Economic Distress and Children's Mental Health: Evidence from the Brazilian High Risk Cohort Study for Mental Conditions*

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Abstract

This paper assesses the effects of adverse economic shocks on children's mental health. We rely on the Brazilian High Risk Cohort Study for Mental Conditions, which provides an unprecedented array of data on psychopathology, life events, family medical history as well as parental behavior and polygenic scores for mental disorders over a 10 year period. Our empirical strategy exploits parental job loss events over time in a differences-in-differences framework. We document that parental job loss has strong and persistent negative effects on parental income and household assets. We then show that parental job loss significantly worsens children's mental health and that this result is robust to different specifications, placebo tests and choices of measurement scales. Turning to potential mechanisms, we document significant effects on children's exposure to abuse and neglect. Yet, these effects dissipate in later follow-ups, as do the effects on mental health outcomes. Effects do not vary with polygenic risk scores for mental disorders, suggesting that negative effects of economic distress on children's mental health might be triggered by environmental factors to a greater extent.

JEL Codes: I12, J13, J63
Keywords: job loss, child mental health, family environment, genetic endowments

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1 Introduction

Mental health conditions account for 14.6% of the years lived with disability globally and can have severe negative economic consequences by impairing cognitive function or distorting beliefs and preferences (Ridley et al., 2020; GBD Collaborators, 2021). Most mental disorders emerge in childhood and adolescence, often amidst an environment of adverse economic conditions and social disadvantage (Patel et al., 2018). Yet, there is scant causal evidence on the extent to which and how socioeconomic disadvantages might lead to childhood adversity and the impairment of children's mental health. Measuring mental health conditions remains particularly challenging, while household conditions and parents' behavior in face of adverse economic shocks are typically not observed. Notwithstanding these challenges, the characterization of the potential pathways connecting socioeconomic disadvantages and children's mental health is crucial for action, and can be instrumental for the prevention of mental health problems and the recovery from mental disorders.

In this paper, we rely on the Brazilian High Risk Cohort Study for Mental Conditions (BHRCS) to assess the effects of adverse economic shocks on children's mental health. The BHRCS provides an unprecedented array of data on psychopathology, life events, family medical history as well as parental behavior and polygenic scores for mental disorders. Children living in the Brazilian cities of São Paulo or Porto Alegre were selected either at random (n = 957 children) or due to an increased risk for mental disorders (n = 1,553).[1] Children have been assessed at three different waves since 2010. Our main indicators of child mental health come from the detailed Development and Wellbeing Assessment (DAWBA) interview. In particular, we use diagnostic-based measures of internalizing (e.g., depression, anxiety) and externalizing (e.g., ADHD, conduct) disorders and clinical ratings performed by child psychiatrists, based on the objective and open-ended questions from DAWBA. We additionally use the Child Behavior Checklist (CBCL), which has been shown to provide valid assessments of psychopathology symptoms. We focus on parental job losses, also recorded in questionnaires, as a marker of a relevant and common adverse economic shock that can lead to spillover effects on children. As reviewed in Ruiz-Valenzuela (2021), negative consequences of job loss may have a direct effect on inputs that enter both the children's production function of cognitive achievement and their health production function.

Our empirical strategy exploits parental job loss events over time in a differences-in-differences (DiD) framework. We use a questionnaire of children's life events to identify those whose parents have reported losing a job between waves. We define treatment groups based on when parents first lose a job, thus rendering a staggered design. Following the recent advances of the DiD literature, we use estimators that are robust to treatment effect heterogeneity across cohorts and time. Our main specification uses children whose parents have never lost a job across waves as the control group, but results are remarkably similar when we use those whose parents will lose a job in the future as the control group of those whose parents lost their jobs earlier. Exploiting the richness of our dataset, we control for a wide range of covariate-specific trends, including socioeconomic characteristics, parental and children's mental health, family environment, exposure to risk factors, and cognitive skills. Our identification strategy relies on the parallel trends assumption conditional on covariates. We follow Callaway and Sant'Anna (2021) and incorporate covariates using semiparametric doubly-robust estimators. Given the large number of control variables available in our dataset, we additionally test

[1]High-risk children were selected based on the percentage of family members, adjusted for relatedness, who screened positively for mental health disorders (Salum et al., 2015).

machine learning techniques to select those to be included in the model (Chernozhukov et al., 2018). We show in placebo tests that pre-trend differentials are statistically insignificant and remarkably close to zero.

We first document that parental job loss has strong and persistent negative effects on parental income and household assets. We then show that parental job loss significantly worsens children's mental health. Our results show that parental job loss increases both internalizing and externalizing symptoms by around 0.17 standard deviation (SD). In a similar vein, overall psychopathology as measured by the CBCL instrument increases by 0.22 SD. These results are supported by clinical ratings. We find that parental job loss increases children's probability of being diagnosed with any mental disorder by 7 percentage points, or 28% relative to the baseline. This result is largely driven by the diagnosis of anxiety disorder. In all cases, we found no impact on mental health outcomes in the longer run, as assessed at a subsequent follow-up wave. In addition to psychopathology outcomes, we also measure the effects of parental job loss on children's school attainment. Point estimates are negative, although imprecisely estimated.

Our results are robust to several specification checks. They remain extremely similar regardless of the way we control for covariate-specific trends. If anything, they become even stronger when we do so. Thus, our estimates are robust as long as selection on observables is informative about selection on unobservables. Similarly, the magnitude of our estimates increases once we restrict the sample to children of parents who eventually lose their job at any point in time and, therefore, solely exploit variation in the timing of the job loss. This reassures the robustness of the results as in this setup treatment and control groups are more likely to be similar in unobservables.

Turning to potential mechanisms, we document significant effects on children's exposure to abuse and neglect, which also dissipate in later follow-ups, similar to mental health outcomes. These results suggest that disruptions in the family environment and consequent exposure to child maltreatment may be a relevant causal mechanism linking economic distress to children's mental health issues. We also investigate whether psychiatric risk factors —genetic endowments and the prevalence of mental illness in the family— moderate our results. We show that the impact on clinical ratings is driven by children scoring high in the index capturing family psychiatric risk for anxiety and depression. However, when analyzing psychopathology symptoms, we find substantial effects even for children without an increased risk for mental disorders. Moreover, the impacts are similar for families with above- and below-median psychiatric family risk scores. Finally, we study treatment effect heterogeneity according to children and parental polygenic risk scores for psychiatric diseases. Taken together, heterogeneous effects are insignificant, suggesting that the impacts of parental job loss on children's mental health are independent of their genetic endowment and that the stronger results among children with high family psychiatric risk for anxiety and depression might be driven by environmental factors.

