im} \tag{3}$$

$$D_{ijw} = \alpha_{ijw} + \delta_1 PJL_i + \delta_2 MJL_i + \gamma_1 M_{im} + \gamma_2 PJL_i M_{im} + \gamma_3 MJL_i M_{im} + \omega \hat{\mathbf{C}}_i^{\perp} + \phi \hat{\mathbf{L}}_i^{\perp} + \epsilon_{ijw} \tag{4}$$

where M_{im} in Equation 3 is one of m = {log of household income, negative parenting} mediators of interest. Equation 4 is the full outcome model, including the mediator of interest and *residualised* post-exposure variables $\hat{\mathbf{L}}_i^{\perp}$. Net of their association with parental job loss thanks to residualization, post-exposure variables help de-confounding the association between a given mediator M_{im} and child outcome D_{ijw} in Equation 4. Our model in Equation 4 also allows for interactions between exposures and a given mediator, here expressed by coefficients γ_2 and γ_3. This flexible specification has been advocated for as the default in the literature on causal mediation (e.g. VanderWeele, 2015: 46-47). In our setting, assuming away such interaction may prove unrealistic if, for example, the effects of household income on child outcomes are stronger in households that have been exposed to, say, paternal job loss rather than no job loss at all or maternal job loss.

Having specified Equation 4, the fourth and last step involves deriving direct and indirect effects. RWR helps retrieve the so called randomized natural direct effect, or R-NDE, and randomized natural indirect effect, or R-NIE (e.g. VanderWeele, 2015: 135-136). Focusing on paternal job loss for illustrative purposes, the R-NDE and R-NIE are derived from Equations 3 and 4 as follows (G. Wodtke & Zhou, 2019):

$$\widehat{\text{R-NDE}} = [\hat{\delta}_1 + \hat{\gamma}_2 \cdot (\hat{\alpha}_{im} + \hat{\theta}_2)] \cdot (a^* - a) \tag{5}$$

$$\widehat{\text{R-NIE}} = [\hat{\theta}_2 \cdot (\hat{\gamma}_1 + \hat{\gamma}_2 a^*)] \cdot (a^* - a) \tag{6}$$

where a^* and a stand for two values of our exposure. Operationally, this reduces to switching from the value of the reference category of no job loss to, say, paternal job loss, i.e. (1 - 0) = 1. The difference $(a^* - a)$ is meant to represent a counterfactual intervention, one in which all population analogues of our sample members experience paternal job loss (a^*) rather than no job loss at all (a). Similar considerations apply to maternal job loss. The R-NDE then captures the direct effect of paternal (maternal) job loss with the mediator set at a value randomly selected from its distribution under the reference level of the exposure (no job loss). For intervention or policy purposes, this captures the effect of parental job loss via other channels than those of the mediator of interest. Conversely, the R-NIE expresses what would be the expected difference in the outcome if all children were counterfactually exposed to paternal (maternal) job loss, and the mediator was randomly selected among its distribution for those exposed to paternal (maternal) job loss. This latter estimate provides us with the effect of parental job loss on child outcomes via the channels of household income or maternal negative parenting, suggesting what would happen if we were to intervene *only* on how these mediators change in response to job loss. Finally, the R-ATE (randomized average total effect) equals the sum of R-NDE and R-NIE. It is defined as an average total effect that contrasts the levels of the exposure (say, paternal job loss against no job loss), assuming an additional randomized intervention on the mediator.

Dealing with estimated rather than observed values for vectors such as $\hat{\mathbf{L}}_i^{\perp}$, standard errors and confidence intervals are computed using the non-parametric bootstrap (with 200 replications).

3. Findings

3.1. Parental job loss and early child development

We report our main findings in Table 2. All models contrast paternal and maternal job loss to the reference of no job loss at all. At age 3, paternal job loss seemingly leads to a small reduction in a child's vocabulary score, of around .08 of a SD (p = .022). This holds when adjusting only for child features in Model 1. For maternal job loss, vice versa, the estimate is positive, but we cannot detect an association (p = .448). Turning to Model 2, and thus accounting for baseline maternal and household characteristics, our estimate for maternal job loss is largely unchanged, yet that for paternal job loss reduces to .02 of a SD (and p = .491). Most of the total effect of paternal job loss on vocabulary scores seems thus due to measured confounding, whereas the association between our cognitive measure and maternal job loss is, unexpectedly, positive.

Moving on to behavioural adjustment at age 3, we find that paternal job loss is associated with an increase of around one tenth of a SD in both internalizing and externalizing problems, focusing on Model 1. In both cases, estimates halve when maternal and household characteristics are adjusted for. In Model 2, indeed, we find an association of around .06 of a SD for internalizing problems (p = .081) and .05 of a SD for externalizing problems (p = .114). The associations between maternal job loss, on the other hand, and behavioural adjustment at age 3 are often smaller in size and more noisy, although in the expected direction (.04 for internalizing problems, p = .370; .003 for externalizing problems, p = .941).

In the lower panel of Table 2 we examine whether the effects of parental job loss during the economic downturn persisted or matured by the time children turned 5. In response to paternal job loss, we find again a reduction in children's vocabulary of around .08 of a SD in Model 1 (p = .014), that more than halves to .03 of a SD in Model 2 (p = .379). For maternal job loss, estimates are this time negative and rather similar across models, hovering around a reduction of .08 SD in Model 1 (p = .060) and .07 of a SD in Model 2 (p = .120).

As for internalizing problems at age 5, we find little evidence of associations with parental job loss. When it comes to the association between internalizing problems and paternal job loss in particular, there might thus be some dissipation as children grow older. On the contrary, for externalizing problems we find stable or even reinforced associations. Paternal job loss is still associated with an increase of .10 SDs for externalizing problems in Model 1, an estimate that roughly halves in Model 2 (p = .141). This mirrors the pattern found at age 3. Maternal job loss is associated instead with a .9-.11 increase in the z-score for externalizing problems at age 5, a significant jump from the previous assessment at age 3.

On balance, we find stronger evidence for an association between parental job loss and behavioural adjustment rather than vocabulary test scores, and with externalizing problems more than internalizing problems. Generally, baseline confounding particularly matters for paternal job loss, as its association with child outcomes is often substantially reduced when we account for maternal and household characteristics. Estimates for maternal job loss are more stable across model specifications and, notably, flip sign when it comes to children's vocabulary, from positive at age 3 to negative at age 5. The associations between parental job loss and child outcomes are thus composite, varying across developmental domains, children's age, and depending on which parent experienced job loss.

(Table 2 around here)

3.2. Mediating pathways of family investment and family stress

Assuming away unmeasured confounding, estimates displayed in Table 2 may be interpreted as the total causal effects of parental job loss on child outcomes. We now decompose such total effects in their direct and indirect components, investigating mediating pathways via parental income and maternal parenting.

Drops in parental income are a likely consequence of job loss. As per Equation 3, we find that paternal (maternal) job loss depresses parental income by around 18% (15%), estimates that are largely in line with previous studies (e.g. Jacobson et al., 1993; Davis & Von Wachter, 2011) and that we report, for the sake of brevity, in Section S2 of the Supplementary material. In Figure 1 we examine how, through such losses in parental income, parental job loss may impinge on children's vocabulary scores. Total effects (R-ATEs), analogous to those in the second column of Table 2, are decomposed in their natural direct (R-NDEs) and indirect (R-NIEs) components, as per Equation 5 and 6 respectively. Similar to our main analyses, these effects are displayed for both age 3 (left panel) and age 5 (right panel).

(Figure 1 around here)

We find that, despite the fact that total and direct effects are not detected, paternal job loss may have adverse consequences on children's vocabulary at age 3 via the channel of parental income *alone*. If only for parental income losses, indeed, paternal job loss would lead to a decrease of around .03 SDs (p = .011) in children's vocabulary scores – as evidenced by the R-NIE in the left panel of Figure 1. Besides this mediation pattern, none other could be detected in Figure 1, not even for the relatively large negative effect of maternal job loss on children's vocabulary at age 5.

Turning to problem behaviour, we consider how parental job loss may hamper this developmental domain by triggering family stress, the latter being captured by maternal negative parenting. When estimating Equation 3 on this candidate mediator (see Section S2 in the Supplementary material), we find that paternal job loss yields an increase of .07 SDs in maternal negative parenting (p = .044). Mothers' own job loss, on the other hand, only leads to a .03 increase in the z-scores of maternal negative parenting (p = .442). Coherently, when looking at the mediating role of maternal negative parenting in Figure 2, we find that a spillover from fathers to mothers partly explains why paternal job loss results in accrued behavioural problems in this Irish cohort.