While there is ample evidence on the effects of parental job loss on children's educational outcomes (Hilger, 2016; Mörk et al., 2020; Ruiz-Valenzuela, 2021), including a recent study for Brazil (Britto et al., 2021), evidence on children's mental health is scarcer. The existing causal studies rely on indirect measures of mental health conditions, such as perceptions reported by household survey respondents or records of health care and prescription drug utilization (e.g. Schaller and Zerpa, 2019; Mörk et al., 2020; Moghani et al., 2021). However, changes in reported measures may result from variation in the respondent perception of a child's health, or even the respondent's own mental health, rather than variation in the child's actual health (Schaller and Zerpa, 2019). Additionally, proxies from health care and prescription drug utilization may be directly related to changes in the income profile and in the consumption of health care, rather than in actual health status. We contribute novel evidence to the literature in different ways. First, we assess the impact of parental job loss on a wide range of mental health outcomes by using a rich array of psychopathology data, including objective clinical diagnosis of specific disorders.[2] Second, we look at parenting practices to illuminate possible mechanisms, assess educational attainment to further infer costs related to human capital formation, and document heterogeneous effects by family history of mental disorders and polygenic scores for psychiatric disorders. In this way, we add efforts to the recent literature that investigates whether the interaction between genetic endowments and childhood environment affects human capital development (Barcellos et al., 2021; Houmark et al., 2020). Finally, most of the literature on the mental health impacts of economic distress, as marked by parental job loss, comes from high-income countries. To the best of our knowledge, our work is the first to assess this relationship in a developing country, where social safety nets are weaker and families may be hit the most by economic fluctuations. Our results are therefore particularly informative for policymaking in relatively more deprived contexts.

The remainder of the paper is organized as follows. Section 2 describes the data and the background of our study. Section 3 outlines the empirical strategy. Section 4 describes our main results, their robustness, and documents potential mechanisms. In Section 5, we examine whether psychiatric risk and genetic endowments moderate our main results. Section 6 concludes.

2 Data and Background

We use data from the Brazilian High Risk Cohort Study for Mental Conditions (BHRCS). The cohort is composed of 2,511 children from the cities of São Paulo and Porto Alegre who were enrolled in 57 different public schools, aged 6-14 at the baseline (year 2010-2011) and who have been followed periodically since then (Salum et al., 2015). São Paulo is Brazil's most populous city, with a population of 11,253,503 inhabitants according to the 2010 Census. Porto Alegre is the largest city in the Southern region of Brazil, with a population of 1,409,351 inhabitants.

The definition of the BHRCS sample started with a voluntary screening with the caregivers of 9,937 children enrolled at 22 and 35 public schools at Porto Alegre and São Paulo, respectively. At that stage, the BHRCS team conducted the Family History Screen (FHS), a structured interview to screen all family members for mental disorders following the Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition (DSM-IV). Using the FHS screening tool results, they defined an index measuring the percentage of family members that screened positive for any psychopathology, adjusted for relatedness to the children. The final sample includes a sub-sample of randomly selected children among all screened (n=957) and a high-risk sub-sample based on the highest remaining scores of the FHS index after the random sampling (n= 1,553). Only one child per family was enrolled in the final sample. For further details about the screening, sampling and data collection procedures, see Salum et al. (2015).

Our working dataset contains information from the baseline (2010-2011) and two follow-up waves (2013-2014 and 2018-2019) of the cohort. All three waves include the Development and Well-Being Assessment (DAWBA), a package of interviews, questionnaires and rating techniques generating DSM-

[2] Mari and Keizer (2021) use psychopathology data from Ireland to estimate the impacts of parental job loss on children's health indicators. However, the authors rely on repeated cross-sections, conditionally only on observable baseline covariates and subject to omitted variables bias.

IV-based psychiatric diagnosis (Goodman et al., 2000). The DAWBA comprises a structured interview, including the Strength and Difficulties Questionnaire (SDQ), a 25-item questionnaire providing four risk groups of behavioral and emotional difficulties, and recorded verbatim responses. Based on answers given by parents and children, an algorithm generates diagnostic probabilities, which are then used to compute DAWBA bands (Goodman et al., 2011). These are ordinal and integer scores from 0 to 5 corresponding to probabilities of satisfying the diagnostic: $< 0.01\%$, 0.5%, 3%, 15%, 50%, and $> 70\%$, respectively. Verbatim responses as well as structured answers are also carefully evaluated by psychiatrists, who then provide clinical diagnosis.

In the current paper, we analyze the combined externalizing DAWBA band scores —which includes attention deficit hyperactivity disorder (ADHD), conduct disorder (CD), and oppositional defiant disorder (ODD)— and the combined internalizing DAWBA band scores —which includes major depression, generalized anxiety disorder, specific phobia, social phobia, separation anxiety disorder, panic disorder, and agoraphobia. To measure overall psychopathology, sometimes we group both internalizing and externalizing scores from DAWBA. What is more, we use clinical ratings for specific disorders given by nine certified child psychiatrists, with an inter-rater reliability of 91%.

In addition to the DAWBA, the baseline and the first follow-up wave include the Child Behavior Checklist (CBCL), a structured questionnaire that records parents answers assessing 120 emotional, behavioral, attention, thought, and social problems in their children. It provides standardized measures of eight different child and adolescent problems, which can be grouped in three broad-band scales: internalizing score (withdrawn, somatic complains and anxious/depressed), externalizing score (rule-breaking behavior and aggressive behavior) and total score (that groups the two aforementioned scores with thought, attention, and social problems) (Bordin et al., 2013). We use CBCL scores to complement DAWBA as a measure of dimensional psychopathology. While DAWBA captures mental health symptoms plus functional impact/impairment due to symptoms (resulting in a diagnostic measure), CBCL does not require the impact/impairment criteria and is just a sum score of parental responses to an extensive symptom checklist. Finally, in sensitivity analysis we also use the SDQ, another dimensional parent-reported measure of psychopathology.

For each follow-up wave, our database includes information on exposure to different life events since the previous wave, including parental job losses, which we use to identify children exposed to this shock between any two waves.[3] Moreover, all three waves contain information about educational attainment, maternal and paternal income, household assets, exposure to parental abuse and neglect and cohabitation/marital status of the parents. We use this information to shed light on the impact of job loss on alternative outcomes and possible mechanisms linking job loss to children's mental health. At the baseline wave, our dataset includes a wide range of covariates: basic parental and child demographics, socio-economic indicators, information on prenatal and perinatal health, exposure to violence or other life stressors, family environment, executive function development, and other cognitive skills. Additionally, it includes data on children and their parents' polygenic risk scores (PRS) for psychiatric diseases, computed from saliva samples.[4]

Appendix Table ?? presents summary statistics at the baseline. Out of the 2511 children in the cohort, 960 (38.2%) were exposed to parental job loss. Children are mostly white (60.5%) or brown

[3] Available information does not detail whether the mother or the father lost her/his job.

[4] PRS estimate the genetic propensity to an specific outcome at the individual level. They are defined by the sum of risk gene variants that correspond to that outcome of interest in each individual, weighted by the association between those gene variants and the outcome of interest according to a genome-wide association study (Choi et al., 2020).

(28.1%), and are on average 9.8 years old at the baseline, with 4.2 years of schooling. Regarding their parents, 14.3% have parents who are divorced, over 40% have parents who are permanently employed, and 21.3% (19,7%) have mothers (fathers) who are self-employed or informal workers. Parents who are temporary workers are less common, with under 3.7% mothers and 1.0% of fathers in that condition, and 19,8% of mothers are housekeepers. Around 26% of children presented any mental health disorder at the baseline, mostly consisting of anxiety disorders (10.9%) and, less frequently, depressive disorders (3.2%). This relatively high prevalence is due to the fact that 61.9% of the sample consists of children identified as having a high risk of developing mental health disorders, based on family history. The existing differences between treatment and control groups, for example in baseline prevalence of disorders, is taken into account in the empirical strategy.

3 Empirical Strategy

Our goal is to assess the average treatment effect of adverse economic shocks, as measured by parental job loss, on children's mental health. While a job loss itself may be transient, its impact may not be. Hence, we define treatment based on when parents first lose a job. In this case, our treatment is staggered by construction. We then primarily follow the identification, estimation, and inference tools Callaway and Sant'Anna (2021) (C&S) propose in staggered DiD setups.

We start defining the notation used throughout the section. Denote a particular wave time by w, where $w = 0, 1, 2$, and let D_w be a binary variable that indicates whether a child's parent has lost a job up to w. Also, define G_g to be a dummy variable that is equal to one if a child is first treated between waves 0 and 1 (let $g = 1$) or between waves 1 and 2 ($g = 2$), and define C as a dummy variable that is equal to one for children who are not treated in any period. Finally, let $Y_w(1)$ and $Y_w(0)$ measure potential children's mental health at time w with and without parental job loss, respectively. The observed outcome in each period can be expressed as $Y_w = D_w Y_w(1) + (1 - D_w)Y_w(0)$. The main building block of our framework is the average treatment effect for children who are member of group g at a particular wave time w, denoted by

$$ATT(g, w) := E[Y_w(1) - Y_w(0)|G_g = 1]. \quad (1)$$

Following C&S, we express our parameter of interest in terms of functionals of (1). In particular, we are mostly interested in

$$\tau_0 := \sum_{j\in\{1,2\}} P(G_j = 1)ATT(j, j), \quad (2)$$

which is the average treatment effect of parental job loss on children's mental health measured in the wave *immediately* after this adverse shock among all groups of children whose parents ever lose a job across our panel data. We are also interested in the dynamic treatment effect $\tau_1 := ATT(1, 2)$, which measures whether the impact of an adverse economic shock on children's mental health is persistent up to two waves after the event, and in the placebo treatment effect $\tau_{-1} := ATT(2, 1)$, which provides evidence on the internal validity of our study.[5]

Our study design is based on a conditional parallel trend assumption. That is, we assume that

[5]Notice that $\tau_1 - \tau_0$ could be the result of not only treatment effect dynamics, but also compositional differences between groups 1 and 2, given that τ_1 is only identified for group 2. As we find that $\widehat{ATT(1,1)} \approx \widehat{ATT(2,2)}$, we believe τ_1 is likely to be a good approximation for the average dynamic treatment effect across *all* groups.

children with the same baseline characteristics X would follow the same trend in mental health status in the absence of parental job loss. We exploit the richness of our dataset and match children based on a wide range of baseline covariates, including basic parental and child demographics (city of residence, race, birth year, gender, marital status), socio-economic indicators (household assets, mother's educational attainment and employment status), prenatal and perinatal health (type of delivery, number of prenatal visits, exposure to stress intra-utero, exposure to alcohol and drugs intra-utero, and height and weight at birth), early life stressors (indexes measuring family environment, parent-child relationship, and exposure to bullying and violence), child cognitive development (an index measuring spatial, working memory, reading, writing, and math skills), and parental and child mental health. By following this route, we deal with potential biases that could arise if the path of mental health outcomes (in the absence of parental job loss) depends on these baseline characteristics.

Under the conditional parallel trend assumption, (1) is identified by

$$E[\omega_g(X) \times (\Delta Y - E[\Delta Y|X, C = 1])], \tag{3}$$

where $\omega_g(X) := \frac{G_g}{E[G_g]} - \frac{p_g(X)C}{1-p_g(X)} \Big/ E\left[\frac{p_g(X)C}{1-p_g(X)}\right]$, $p_g(X)$ being the probability of being first treated between waves $g-1$ and g conditional on covariates, and $\Delta Y := Y_w - Y_{g-1}$. We estimate (3) and, consequently, $\{\tau_i\}_{i\in\{-1,0,1\}}$ using sample analogues and parametric estimators. In particular, we estimate $p_g(X)$ using a logit model, and $E[\Delta Y|X, C = 1]$ using OLS. Our estimator has the double robustness property: it only requires one to correctly specify either (but not necessarily both) the outcome evolution for the comparison group or the propensity score model (Sant'Anna and Zhao, 2020). In order to conduct asymptotically valid inference, we use a bootstrap procedure that computes simultaneous confidence bands for the entire path of group-time average treatment effects. Unlike pointwise inference, simultaneous confidence bands do not suffer from multiple-testing problems. Our inference procedure also accounts for the autocorrelation of the data by using clustered bootstrapped standard errors at the child level.

We additionally test several alternative specifications. Given the large number of covariates available in our dataset, we combine double robust estimators with machine learning techniques to select the control variables to be included in the model following Chernozhukov et al. (2018). We also test OLS estimators in which covariates are included linear and additively. Moreover, we test the sensitivity of our results to the inclusion of covariates itself. We also test the not-yet treated group (that is, children such that $G_2 = 1$ but $D_1 = 0$) as an alternative control group to C. In this case, we restrict the sample to only treated children and, hence, solely exploit variation in the timing of the job loss. Our results are remarkably similar across all these alternative specifications. We further provide support to our study design's internal validity by showing that $\widehat{\tau}_{-1} \approx 0$ for several different outcomes.

4 Results

We present our main results graphically, plotting in the same figure the estimated treatment effects for the event times 0 (wave immediately after parental job loss) and 1 (second wave after parental job loss). Additionally, all plots include placebo treatment effects (effect for event time -1), which exploit solely variation that precedes parental job losses and provides evidence on the credibility of the underlying parallel trends assumption. In all cases, we plot simultaneous 95% confidence bands computed with a child-level clustered bootstrap. Point estimates and corresponding standard errors for each event time are shown in tables in the Appendix. We begin by showing the impact of parental job loss on economic outcomes. Next, we present the effects of parental job loss on different measures of children's mental health and provide evidence on the robustness of the results to alternative model specifications. We then assess educational attainment to further infer costs related to human capital formation. Finally, we test for disrupted family environment as a potential mechanism linking economic distress to children's outcomes.

4.1 Parental Job Loss and Economic Outcomes

This paper focuses on parental job loss as a marker of a relevant adverse economic shock that can lead to spillover effects on children. However, it is not obvious to what extent parental job loss leads to economic distress. In particular, previous papers from high-income countries have found limited effects of parental job loss on household income, potentially due to the presence of welfare institutions that insure families against economic distress (Mörk et al., 2020; Moghani et al., 2021).

We start characterizing the relationship between parental job loss and relevant economic outcomes in our context. Figure 1 plots our primary results in an event-study fashion (results are also available in Appendix Table A1). Point estimates indicate that treatment has strong and significant negative effects on economic outcomes. The income of both parents drops by 0.20 standard deviation (SD) in the wave immediately after parental job loss (Panels A and B). While the impact on mothers' income is persistent in the long-term follow-up (-0.25 SD), fathers seem to recoup from the negative shock. This is consistent with evidence from several other countries that women are more likely than men to become disconnected from the labor market and experience longer spells of inactivity after displacement (Quintini and Venn, 2013). We also compute treatment effects on an asset ownership index commonly used in Brazil to define socio-economic strata (Panel C). Consistent with previous results, we find strong and persistent negative impacts of parental job loss on household assets ownership: -0.15 SD and -0.12 SD for event-times 0 and 1, respectively. Notice that placebo effects are very close to zero across the board.

Finally, we assess whether the shock of job loss increases the probability of receiving welfare transfers. Panel D provides evidence this does not seem to be the case. The effects of job loss on access to government financial aid are flat and close to zero across event times. This is probably because cash transfers in Brazil are designed to target families that are structurally poor rather than as a buffer against temporary negative income shocks.