(Figure 2 around here)

Starting from the top half of Figure 2, we observe that children's internalizing problems increase by around .06 SDs at age 3 in response to paternal job loss, analogously to what we displayed in the fourth column of Table 2. Moving from this R-ATE to the R-NDE, the direct effect, the estimate reduces to roughly .04 SDs. The indirect effect R-NIE further shows that, via its effect on maternal negative parenting alone, paternal job loss results in .02 SDs more in internalizing problems (p = .040). A similar pattern is also found for the R-NIEs of paternal job loss on externalizing problems at age 3 (.03, p = .029) and age 5 (.02, p = .033). We could not detect, conversely, any role for maternal negative parenting in mediating the (larger) effect of maternal job loss on externalizing problems at age 5.

So far, we have paired together parental income and cognitive development, and negative parenting and behavioural development, following previous studies (e.g. Yeung et al., 2002). In Section S3 of the Supplementary material, we explore crossing mediators and outcomes to provide a complete, and perhaps more integrated, account of family investment and family stress dynamics (e.g. Layte, 2017). As displayed in Figure 1S though, we could not detect any indirect effect flowing from parental job loss to cognitive development via maternal negative parenting. Differently, for both internalizing and externalizing problems at age 3, we find some role for parental income losses, as triggered by paternal job loss. Via this channel alone, and thus looking at the R-NIEs in Figure 2S, internalizing problems at age 3 increase by .03 SDs (p = .058) and externalizing problems by .04 SDs (p = .008).

3.3. Delving into the mechanisms: childcare enrolment and heterogeneous effects

Our mediation analyses suggest that parental income losses triggered by job displacement might harm children across multiple developmental domains and especially so at age 3. Yet, particularly for vocabulary scores at age 3, the negative indirect effects via parental income are coupled with noisy estimates of the total and direct effects of job loss, the latter turning out even positive for maternal job loss. To make sense of these patterns, we performed a number of complementary analyses.

First, our hunch is that these negative indirect effects via parental income express a reduced ability among families to enrol children into formal childcare. We therefore examined if parental job loss affected the chances of attending formal childcare among this Irish cohort during the Great Recession, and to what extent this relates to income losses. We ran a new mediation analysis, in line with the procedures followed throughout the paper but with enrolment in formal childcare at the age of 3 as the main outcome (coded 1 if the child is enrolled at Wave 2, 0 otherwise).

Results displayed in Figure 3 support our expectation. To begin with the total effects (R-ATEs), children's chances of being enrolled in formal childcare are roughly 4 percentage points lower in response to both paternal (p = .005) and to maternal job loss (p = .057), as compared to households in which no job loss occurred. Direct effects or R-NDEs, operating via all other channels but that of parental income, are substantially reduced. Indirect effects conversely show that, for a change in parental income such as that triggered by job loss, the chances to be enrolled in childcare decrease by around 2 percentage points for paternal job loss ($p < .001$) and 4 percentage points for maternal job loss ($p < .001$).

(Figure 3 around here)

In light of such forgone investments in formal childcare, parents may compensate with investments of their own, for example spending more time in educational activities with their children. This could explain why some of the total and direct effects of job loss are null or even positive, when it comes to children's verbal ability at age 3. It could be though that parental educational inputs might better substitute those from formal childcare when parents are affluent or highly educated (e.g. Fort et al., 2020). Hence, lacking data on time spent on specific parent-child activities, we performed a second round of additional analyses splitting our sample by maternal education, to gauge possible compensation patterns.

All our analyses split by maternal education are presented and discussed more at length in Section S4 of our Supplementary material. In short, and perhaps unexpectedly, we do find that compensation for a lack of investment in formal childcare is more plausible for children whose mother had upper-secondary education at most, rather than a tertiary degree. In households where mothers have no more than high-school diplomas, indeed, we find a large and positive direct effect of maternal job loss on children's vocabulary score at age 3 (.19 SDs, p = .012), as per Figure 3S. This is coupled with a negative indirect effect of maternal job loss via parental income (–.07 SDs, p = .004), a combination we cannot detect for households in which the mother has tertiary education. Differently, for paternal job loss, we find negative indirect effects of paternal job loss on vocabulary scores at age 3, flowing via income losses and similarly so regardless of maternal education. For problem behaviour, in Figures 4S and 5S, we typically find larger associations in households with higher maternal education.

Further, moving on to Figure 6S, maternal job loss is associated with the largest total drop in the chances of childcare enrolment at age 3 (–9 percentage points, p = .005), when the mother has upper-secondary education or less. This partly flows via income losses, looking at the indirect effect or R-NIE (≈ –2 percentage points, p = .044). Taken together, these estimates support the idea of some compensatory investment at age 3 by displaced mothers with lower education in our sample. At the same time, income-related indirect effects on childcare enrolment are invariably negative and similar in size, across sub-samples split by maternal education and regardless of which parent was displaced.

If we take lower maternal education as a proxy of disadvantage at the baseline, parental job loss does not only affect the least well-off households in our sample. Rather, detrimental effects are found across households for both verbal ability and childcare enrolment, whereas estimates for problem behaviour are, if anything, larger in households with higher maternal education.

4. Discussion

Overall we find evidence linking parental job loss and early child development in a recent Irish cohort. Parental job loss seems to affect problem behaviour more than verbal ability, and externalizing problems in particular. For verbal ability, however, null total effects hide composite direct and indirect effects that emerge through our effect decomposition. The latter suggests that, if only via parental income, children of displaced fathers would lag behind in their verbal ability at age 3. Similar, via the same channel alone, children of displaced mothers – particularly of those with high school or less – would also lag behind if not for some "compensatory" effect via unobserved channels. A reduced capacity to invest in formal childcare, due to job and income losses, might further explain these patterns. We also find some role for negative parenting, as triggered by job loss, in explaining accrued behavioural problems in children of displaced parents. Notably though, income losses are found to matter to a similar or larger degree than parenting when it comes to behavioural problems.

On balance, whether total, direct, or indirect, the effects of parental job loss reach at most one tenth of a standard deviation for any given child outcome in our study. To the best of our knowledge, only Peters (2016) similarly considered development in pre-school age, finding associations up to five times larger than ours when focusing on maternal job loss and total SDQ scores in a small German sample. Differences in sample size and construction, context, exposure and outcome definitions, could all be at play. Evidence from multiple and diverse studies is paramount to get a clearer picture. We note that our estimates are similar in magnitude to those for other "economic" inputs into child development (e.g. Washbrook et al., 2014; Khanam & Nghiem, 2016) and of larger substantial significance than those identified for parental job loss and children's physical health in this Irish cohort (Reinhard et al., 2018). If small in an absolute sense, it is worth stressing that we could not model a possible accumulation of effects depending on the length of job displacement, and future studies could shed light on this. Additionally, our reference group might comprise households that, whilst untouched by job loss, might have been nonetheless hit by the recession, for example via cuts in wages or public services (Whelan et al., 2016). If such facets of economic hardship also hamper child development, the contrast with exposure to job loss in this cohort might have provided us with lower bounds for the effects of parental job loss on early child development.

Our estimates can also be granted a causal interpretation, but only to the extent that our assumptions hold. Differently from previous studies, we address potential sources of post-exposure confounding. Our estimates can hardly be imputed to behaviours of families themselves following job loss (separations, new children, family moves), as these are adjusted for in our models. Nonetheless, our analyses might be biased by *unmeasured* common causes of our exposure, outcomes, and mediators. If robust to such lurking variables, our study highlights how more generous income support to displaced parents might have developmental benefits for their children. In particular, we suggest that subsidising childcare expenses might partly mitigate the adverse effects of job loss across socio-economic strata. This finding may reflect two features of the Great Recession in Ireland, namely its adverse impact on the middle class, on the one hand, and the cuts to already expensive childcare arrangements on the other (Whelan & Maître, 2014; Nolan & Maître, 2017). More broadly, our results speak to previous studies showing how income losses due to job displacement might be more consequential when timed around a specific parental investment in formal education. While previous studies ascertained this for secondary and tertiary education (Coelli, 2011; Schmidpeter, 2020), we provide evidence for pre-school education in the form of childcare enrolment.