4.2 Economic Distress and Children's Mental Health

Next, we estimate the effects of parental to loss on a comprehensive range of mental health outcomes. Estimates shown in Figure 2 and Appendix Table A2 indicate that parental job loss significantly worsens children's mental health. We find increased symptoms of internalizing and externalizing disorders (by 0.17 SD) in the wave immediately after the shock (Panels A and B). We complement this evidence by estimating effects on overall psychopathology measured by the CBCL (Panel C). Results confirm that parental job loss increases mental illness symptoms (0.22 SD). We find remarkably similar results when analyzing the CBCL scales that reflect externalizing and internalizing disorders separately. The same is true when we use the well-known SDQ (see Appendix Table A3).

We also assess impacts on clinical ratings by child psychiatrists. Figure 2, panel D, depicts that parental job loss increases the probability of a mental disorder diagnosis by 6.8 percentage points, or a 28% increase relative to the mean at the baseline. Although statistical power limitations prevent us from reaching definite conclusions when analyzing different diagnoses separately, Appendix Table A4 suggests that diagnoses of anxiety drive this result and that parental job loss did not affect ADHD. The strong impact we find for externalizing psychopathology is not contradictory to this evidence. Most studies of children find internalizing and externalizing domains to be highly correlated. In particular, an initial disorder, like anxiety, may become a risk factor for the development of emotional and behavioral problems spamming a different domain (Caron and Rutter, 1991).

Turning to long-run impacts, we show that effects assessed in the second follow-up wave are statistically insignificant and close to zero. So, while the effect of parental job loss on children's mental health is large amidst the adverse economic shock, it vanishes over the long run. One possibility is that shocks do not last throughout sufficient time to generate permanent changes in children's mental health. Indeed, we document that the impact of job loss on fathers' income also vanishes over the long run.[6] Alternatively, there may be a hedonic adaptation effect in which mental health eventually adapts to economic circumstances changes (Ridley et al., 2020).

We show that placebo effects are remarkably close to zero across all the results. This suggests that any increase in children's mental illness symptoms associated with parental job loss does not reflect children's health before job loss occurs, mitigating concerns about reverse causality and omitted variable bias. It is also important to highlight the consistency of all our results to alternative questionnaires and rating techniques used to measure children's mental health. This mitigates concerns about non-random measurement error.

Our results are robust to many other specification checks (see Appendix Figure A.1). First, they remain similar regardless of the way we control for covariate-specific trends – if we include them in a linear and additive fashion, if we use the estimator proposed by C&S, or if we use a doubly-robust estimator combined with double lasso variable selection. Second, our results are robust to including covariate-specific linear trends or matching based on baseline covariates. If anything, they become even stronger when we do so. Thus, our estimates are robust as long as selection on observables is informative about selection on unobservables (Oster, 2019; Altonji et al., 2005). Similarly, the magnitude of our estimates increases when we restrict the sample to children of parents who eventually lose their job at any point in time and, therefore, solely exploit variation in the timing of the job loss. This reassures the robustness of the results as in this setup treatment and control groups are more likely to be similar in unobservables.

4.3 Economic Distress and Human Capital Formation

Past research suggests that mental health impacts may lead to additional costs by affecting overall human capital accumulation. To infer these costs, we measure the effects of parental job loss on school attainment (see Appendix Table A5). Point estimates are negative and persistent: -0.06 (s.e. 0.04) and -0.05 (s.e. 0.09) SD at event-times 0 and 1, respectively. Although imprecisely estimated, these results align with Britto et al. (2021), which studied the whole Brazilian school census and found that parental job loss impacts school enrollment negatively and age-grade distortion positively. One of their

[6] In particular, the literature has systematically shown that children's outcomes are more responsive to fathers than mothers' job loss (Ruiz-Valenzuela, 2021).

hypotheses is that these results could be driven by worsened children's mental health, although data availability impedes them to test this mechanism. The link between hampered children's mental health and worse educational and labor market outcomes later in life is supported by evidence (Currie et al., 2010). Therefore, our results suggests that, even if temporary, adverse effects of economic distress on children's mental health might have long-lasting consequences on human capital formation.

4.4 Economic Distress and Family Environment

We focus on two potential mechanisms for our results related to the family environment: children's exposure to abuse and neglect and family composition. Figure 3 shows significant effects on children's exposure to abuse and neglect in the first wave after parental job loss, which also dissipate in later follow-ups, similar to mental health outcomes (panel A). The effects on children's exposure to traumatic experiences are independent of being measured according to parents' or children's recorded answers (see Appendix Table A6). These results suggest that disruptions in the family environment and consequent exposure to maltreatment may be a relevant mechanism linking parental job loss to children's mental health issues. This is in line with evidence suggesting that exposure to maltreatment during childhood is associated with increased internalizing and externalizing psychopathology (Keyes et al., 2012). Finally, we do not find any significant effects on parental cohabitation (panel B). This result aligns with the available evidence, which does not support parental civil status changes as a potential mechanism linking parental job loss to children's outcomes (Ruiz-Valenzuela, 2021).

5 The Role of Psychiatric Risk Factors and Genetic Endowments

Child development theory suggests that genetic and environmental factors do not only have direct effects on children's development, but may also have interactive effects (Houmark et al., 2020; Scarr and McCartney, 1983). Genetic endowments have been argued to largely determine biological responsiveness to environmental effects. This raises the question of whether effects from exposure to economic shocks are moderated by initial psychiatric genetic endowments.

We start analyzing how exposure to parental job loss affects children according to psychiatric risk measures. We use data from the FSH, an instrument used in the screening phase by researchers to rank and define high-risk children according to the percentage of members in their families presenting symptoms of mental health disorders. Figure 4 plots the effects of parental job loss for children selected either at random or due to an increased risk for mental disorders and children with high and low FHS scores. Looking at the effects of economic distress on overall psychopathology (panel A) we find substantial impacts for all groups. Still, the impacts seem to be stronger for the high-risk children, especially those from families with a high percentage of members screening for anxiety and depression in the baseline (difference of almost 0.10 SD). However, the difference across groups is not statistically significant.

When assessing psychiatric clinical diagnosis, we find that the effect is mostly driven by children belonging to the high-risk subsample and with above-median values in the FHS score for depression or anxiety (panel B). Therefore, while parental job loss increases symptoms of psychiatric illness among all groups of children, such effects only translate into clinical ratings for the high-risk group. The relatively stronger impact we find on overall psychopathology for children with high family risk of anxiety and depression might be relevant for a sufficient number of children to reach a clinical threshold for diagnosing mental illness.

FHS scores might confound genetic and environmental factors –i.e., children with higher scores could be more prone to develop any psychopathology either because of inherited risk or because they live together with individuals with mental disorders. We therefore look at heterogeneous effects of parental job loss according to children and parental PRS for psychiatric diseases, which provide a measure of genetic propensity to develop mental disorders at the individual level. As several psychiatric disorders share genetic risks, we test for heterogeneous effects according to cross-disorder PRS, which capture polygenic risk for five major psychiatric disorders: ADHD, autism, bipolar disorder, major depressive disorder, and schizophrenia (Cross-Disorder Group of the Psychiatric Genomics Consortium, 2013). We additionally exploit data on PRS from one externalizing and one internalizing disorder separately: ADHD and depression, respectively.