In one instance, we found evidence of some form of parental compensation counteracting the adverse effects of job loss on verbal ability. We can speculate that time investments in educational activities might be key in such compensatory efforts. Children reap benefits from parental time in educational activities especially when it comes to cognitive ability, and returns to such activities are similar regardless of parental education (e.g. Hsin & Felfe, 2014; Cano, 2019). Further, previous research has found that mothers with lower educational attainment are less able to combine their often inflexible work schedules and such "productive" childcare (Hsin & Felfe, 2014). Our finding that, for such mothers, job loss *per se* improves their children's vocabulary scores coherently suggests that job loss might free up time to make time investments in children's education. Yet it is worth stressing that such compensation is at best narrow in scope, as we do find "uncompensated" detrimental effects of maternal job loss on verbal ability and externalizing problems at a later age.

Future research could thus shed further light on such compensation of income loss via time investments in children, in response to job loss. Alternatively, what we called compensation could actually be an artefact of biased estimates. Specifically, including a mediator like household income may have engendered collider bias. This is due to the fact that mediators may be common effects of both the exposure, by definition, and of mediator-outcome confounders. If any of the latter are omitted and/or unobservable, the effect of the exposure partly flows through the spurious path opened by the mediator and passing through the omitted confounder (e.g. VanderWeele, 2015); direct (and indirect) effects, in short, cannot be correctly identified. A likely candidate in our setting is parental cognitive ability, which could contribute to both household income and to children's verbal ability. We expect both contributions to be positive in sign, and, if so, our estimates of R-NDEs and R-NIEs could be biased away from 0. This suggests, for example, that we might be overestimating maternal compensation at age 3, if the positive R-NDE of maternal job loss on verbal ability is indeed upwardly biased. Conversely, we might overestimate the role that income plays in mediating the effects of job loss on children's cognitive development. We note, nonetheless, that maternal education and children's ASQ assessment at 8 months were included as proxies, however imperfect, for parental and children's extant cognitive ability (Charkaluk et al., 2017).

Concluding remarks

These limitations notwithstanding, our work is among the first to assess how parental job loss may affect children's cognitive and behavioural development during pre-school years. Our findings may bear significance for the larger literature on the intergenerational effects of job loss. By disentangling composite direct and indirect effects, we suggest that formal mediation analyses may contribute to the literature in the field. Previous studies on long-term effects have suggested that income losses play only a little role for the outcomes of children whose parents were displaced (e.g. Bratberg et al., 2008; Rege et al., 2011; Hilger, 2016; Lehti et al., 2019). The same conclusion was drawn for problem behaviours at an early age and maternal job loss (Peter, 2016). We highlight that, when isolated, negative indirect effects via parental income can be detected for both cognitive and behavioural development. Maternal negative parenting matters, to an extent, only when it comes to behavioural problems. Our analyses thus show how family investment and family stress channels may co-exist and shape early development in response to adverse economic circumstances. This may provide a further piece of evidence supporting "integrated" or "hybrid" accounts of how investment and stress contribute to children's life chances, in line with appraisals in developmental psychology (Conger & Donnellan, 2007), sociology (Layte, 2017), and economics (Cunha, 2015; Cobb-Clark et al., 2019).

Associations between parental job loss and problem behaviours hold promise to shed light on long-term intergenerational effects too. Previous research has found negative effects on school performance, but only mixed evidence for a (negative) effect of parental job loss on children's future earnings (Bratberg et al., 2008; Gregg et al., 2012; Hilger, 2016). We show that parental job loss may be associated with multiple behavioural problems at an early age, and recent research suggests that internalizing and externalizing behaviours may have opposite returns in school and the labour market (Papageorge et al., 2019). Future research could thus benefit from considering early child development as part of the process by which the effects of job loss reach across generations.

This study contributes to our understanding of family processes during times of economic hardship, suggesting which policy levers might help undo the intergenerational toll of parental job loss. During the first months of 2020, Ireland began facing the fallout of a global pandemic. Based on claims of the new Pandemic Unemployment Payment, unemployment is estimated to have soared to 16.5% in March 2020 (Central Statitics Office [CSO], 2018), a figure already higher than the peak reached during the Great Recession. The scale, patterns, and consequences of this new wave of job loss are still emerging, in Ireland and worldwide. Among others, the intergenerational consequences of job loss are salient, therefore, and easing childcare costs might be an important part of future policy responses directed at families facing hardship.

References

Bates, J. E., Freeland, C. A. B., & Lounsbury, M. L. (1979). Measurement of infant difficultness. *Child Development*, *50*(3), 794–803.

Billari, F. C., & Liefbroer, A. C. (2010). Towards a new pattern of transition to adulthood? *Advances in Life Course Research*, *15*(2-3), 59–75.

Bratberg, E., Nilsen, Ø. A., & Vaage, K. (2008). Job losses and child outcomes. *Labour Economics*, *15*(4), 591–603.

Browne, J., & Neumann, D. (2017). OECD Tax Wedge and Effective Tax Rates on Labour: Childcare costs in 2015. *OECD No. VS/2015/0427 (DI150030)*, https://taxben.oecd.org/tax-ben-resources/Childcare-costs-in-2015.pdf.

Cabrera, N. J., Fagan, J., Wight, V., & Schadler, C. (2011). Influence of mother, father, and child risk on parenting and children's cognitive and social behaviors. *Child Development*, *82*(6), 1985–2005.

Cano, T. (2019). Changes in Fathers' and Mothers' Time with Children: Spain, 2002–2010. *European Sociological Review*, *35*(5), 616–636.

Central Statitics Office [CSO]. (2018). Monthly Unemployment 2020. *Statistical release, 09 April 2020*, https://www.cso.ie/en/releasesandpublications/er/mue/monthlyunemploymentmarch2020/.

Charkaluk, M.-L., Rousseau, J., Calderon, J., Bernard, J. Y., Forhan, A., Heude, B., … others (2017). Ages and Stages questionnaire at 3 years for predicting IQ at 5–6 years. *Pediatrics*, *139*(4), e20162798.

Cobb-Clark, D. A., Salamanca, N., & Zhu, A. (2019). Parenting style as an investment in human development. *Journal of Population Economics*, *32*(4), 1315–1352.

Coelli, M. B. (2011). Parental job loss and the education enrollment of youth. *Labour Economics*, *18*(1), 25–35.

Condon, J. T., & Corkindale, C. J. (1998). The assessment of parent-to-infant attachment: Development of a self-report questionnaire instrument. *Journal of Reproductive and Infant Psychology*, *16*(1), 57–76.

Conger, R. D., & Donnellan, M. B. (2007). An interactionist perspective on the socioeconomic context of human development. *Annu. Rev. Psychol.*, *58*, 175–199.

Conti, G., & Heckman, J. J. (2014). Economics of Child Well-Being. In A. Ben-Arieh, F. Casas, I. Frønes, & J. Korbin (Eds.), *Handbook of Child Well-Being.* Springer.

Cunha, F. (2015). Subjective rationality, parenting styles, and investments in children. In P. Amato, A. Booth, S. McHale, & J. Van Hook (Eds.), *Families in an era of increasing inequality* (pp. 83–94). Springer.

Currie, J. (2009). Healthy, wealthy, and wise: Socioeconomic status, poor health in childhood, and human capital development. *Journal of Economic Literature*, *47*(1), 87–122.

Davis, S. J., & Von Wachter, T. (2011). Recessions and the Costs of Job Loss. *Brookings Papers on Economic Activity*, *42*(2 (Fall)), 1-72.

Duncan, G. J., & Magnuson, K. (2013). Investing in Preschool Programs. *Journal of Economic Perspectives*, *27*(2), 109–32.

Felfe, C., & Lalive, R. (2018). Does early child care affect children's development? *Journal of Public Economics*, *159*, 33–53.

Fort, M., Ichino, A., & Zanella, G. (2020). Cognitive and noncognitive costs of day care at age 0–2 for children in advantaged families. *Journal of Political Economy*, *128*(1), 158–205.

Gershoff, E. T., Aber, J. L., Raver, C. C., & Lennon, M. C. (2007). Income is not enough: Incorporating material hardship into models of income associations with parenting and child development. *Child Development*, *78*(1), 70–95.

Goodman, A., & Goodman, R. (2009). Strengths and difficulties questionnaire as a dimensional measure of child mental health. *Journal of the American Academy of Child & Adolescent Psychiatry*, *48*(4), 400–403.

Goodman, A., Lamping, D. L., & Ploubidis, G. B. (2010). When to use broader internalising and externalising subscales instead of the hypothesised five subscales on the Strengths and Difficulties Questionnaire (SDQ): data from British parents, teachers and children. *Journal of Abnormal Child Psychology*, *38*(8), 1179–1191.

Grant, K. E., Compas, B. E., Stuhlmacher, A. F., Thurm, A. E., McMahon, S. D., & Halpert, J. A. (2003). Stressors and child and adolescent psychopathology: moving from markers to mechanisms of risk. *Psychological Bulletin*, *129*(3), 447.

Gregg, P., Macmillan, L., & Nasim, B. (2012). The impact of fathers' job loss during the recession of the 1980s on their children's educational attainment and labour market outcomes. *Fiscal Studies*, *33*(2), 237–264.

Heckman, J. J., Stixrud, J., & Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, *24*(3), 411–482.

Hilger, N. G. (2016). Parental job loss and children's long-term outcomes: evidence from 7 million fathers' layoffs. *American Economic Journal: Applied Economics*, *8*(3), 247–83.

Hill, V. (2005). Through the past darkly: a review of the British Ability Scales Second Edition. *Child and Adolescent Mental Health*, *10*(2), 87–98.

Hsin, A., & Felfe, C. (2014). When does time matter? Maternal employment, children's time with parents, and child development. *Demography*, *51*(5), 1867–1894.

Huttunen, K., Møen, K., & Salvanes, K. G. (2018). Job Loss and Regional Mobility. *Journal of Labor Economics*, *36*(2), 479–509.

Jacobson, L. S., LaLonde, R. J., & Sullivan, D. G. (1993). Earnings losses of displaced workers. *The American Economic Review*, *83*(4), 685–709.

Jansen, E., Daniels, L. A., & Nicholson, J. M. (2012). The dynamics of parenting and early feeding–constructs and controversies: a viewpoint. *Early Child Development and Care*, *182*(8), 967–981.

Jansen, P. W., Raat, H., Mackenbach, J. P., Hofman, A., Jaddoe, V. W., Bakermans-Kranenburg, M., . . . Tiemeier, H. (2012). Early determinants of maternal and paternal harsh discipline: The Generation R study. *Family Relations*, *61*(2), 253–270.

Khanam, R., & Nghiem, S. (2016). Family income and child cognitive and noncognitive development in Australia: Does money matter? *Demography*, *53*(3), 597–621.

Kiernan, K. E., & Huerta, M. C. (2008). Economic deprivation, maternal depression, parenting and children's cognitive and emotional development in early childhood. *The British Journal of Sociology*, *59*(4), 783–806.

Kühhirt, M., & Klein, M. (2018). Early maternal employment and children's vocabulary and inductive reasoning ability: a dynamic approach. *Child Development*, *89*(2), e91–e106.

Layte, R. (2017). Why do working-class kids do worse in school? An empirical test of two theories of educational disadvantage. *European Sociological Review*, *33*(4), 489–503.

Layte, R., & McCrory, C. (2018). Fiscal crises and personal troubles: the Great Recession in Ireland and family processes. *Social Psychiatry and Psychiatric Epidemiology*, *53*(9), 987–1001.

Lehti, H., Erola, J., & Karhula, A. (2019). The heterogeneous effects of parental unemployment on siblings' educational outcomes. *Research in Social Stratification and Mobility*, *64*.

Leibowitz, A. (1974). Home investments in children. *Journal of Political Economy*, *82*(2, Part 2), S111–S131.

Lindo, J. M. (2011). Parental job loss and infant health. *Journal of Health Economics*, *30*(5), 869–879.

Marcus, J. (2013). The effect of unemployment on the mental health of spouses–Evidence from plant closures in Germany. *Journal of Health Economics*, *32*(3), 546–558.

McCrory, C., Williams, J., Murray, A., Quail, A., & Thornton, M. (2013). *Growing Up in Ireland National Longitudinal Study of Children: Infant Cohort. Design, Instrumentation and Procedures for the Infant Cohort at Wave Two (3 years).* Department of Children and Youth Affairs, Dublin: Ireland.

Mendolia, S. (2014). The impact of husband's job loss on partners' mental health. *Review of Economics of the Household*, *12*(2), 277–294.

Nolan, B., & Maître, B. (2017). Children of the Celtic Tiger during the Economic Crisis: Ireland. In B. Cantillon, Y. Chzhen, S. Handa, & B. Nolan (Eds.), *Children of Austerity. Impact of the Great Recession on Child Poverty in Rich Countries* (pp. 146–169). UNICEF & Oxford University Press.

Oreopoulos, P., Page, M., & Stevens, A. H. (2008). The intergenerational effects of worker displacement. *Journal of Labor Economics*, *26*(3), 455–483.

Papageorge, N. W., Ronda, V., & Zheng, Y. (2019). The Economic Value of Breaking Bad: Misbehavior, Schooling and the Labor Market. *NBER Working Paper No. 25602*.

Pearl, J. (2012). The causal mediation formula - a guide to the assessment of pathways and mechanisms. *Prevention Science*, *13*(4), 426–436.

Peter, F. (2016). The effect of involuntary maternal job loss on children's behaviour and non-cognitive skills. *Labour Economics*, *42*, 43–63.

Radloff, L. S. (1977). The CES-D scale: A self-report depression scale for research in the general population. *Applied Psychological Measurement*, *1*(3), 385–401.

Rege, M., Telle, K., & Votruba, M. (2011). Parental job loss and children's school performance. *The Review of Economic Studies*, *78*(4), 1462–1489.

Reinhard, E., Layte, R., McCrory, C., Panico, L., & Avendano, M. (2018). The Great Recession and the Health of Young Children: a Fixed-Effects Analysis in Ireland. *American Journal of Epidemiology*, *187*(7), 1438–1448.

Robins, J. M., Hernán, M. A., & Brumback, B. (2000). Marginal Structural Models and Causal Inference in Epidemiology. *Epidemiology*, *11*(5), 551–560.

Savage, M., Callan, T., Nolan, B., & Colgan, B. (2019). The Great Recession, austerity and inequality: lessons from Ireland. *Review of Income and Wealth*, *65*(2), 312–336.

Schaller, J., & Zerpa, M. (2019). Short-run effects of parental job loss on child health. *American Journal of Health Economics*, *5*(1), 8–41.

Schmidpeter, B. (2020). The Long-Term Labor Market Effects of Parental Unemployment. *Available at SSRN*, http://dx.doi.org/10.2139/ssrn.3283144.

Seaman, S. R., & White, I. R. (2013). Review of inverse probability weighting for dealing with missing data. *Statistical Methods in Medical Research*, *22*(3), 278–295.

Squires, J., Bricker, D., & Potter, L. (1997). Revision of a parent-completed developmental screening tool: Ages and Stages Questionnaires. *Journal of Pediatric Psychology*, *22*(3), 313–328.

Stevens, A. H., & Schaller, J. (2011). Short-run effects of parental job loss on children's academic achievement. *Economics of Education Review*, *30*(2), 289–299.

VanderWeele, T. (2015). *Explanation in causal inference: methods for mediation and interaction*. Oxford: Oxford University Press.

Washbrook, E., Gregg, P., & Propper, C. (2014). A decomposition analysis of the relationship between parental income and multiple child outcomes. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *177*(4), 757–782.

Watson, D., Whelan, C. T., , Maitre, B., & Williams, J. (2015). Family economic vulnerability and the Great Recession: An analysis of the first two waves of the Growing Up in Ireland study. *Longitudinal and Life Course Studies*, *6*(3), 230–244.

Whelan, C. T., & Maître, B. (2014). The Great Recession and the changing distribution of economic vulnerability by social class: The Irish case. *Journal of European Social Policy*, *24*(5), 470–485.

Whelan, C. T., Russell, H., & Maître, B. (2016). Economic stress and the great recession in Ireland: Polarization, individualization or 'middle class squeeze'? *Social Indicators Research*, *126*(2), 503–526.

Wodtke, G., & Zhou, X. (2019). Effect Decomposition in the Presence of Treatment-induced Confounding: A Regression-with-residuals Approach. , *Available at SocArXiv*, https://osf.io/preprints/socarxiv/86d2k/.

Wodtke, G. T. (2018). Regression-based adjustment for time-varying confounders. *Sociological Methods & Research*(DOI:10.1177/0049124118769087).