Although predetermined, PRS are not exogenous. They mechanically reflect parental genes, which in turn could influence children's environmental factors. However, because of Mendelian inheritance, one's PRS is randomly assigned conditional on the PRS of the parents. As shown next, conditioning on mothers' PRS barely changes our estimates for the heterogeneous treatment effects according to children's PRS. Further conditioning on the FHS scores does not change the results either. Therefore our estimates might indeed capture how an adverse economic shock affects children's mental health according to their genetic endowment and not to environmental factors correlated to the parental risk of developing psychiatric disorders.

Figure 5 plots the interaction between parental job loss and children's and mothers' PRS for different outcomes and psychiatric PRS. Overall, heterogeneity effects are close to zero and not statistically significant. These results suggest that the negative effects of parental job loss on children's mental health are independent of their genetic endowment as measured by the PRS. Therefore, the stronger impacts among children from families with a high percentage of members screening for anxiety and depression might be driven by environmental factors. This is consistent with previous correlational evidence showing no significant effects on mental health for the interaction between PRS and exposure to stressful life events or other environmental factors (Musliner et al., 2015; Østergaard et al., 2020). Our results suggest that economic distress has the potential to damage children's mental health independently of their genetic propensity to develop mental disorders, which highlights the necessity of broad-ranging buffering measures to potential spillover effects of parental job loss on children's development.

6 Conclusion

This paper studies the effects of adverse economic shocks on children's mental health using detailed data from the Brazilian High Risk Cohort Study for Psychiatric Disorders. Our empirical strategy exploits parental job loss events over time in a differences-in-differences framework. We first document that parental job loss has strong and persistent negative effects on parental income and household assets. Turning to the children of the affected workers, we show that parental job loss significantly worsens children's mental health. Looking to potential mechanisms, we show that parental job loss leads to heightened levels of children's exposure to abuse and neglect, a factor previously associated with higher susceptibility to developing externalizing and internalizing psychopathology. We further show that the detrimental effects of parental job loss on mental health do not vary according to the genetic risk for developing mental disorders. In this sense, they suggest that genetic endowments do not necessarily buffer or amplify the impact of adverse economic shocks on children's mental health. Our results are particularly informative for policymaking in developing countries. Previous evidence on the impact of parental job loss on children's mental health comes from high-income countries, where welfare institutions are typically able to insure families against adverse income shocks. In more deprived contexts, where social safety nets are weaker and families may be hit the most by economic fluctuations, buffering potential spillover effects of job loss on children's development is crucial.

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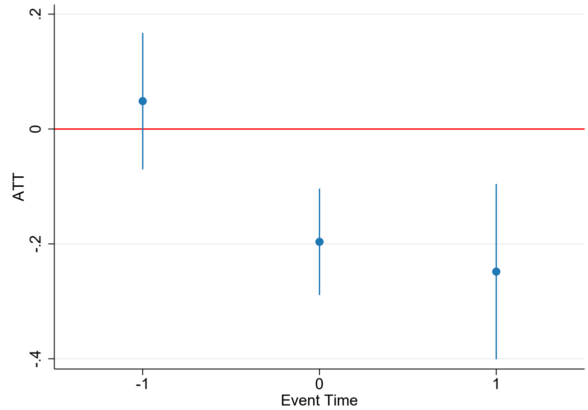
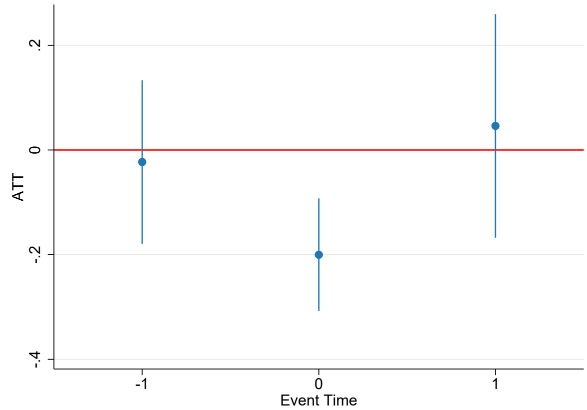
Figure (1) Treatment effects of parental job loss on economic distress

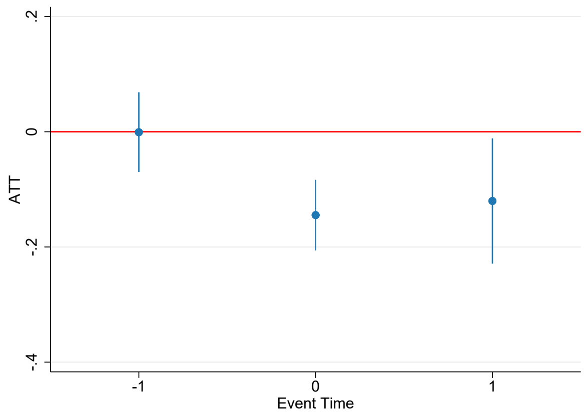
(a) Mothers' monthly income



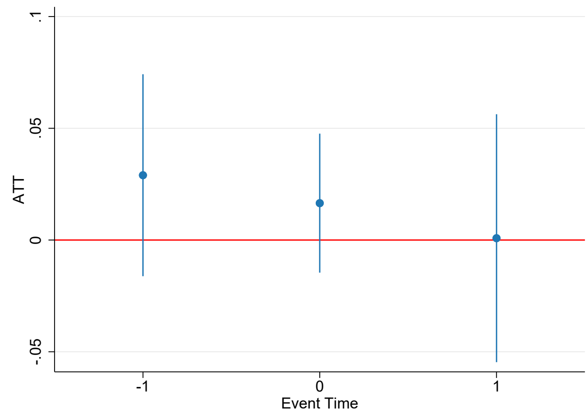
(b) Fathers' monthly income



(c) Household assets



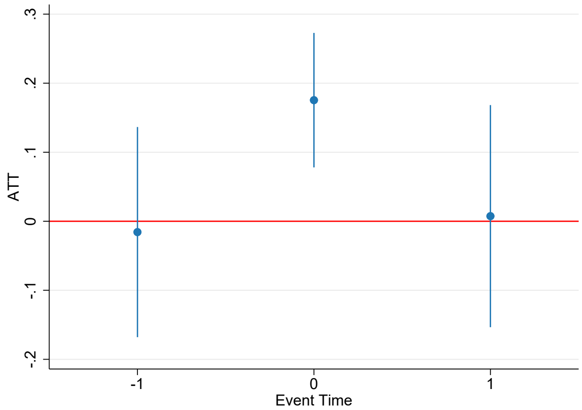
(d) 1(Financial government help)



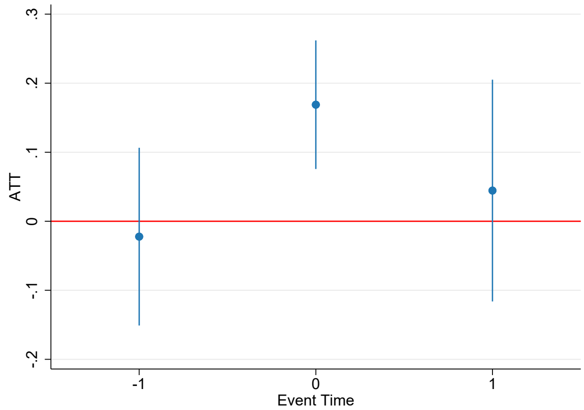
Note: This figure plots simultaneous 95% confidence bands computed with an individual-level clustered bootstrap and DiD estimators for the effects of parental job loss on mothers' monthly income (panel A), fathers' monthly income (panel B), an asset ownership index (panel C), and the probability of receiving financial aid from the government (panel D). Mothers' income, fathers' income, and the household asset index are standardized to a distribution with zero mean and a unit standard deviation. This procedure is applied for each age-bin $\times$wave combination. Estimates at event-time 0 measure the impact of parental job loss at the subsequent wave after the event. Analogously, estimates at event-time +1 assess the effects two waves after. Estimates at event-time -1 are placebo effects, which only exploit variation that precedes parental job losses. We control for a wide range of baseline covariate-specific trends using doubly-robust methods (Callaway and Sant'Anna, 2021). Controls include basic parental and child demographics (age, race, and gender), socio-economic indicators (household assets, and parental employment and educational outcomes), prenatal and perinatal health (height and weight at birth, exposure to alcohol and drugs intra-utero, prenatal care, and delivery conditions), early life stressors (indicators capturing family environment, parent-child relationship, and exposure to bullying and violence), parental and child mental health indicators, and child cognitive development (spatial, working memory, reading, writing, and math skills).