Wodtke, G. T., Alaca, Z., & Zhou, X. (2020). Regression-with-residuals estimation of marginal effects: a method of adjusting for treatment-induced confounders that may also be effect modifiers. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *183*(1), 311–332.

Yeung, W. J., Linver, M. R., & Brooks-Gunn, J. (2002). How money matters for young children's development: Parental investment and family processes. *Child Development*, *73*(6), 1861–1879.

Zubrick, S. R., Lucas, N., Westrupp, E. M., & Nicholson, J. M. (2013). *Parenting measures in the Longitudinal Study of Australian Children: Construct validity and measurement quality, Waves 1 to 4*. Canberra: Department of Social Services.

Tables and graphs

Table 1: Baseline sample features of the analytical sample (GUI, Wave 1).

Baseline sample features (Wave 1)	**Mean (sd)/Proportion**
Maternal age	32.5 (4.7)
Lone-parent household (*ref.* two-parent household)	.09
Mother has tertiary education (*ref.* upper-secondary or less)	.62
Mother employed part-time prior to birth (*ref.* employed full-time)	.22
Mother out of paid work prior to birth (*ref.* employed full-time)	.17
Mother is of Irish descent (*ref.* not)	.88
Household receives any welfare payment (*ref.* does not)	.17
Parental income: Second quintile (groups based on quintiles*, *ref.* first)	.17
Parental income: Third quintile	.21
Parental income: Fourth quintile	.25
Parental income: Fifth quintile	.23
N	6,303

*Quintiles are defined with reference to the income distribution for the original cohort sample at W1.

Table 2: OLS models for parental job loss and child outcomes at age 3 and 5. Model 1 adjusts for child features, Model 2 adds baseline maternal and household features (unweighted, GUI 2008-2013).

	Vocabulary		Internalizing problems		Externalizing problems	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
	Age 3					
Paternal job loss	-0.077**	-0.023	0.105***	0.059*	0.098***	0.052
	(0.034)	(0.033)	(0.033)	(0.034)	(0.033)	(0.033)
Maternal job loss	0.035	0.054	0.064	0.040	0.032	0.003
	(0.046)	(0.044)	(0.045)	(0.045)	(0.045)	(0.044)
	Age 5					
Paternal job loss	-0.083**	-0.030	0.025	-0.011	0.096***	0.049
	(0.034)	(0.034)	(0.034)	(0.034)	(0.033)	(0.033)
Maternal job loss	-0.087*	-0.070	0.036	0.010	0.118***	0.090**
	(0.046)	(0.045)	(0.046)	(0.045)	(0.045)	(0.044)
N	6,303	6,303	6,303	6,303	6,303	6,303

*$p < .10$, **$p < .05$, ***$p < .01$.

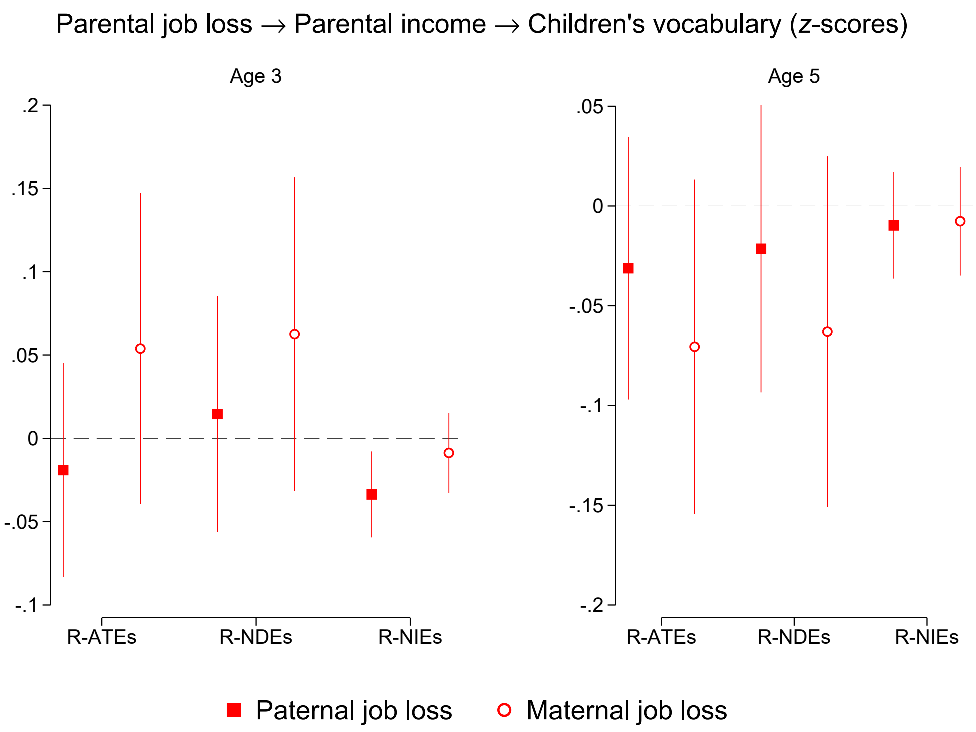

Figure 1: Mediation analyses for the effects of parental job loss on children's vocabulary via parental income. *Notes*: R-ATEs = Randomized Average Total Effects; R-NDEs = Randomized Natural Direct Effects; R-NIEs = Randomized Natural Indirect Effects. Standard errors are bootstrapped with 200 replications.

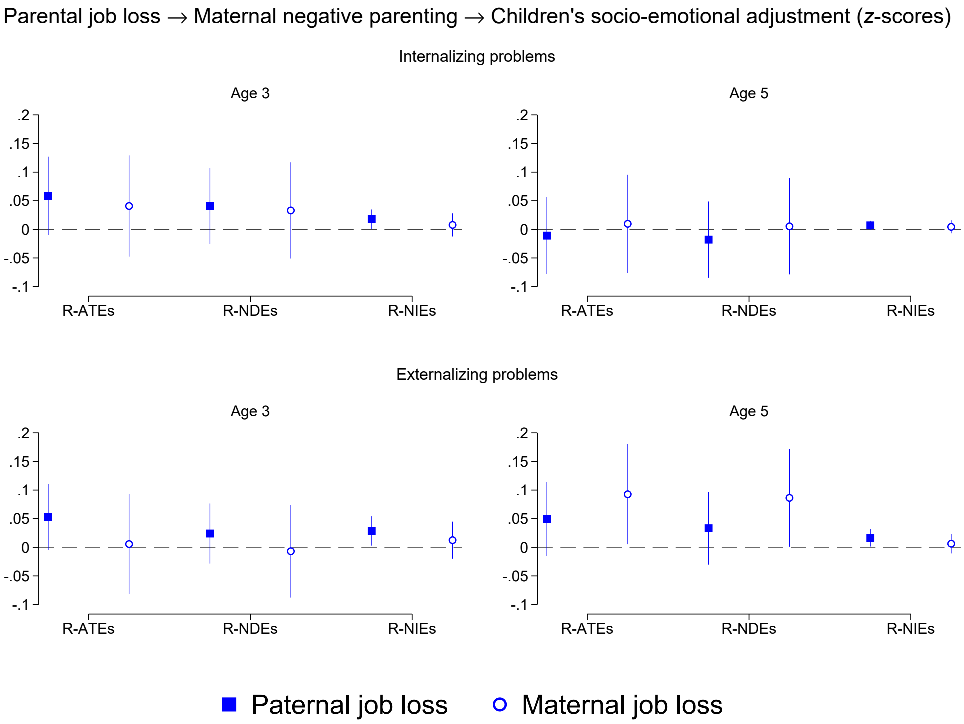

Figure 2: Mediation analyses for the effects of parental job loss on children's internalizing and externalizing problems, via maternal negative parenting. *Notes*: R-ATEs = Randomized Average Total Effects; R-NDEs = Randomized Natural Direct Effects; R-NIEs = Randomized Natural Indirect Effects. Standard errors are bootstrapped with 200 replications.