Figure (2) Treatment effects of parental job loss on children's mental health

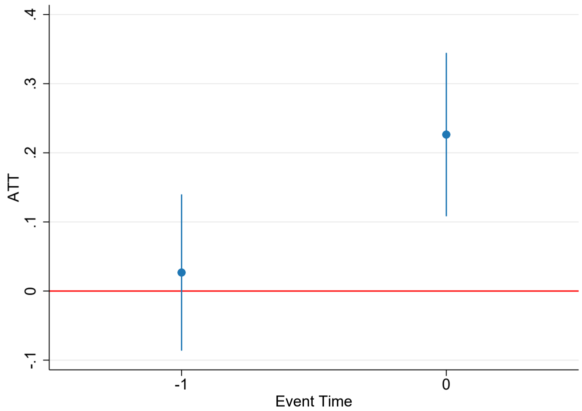
(a) Internalizing psychopathology [DAWBA bands]



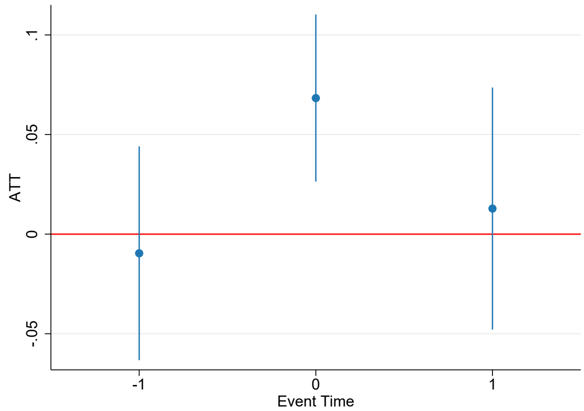
(b) Externalizing psychopathology [DAWBA bands]



(c) Child Behavior Checklist total score



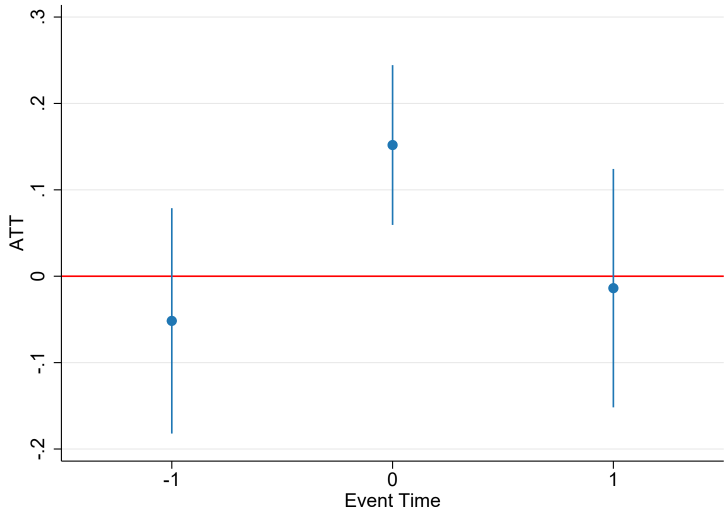
(d) 1(Any mental health disorder) [Clinical rating]



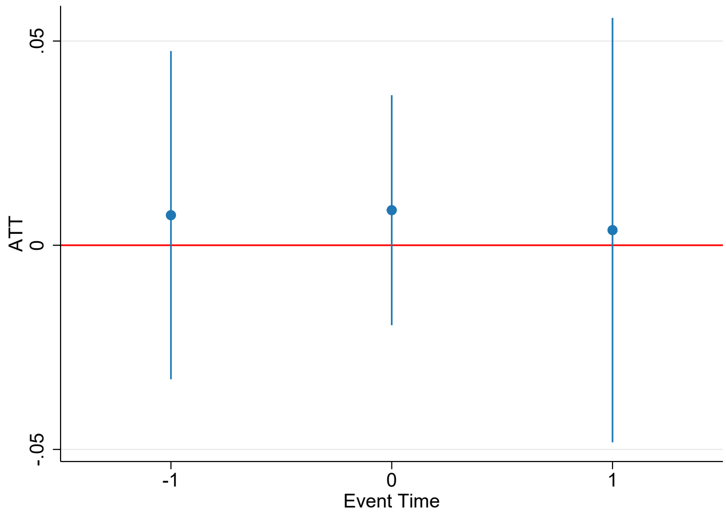
Note: This figure plots simultaneous 95% confidence bands computed with an individual-level clustered bootstrap and DiD estimators for the effects of parental job loss on children's internalizing psychopathology (panel A), externalizing psychopathology (panel B), overall psychopathology assessed by the CBCL score (panel C), and probability of being diagnosed with any mental disorder (panel D). The internalizing, externalizing, and CBCL scores are standardized to a distribution with zero mean and a unit standard deviation. This procedure is applied for each age-bin $\times$wave combination. Estimates at event-time 0 measure the impact of parental job loss at the subsequent wave after the event. Analogously, estimates at event-time +1 assess the effects two waves after. Estimates at event-time -1 are placebo effects, which only exploit variation that precedes parental job losses. The CBCL instrument was not collected in the last wave, so we do not present effects on event-time 1 for the CBCL scores. We control for a wide range of baseline covariate-specific trends using doubly-robust methods (Callaway and Sant'Anna, 2021). Controls include basic parental and child demographics (age, race, and gender), socio-economic indicators (household assets, and parental employment and educational outcomes), prenatal and perinatal health (height and weight at birth, exposure to alcohol and drugs intra-utero, prenatal care, and delivery conditions), early life stressors (indicators capturing family environment, parent-child relationship, and exposure to bullying and violence), parental and child mental health indicators, and child cognitive development (spatial, working memory, reading, writing, and math skills).

Figure (3) Treatment effects of parental job loss on exposure to abuse and neglect and family composition

(a) Exposure to abuse and neglect



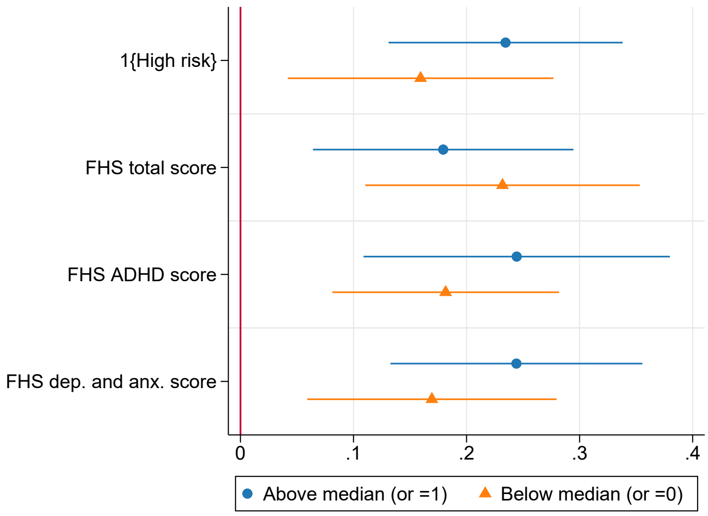
(b) 1(parents living together)



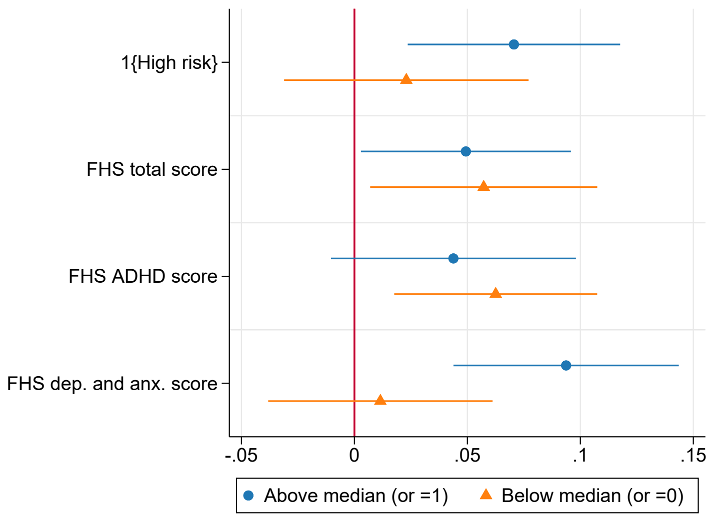
Note: This figure plots simultaneous 95% confidence bands computed with an individual-level clustered bootstrap and DiD estimators for the effects of parental job loss on exposure to abuse and neglect (panel A), and the probability of parents living together (panel B). The index measuring exposure to abuse and neglect is standardized to a distribution with zero mean and a unit standard deviation. This procedure is applied for each age-bin $\times$wave combination. Estimates at event-time 0 measure the impact of parental job loss at the subsequent wave after the event. Analogously, estimates at event-time +1 assess the effects two waves after. Estimates at event-time -1 are placebo effects, which only exploit variation that precedes parental job losses. We control for a wide range of baseline covariate-specific trends using doubly-robust methods (Callaway and Sant'Anna, 2021). Controls include basic parental and child demographics (age, race, and gender), socio-economic indicators (household assets, and parental employment and educational outcomes), prenatal and perinatal health (height and weight at birth, exposure to alcohol and drugs intra-utero, prenatal care, and delivery conditions), early life stressors (indicators capturing family environment, parent-child relationship, and exposure to bullying and violence), parental and child mental health indicators, and child cognitive development (spatial, working memory, reading, writing, and math skills).

Figure (4) Treatment effects of parental job loss on children's mental health according to family psychiatric history

(a) Overall psychopathology



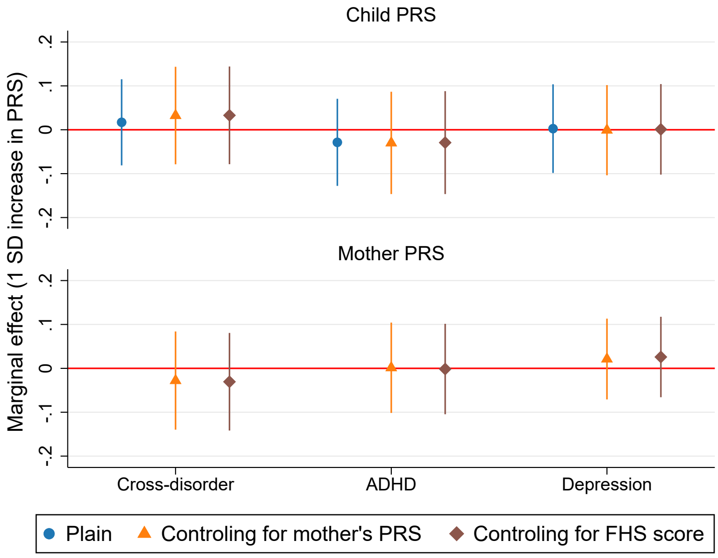
(b) 1(Any mental health illness)



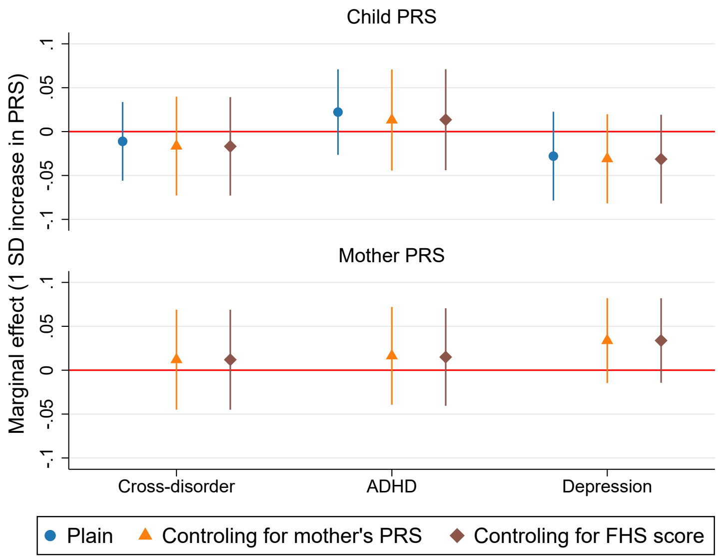
Note: This figure plots simultaneous 95% confidence bands computed with an individual-level clustered bootstrap and DiD estimators for the effects of parental job loss on overall psychopathology (panel A), and the probability of being diagnosed with any mental disorder (panel B) at event-time 0 according to family psychiatric history. The first line of each panel shows the results separately for children that belong to the high-risk subsample and children that belong to the random subsample of the BHRC. The other three lines display the results separately for children with above-median and below-median FHS score (total, ADHD and depression and anxiety), which was obtained at baseline according to family history of psychiatric disorders. The index measuring overall psychopathology is a combination of the indexes for internalizing psychopathology and externalizing psychopathology from DAWBA, and it is standardized to a distribution with zero mean and a unit standard deviation. This procedure is applied for each age-bin ×wave combination. In all cases, we control for a wide range of baseline covariate-specific trends using doubly-robust methods (Callaway and Sant'Anna, 2021). Controls include basic parental and child demographics (age, race, and gender), socio-economic indicators (household assets, and parental employment and educational outcomes), prenatal and perinatal health (height and weight at birth, exposure to alcohol and drugs intra-utero, prenatal care, and delivery conditions), early life stressors (indicators capturing family environment, parent-child relationship, and exposure to bullying and violence), parental and child mental health indicators, and child cognitive development (spatial, working memory, reading, writing, and math skills).