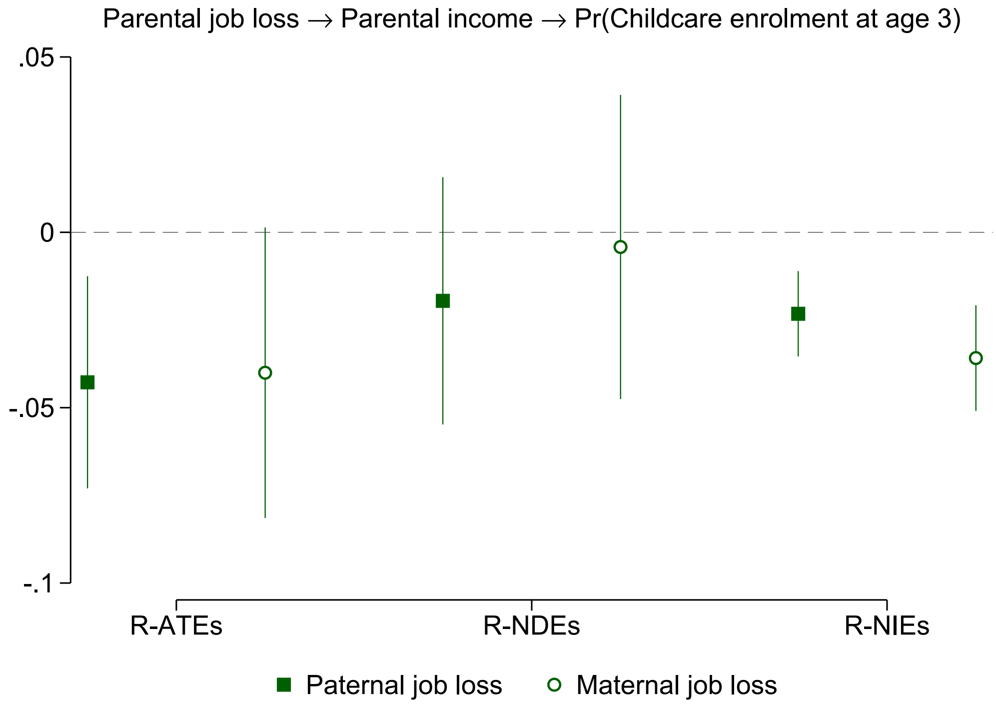

Figure 3: Mediation analyses for the effects of parental job loss on children's chances of enrolment in formal childcare, via parental income. *Notes*: R-ATEs = Randomized Average Total Effects; R-NDEs = Randomized Natural Direct Effects; R-NIEs = Randomized Natural Indirect Effects. Standard errors are bootstrapped with 200 replications.

Supplementary material for

"Parental job loss and early child development in the Great Recession"

S1. Weighting for loss to follow-up and complete-case analysis

Sample exclusions in our analyses are mainly due to loss to follow-up and to missing values on relevant covariates. To inspect if biases ensued as a result of these sample restrictions, we devised a number of probability weights. First, we built weights for loss to follow-up between, respectively, Waves 1 and 2, and Waves 2 and 3. Let $A_{h,w}$ be a dummy variable for whether households h were lost to follow-up ($A_{h,w} = 1$) or not ($A_{h,w} = 0$) in a given Wave w. We estimated stabilised inverse probability weights swa_h for such sample attrition (Robins et al., 2000; Kühhirt & Klein, 2018) as follows:

$$swa_h = \prod_{w>1} \frac{P(A_{h,w} = 0|A_{h,w-1} = 0)}{P(A_{h,w} = 0|A_{h,w-1} = 0, Z_{i,h,1}, Z_{(i,h,w-1)})} \tag{1}$$

The probability of not being lost to follow-up in a given Wave $P(A_{h,w} = 0)$ is at the numerator and was estimated via an "empty" logistic model with $A_{h,w}$ as the outcome. This is, by default, conditional on being observed in the Wave prior ($A_{h,w-1} = 0$). For Wave 2, we thus estimated our weights using the whole original sample (N = 11,134), whereas for Wave 3 we estimated weights on those who "survived" up to the Wave 2 (N = 9,773). At the denominator, we take the probability of not being lost to follow-up in a given Wave $P(A_{h,w} = 0)$ conditional on a set of covariates. The choice of covariates reflects the observation that loss to follow-up in GUI is disproportionately likely for one-parent households and families with lower socioeconomic background (McCrory et al., 2013). For Wave 2, we estimated a logistic regression for our dummy $A_h, 2$ on the following set of individual and household covariates $Z_{i,h,1}$, measured at Wave 1: dummies for lone-parent household, father not resident, whether the family lives in an urban/rural area, sex of the child, whether the child has siblings, maternal work status prior to birth, maternal age in ten-year bins, housing tenure, current social class (eight-fold classification), and whether the primary respondent's family struggled to make ends meet when the primary respondent was 16. For Wave 3, we regressed $A_{h,3}$ on the same set $Z_{i,h,1}$ and on additional variables measured at Wave 2 (i.e. $Z_{i,h,w-1}$), namely: dummies for parental job loss (our exposure), the birth of a new sibling for the study child, whether the family moved, whether parents of the study child separated. Weights for Waves 2 and 3 are then combined via multiplication ($\prod_{w>1}$ in Equation 1) to obtain swa_i.

We followed a similar procedure to estimate inverse probability weights for the inclusion in the analytical sample (Seaman & White, 2013). All in all, 8,712 households were followed across all three Waves of GUI. Yet, mainly due to missing values on relevant covariates, our main analytical sample comprises only 6,303 households. Let I_h denote a dummy variable equal to 1 if a household is included in this main analytical sample and 0 when a household h is only observed up to Wave 3 yet not part of the analytical sample. We then computed the following stabilised inverse probability weight swi_h for inclusion in the main analytical sample:

$$swi_h = \frac{P(I_h = 1|A_{h,2} = 0, A_{h,3} = 0)}{P(I = 1|A_{h,2} = 0, A_{h,3} = 0, W_{i,h,w})} \tag{2}$$

At the numerator, we have the probability of being included in the final sample $P(I_h = 1)$ conditional on being observed up until Wave 3 ($A_{h,2} = 0$, $A_{h,3} = 0$). At the numerator, we modelled the probability of inclusion conditional on a set of individual- and household-level covariates $W_{i,h,w}$, namely: dummies for lone-parent household, father not resident, whether the family lives in an urban/rural area, sex of the child, whether the child has siblings, maternal work status prior to birth, maternal age in ten-year bins, housing tenure, current social class (eight-fold classification), and whether the primary respondent's family struggled to make ends meet when the primary respondent was 16 – all of which are measured at Wave 1 – and parental job loss, measured at Wave 2. All probabilities were estimated via logistic regression.

We then combined weights swa_h and swi_h by means of multiplication and top- and bottom-coded, respectively at the 99th and 1st percentile, our final weight w_h (Mean = .99, SD = .3). Table 1S replicates our main analyses for the analytical sample reweighted by w_h. Weighted estimates in Table 1S are close in size and uncertainty to their unweighted counterparts in Table 2. Our substantial conclusions regarding the effects of parental job loss on child outcomes are therefore unaltered.

Table 1S: OLS models for parental job loss and child outcomes at age 3 and 5. Model 1 adjusts for child features, Model 2 adds baseline maternal and household features (weighted by w_h, GUI 2008-2013).

	Vocabulary		Internalizing problems		Externalizing problems	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
			Age 3			
Paternal job loss	-0.087**	-0.023	0.120***	0.076*	0.086**	0.035
	(0.039)	(0.037)	(0.039)	(0.040)	(0.037)	(0.037)
Maternal job loss	0.028	0.036	0.028	0.008	-0.012	-0.029
	(0.052)	(0.048)	(0.046)	(0.046)	(0.047)	(0.046)
			Age 5			
Paternal job loss	-0.101**	-0.034	0.031	0.004	0.054*	0.008
	(0.039)	(0.037)	(0.039)	(0.040)	(0.036)	(0.036)
Maternal job loss	-0.097*	-0.087*	0.014	0.001	0.119**	0.107**
	(0.051)	(0.048)	(0.048)	(0.047)	(0.052)	(0.051)
N	6,303	6,303	6,303	6,303	6,303	6,303

$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

S2. Main effects of parental job loss on candidate mediators

Table 2S: OLS models for parental job loss and candidate mediators. All models adjust for child features (unweighted, GUI 2008-2013).

	Parental income	Maternal negative parenting
Paternal job loss	-.176***	0.067**
	(.012)	(0.033)
Maternal job loss	-.153***	0.035
	(0.016)	(0.044)
N	6,303	6,303

$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

S3. Crossing mediators and outcomes

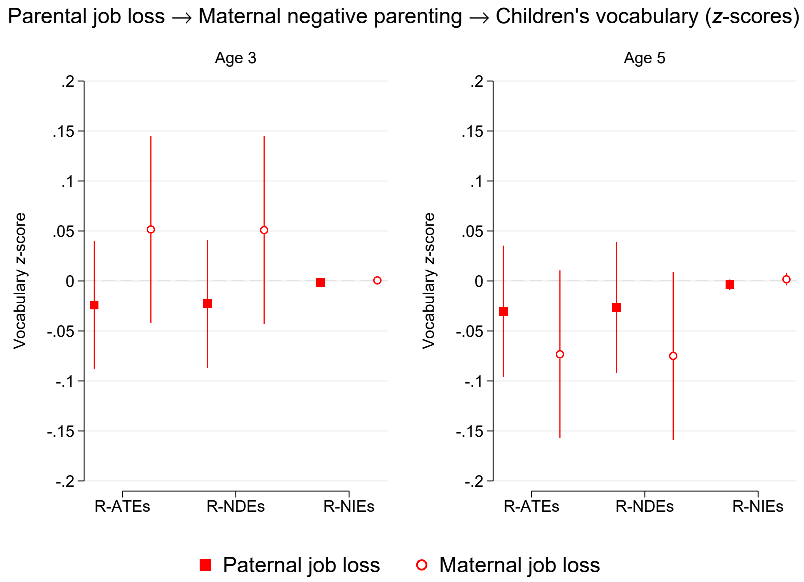

Figure 1S: Mediation analyses for the effects of parental job loss on children's vocabulary via maternal negative parenting. *Notes*: R-ATEs = Randomized Average Total Effects; R-NDEs = Randomized Natural Direct Effects; R-NIEs = Randomized Natural Indirect Effects. Standard errors are bootstrapped with 200 replications.

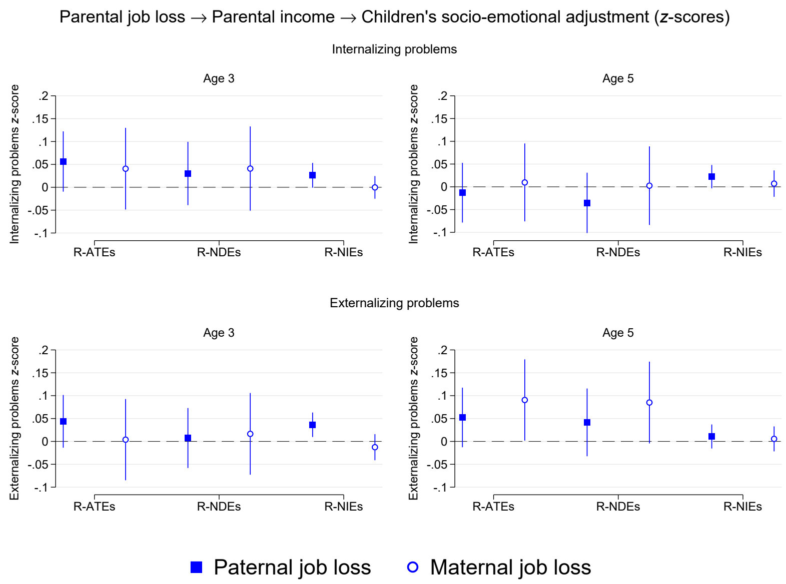

Figure 2S: Mediation analyses for the effects of parental job loss on children's internalizing and externalizing problems, via parental income. *Notes*: R-ATEs = Randomized Average Total Effects; R-NDEs = Randomized Natural Direct Effects; R-NIEs = Randomized Natural Indirect Effects. Standard errors are bootstrapped with 200 replications.

S4. Heterogeneous effects by maternal education

In this section, we present analyses split by maternal education. We break down our sample into two groups, one comprising households in which the mother has upper-secondary education or less (2,397 households, 38% of the original sample), the other in which mothers have tertiary education (3,906 households, 62% of the original sample). We ran the same models detailed in the main text on such separate samples, performing our mediation analyses as per Equations 3 to 6. Exposure to parental job loss is as follows: for those with lower maternal education, 1,726 households experienced no job loss ($\approx$ 72%), 475 were affected by paternal job loss ($\approx$ 20%), and 196 by maternal job loss ($\approx$ 8%); for those with higher maternal education, 3,037 households experienced no job loss at all ($\approx$ 78%), 553 were affected by paternal job loss ($\approx$ 14%), and 316 by maternal job loss ($\approx$ 8%). In line with previous studies (Watson et al., 2015; Nolan & Maître, 2017), we find that parental job loss was somewhat more pronounced among, but by no means limited to, more disadvantaged families during the Great Recession in Ireland.

Table 3S displays the associations of our exposure with each mediator, split by maternal education. Concerning parental income, estimates for both paternal job loss and maternal job loss are quite similar across sub-samples and largely in line with those for the whole sample, as per Table 2S. For negative parenting, on the other hand, associations are somewhat more pronounced in the tertiary educated sub-sample. Overall, when it comes to parental job loss and the mediators in this study, households with highly-educated mothers appear equally or even more adversely affected than their relatively lower-educated counterparts.

Table 3S: OLS models for parental job loss and candidate mediators, split by maternal education. All models adjust for child features (unweighted, GUI 2008-2013).

	Parental income		Maternal negative parenting	
	Upper-sec. or less	Tertiary	Upper-sec. or less	Tertiary
Paternal job loss	-.172***	-.179***	.039	.087**
	(.017)	(.016)	(.052)	(.043)
Maternal job loss	-.135***	-.158***	-.044	.079
	(.025)	(.021)	(,075)	(.055)
N	2,397	3,906	2,397	3,906

*p < .10, **p < .05, ***p < .01.

In Figure 3S we turn to the effects of parental job loss on children's verbal ability, via the channel of parental income and separate across levels of maternal education. Similar to our main analyses, we cannot detect total effects (R-ATEs) on verbal ability at age 3 in either sub-group. This holds regardless of which parent was displaced, and net of baseline features of the study child, their mother, and the household they belong to. Among households with lower maternal education, however, we find opposite direct and indirect effects. A positive direct effect (R-NDE = .19, p = .012) of maternal job loss is coupled with a negative indirect effect (R-NIE = −.07, p = .004), via the channel of parental income. Keeping the focus on verbal ability at age 3, the same pattern is not detected for maternal job loss in households where the mother has tertiary education (R-NDE = −.01, p = .873; R-NIE = .02, p = .156).

Turning to paternal job loss, we can only detect negative indirect effects amounting to around .04 SDs for children's vocabulary test scores at age 3. These are similar across sub-samples in Figure 3S and comparable to our findings for the whole sample, as per Figure 1. As for vocabulary test scores at age 5, estimates do not differ substantially across sub-samples or from those for the whole sample. Across groups in Figure 3S, we can only detect a negative indirect effect via parental income for maternal job loss, for mothers with upper-secondary education or less (R-NIE = −.04, p = .040) and not among those with tertiary degrees (R-NIE = .01, p = .478).

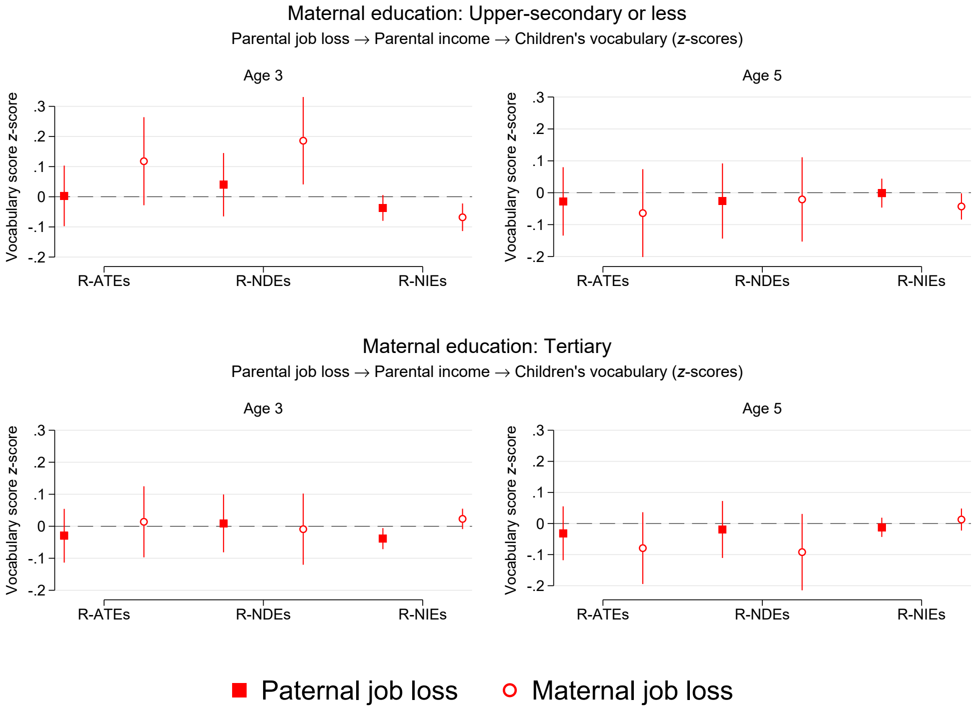

Figure 3S: Mediation analyses for the effects of parental job loss on children's vocabulary scores, via parental income and split by maternal education. *Notes*: R-ATEs = Randomized Average Total Effects; R-NDEs = Randomized Natural Direct Effects; R-NIEs = Randomized Natural Indirect Effects. Standard errors are bootstrapped with 200 replications.

In Figures 4S and 5S, we examine problem behaviour. Similar to Figure 2 in the main text, we focus on its association with parental job loss via maternal negative parenting. Overall, estimates are often comparable across sub-samples and suggest at most a limited role of maternal negative parenting in contributing to behavioural problems, at least in response to parental job loss. If anything, we find that total and direct effects are larger in size for households in which mothers have a tertiary degree rather than high school or less. For example, among the former households, we detect sizeable ($\approx$ .1 SDs) total effects of both paternal job loss and maternal job loss on externalizing problems at age 5, as per Figure 5S. This does not hold for the relatively lower educated sub-sample, although, focusing on maternal job loss, estimates are closer to each other across the two sub-samples. Throughout, indirect effects via maternal negative parenting are never larger than $\approx$ .02 SDs and, differently from total effects, differences across sub-samples are statistically and substantially negligible.

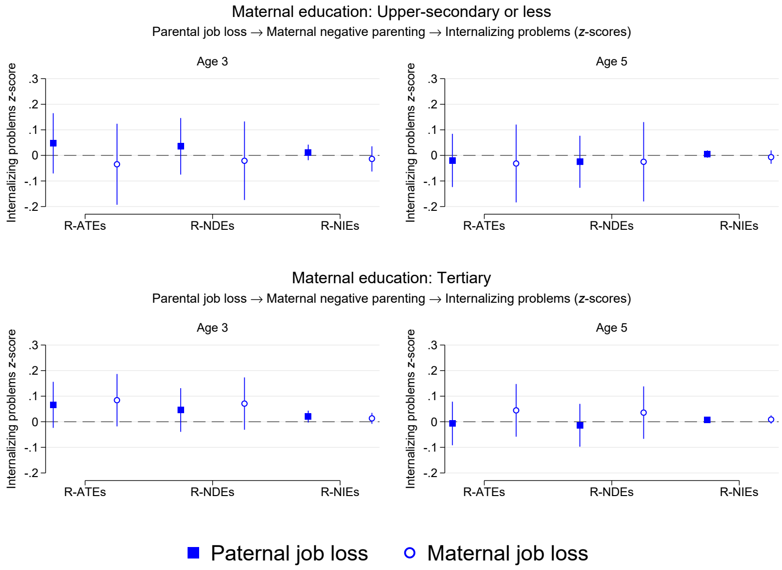

Figure 4S: Mediation analyses for the effects of parental job loss on children's internalizing problems, via maternal negative parenting and split by maternal education. *Notes*: R-ATEs = Randomized Average Total Effects; R-NDEs = Randomized Natural Direct Effects; R-NIEs = Randomized Natural Indirect Effects. Standard errors are bootstrapped with 200 replications.

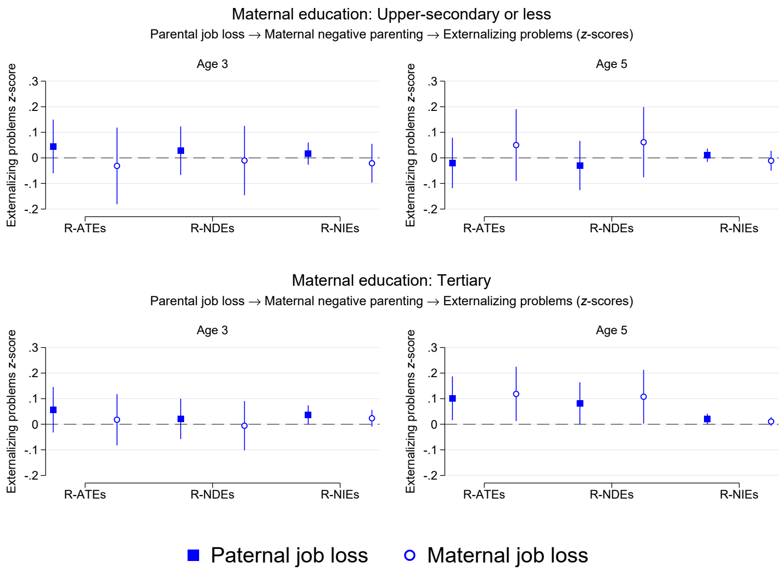

Figure 5S: Mediation analyses for the effects of parental job loss on children's externalizing problems, via maternal negative parenting and split by maternal education. *Notes*: R-ATEs = Randomized Average Total Effects; R-NDEs = Randomized Natural Direct Effects; R-NIEs = Randomized Natural Indirect Effects. Standard errors are bootstrapped with 200 replications.

Finally, we turn to whether job and income losses impaired parental investment in formal childcare. As mentioned in the main text, we find that maternal job loss has the largest total effect among households with lower maternal education. Yet, we also detect a negative total effect of paternal job loss among households in which mothers have tertiary qualifications (R-ATE = $-.07$, $p = .002$). Indirect effects via parental income are similar in size and always negative across sub-group, and regardless of which parent experiences job loss.

All in all, this sub-group analyses do not provide evidence of a clear-cut stratification of the costs of job loss across households, at least for this Irish cohort. Rather, early child development might be negatively affected by parental job loss, but not always directly, and not only among the least well-off households. Findings for childcare investments, in particular, underscore that support to ease childcare costs – in response to job loss – could be effective if inclusive of households in different socioeconomic strata. This speaks to the importance of considering the specific distributional impact of a given recession or wave of job loss. Previous studies pointed to a significant rise in economic vulnerability among the middle class in Ireland after the Great Recession (e.g. Whelan & Maître, 2014). We find echoes of that in the intergenerational costs of job loss among households with higher maternal education in our analyses.

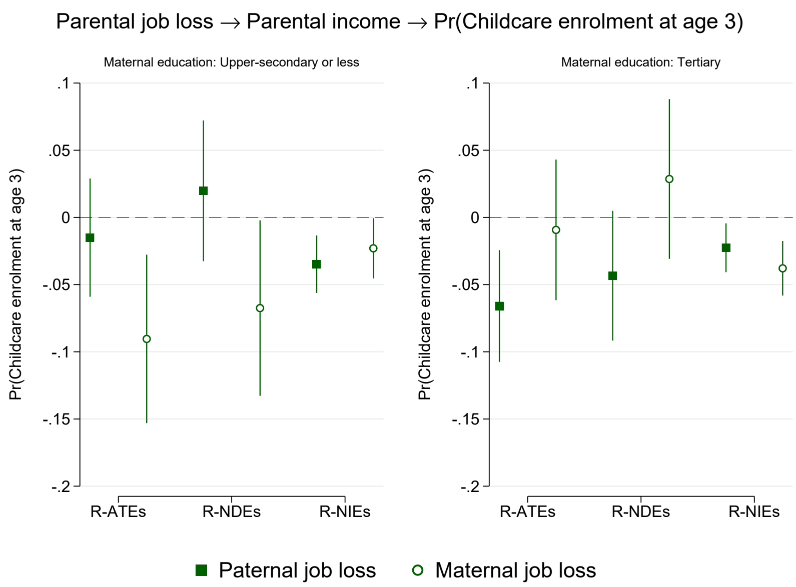

Figure 6S: Mediation analyses for the effects of parental job loss on children's chances of enrolment in formal childcare, via parental income and split by maternal education. *Notes*: R-ATEs = Randomized Average Total Effects; R-NDEs = Randomized Natural Direct Effects; R-NIEs = Randomized Natural Indirect Effects. Standard errors are bootstrapped with 200 replications.