Figure (5) Heterogeneity of treatment effects of parental job loss on children's mental health by polygenic risk scores

(a) Overall psychopathology



(b) 1(Any mental health illness)



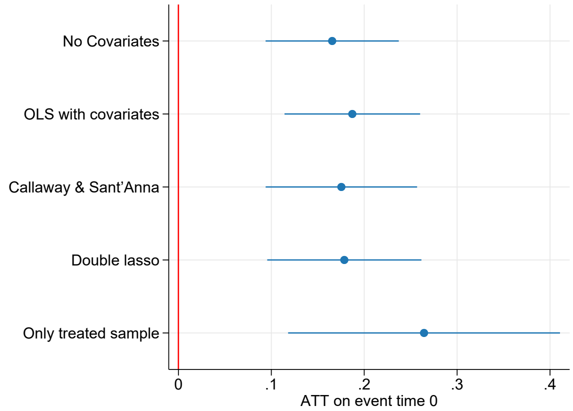
Note: This figure plots simultaneous 95% confidence bands computed with an individual-level clustered bootstrap and DiD estimators for the marginal effect of the interaction between parental job loss combined and a 1 SD increase in polygenic risk scores on overall psychopathology (panel A), and the probability of being diagnosed with any mental disorder (panel B) at event-time 0.

Appendix

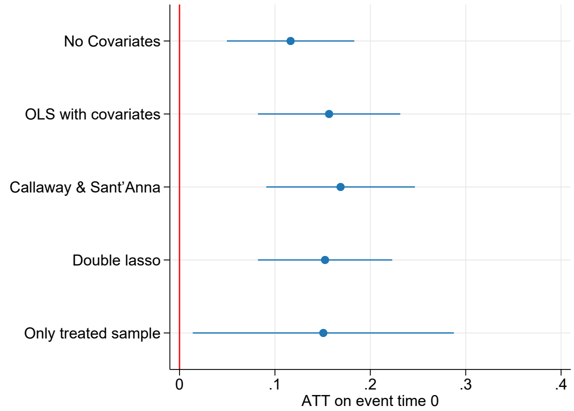
A Additional Figures and Tables

Figure (A.1) Stability of the results to alternative specifications

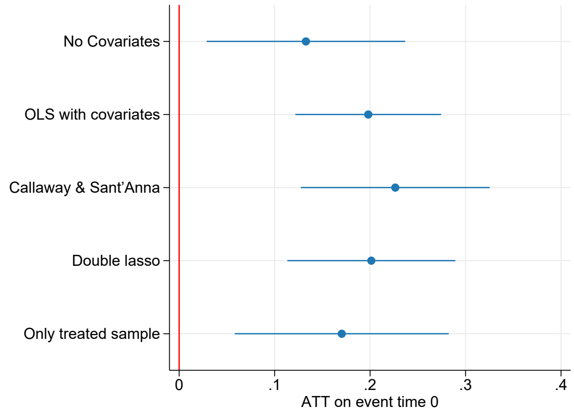
(a) Internalizing psychopathology [DAWBA bands]



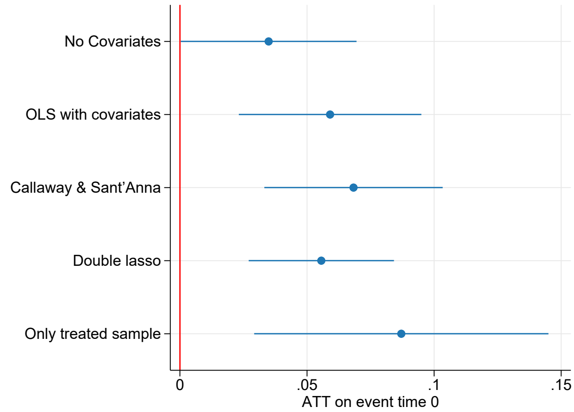
(b) Externalizing psychopathology [DAWBA bands]



(c) Child Behavior Checklist total score



(d) 1(Any mental health illness) [Clinical rating]



Note: This figure plots 95% confidence intervals computed with an individual-level clustered bootstrap and DiD estimators for the effects of parental job loss on children's mental health at event-time 0 across different specifications. "No Covariates" plots the results estimated under an unconditional parallel trends assumption, so our models do not include any covariates. "OLS with covariates", "Callaway & Sant'Anna", "Double lasso", and "Only treated sample" plot the results estimated under a conditional parallel trends assumption. The first includes covariate-specific trends in a linear and additive fashion and, hence, estimates our results by OLS. The second uses the doubly-robust estimator by Callaway and Sant'Anna (2021) and is our baseline specification. The third also uses a doubly-robust method (augmented inverse probability weighting) but chooses the covariates to include in the model using double machine learning techniques (based on Lasso estimators) following Chernozhukov et al. (2018). The fourth uses our baseline estimator but restricts the sample to children of parents who eventually lose their job at any point in time, thus solely exploiting variation in the timing of the job loss. For additional details, see Figure 2.

	All	Control	Treatment	t
Count	2510	1550	960	
High Risk	62%	60%	64%	-2.1
Age	9.8	10.0	9.6	5.1
Educational Attainment (Years)	4.2	4.3	4.0	5.0
Race				
White	60%	62%	58%	2.0
Black	11%	10%	11%	-0.7
Brown	28%	27%	30%	-1.4
Other	1%	1%	1%	-1.1
Divorced Parents	14%	14%	15%	-0.3
Parents' Employment				
Mother				
Permanent	43%	41%	47%	-3.0
Temporary	4%	4%	4%	0.3
Unemployed	9%	8%	10%	-1.4
Housekeeper	20%	21%	18%	2.1
Father				
Permanent	41%	39%	44%	-2.5
Temporary	1%	1%	2%	-2.0
Unemployed	4%	3%	5%	-2.0
Self-Employed	20%	21%	17%	2.8
Housekeeper	0%	0%	0%	1.0
Parental Job Loss				
2010-2014	16%	0%	43%	-27.0
2014-2018	30%	0%	78%	-58.9
Both periods				
Mental Health				
Any Disorder	26%	23%	31%	-4.0
Any Anxiety Disorder	11%	10%	13%	-2.6

Note: The table presents means of sociodemographic and mental health statistics at the baseline. Means for all children are shown in column (1), for the control and treatment groups in columns (2) and (3), and the t statistic for different means between treatment and control groups in column (4). All statistics are measured at the baseline, with the exception of job loss, which refers to the percentage of each group that experienced parental job loss between years 2010-2014 or 2014-2018.

Table (A1) Treatment effects of parental job loss on economic distress

	Mothers' monthly income	Fathers' monthly income	Household asset	1(Financial government help)
	(1)	(2)	(3)	(4)
Event-time				
-1	0.049	-0.023	-0.001	0.029
	(0.061)	(0.095)	(0.042)	(0.028)
0	-0.196	-0.200	-0.145	0.017
	(0.047)	(0.066)	(0.037)	(0.019)
1	-0.248	0.046	-0.120	0.001
	(0.078)	(0.130)	(0.066)	(0.034)
Mean at baseline	-	-	-	0.236

Note: This table shows the effects of parental job loss on mothers' monthly income (column 1), fathers' monthly income (column 2), an asset ownership index (column 3), and the probability of receiving financial aid from the government (column 4). Standard errors (in parenthesis) are computed with an individual-level clustered bootstrap. Mothers' income, fathers' income, and the household asset index are standardized to a distribution with zero mean and a unit standard deviation. This procedure is applied for each age-bin $\times$wave combination. Estimates at event-time 0 measure the impact of parental job loss at the subsequent wave after the event. Analogously, estimates at event-time $+1$ assess the effects two waves after. Estimates at event-time -1 are placebo effects, which only exploit variation that precedes parental job losses. We control for a wide range of baseline covariate-specific trends using doubly-robust methods (Callaway and Sant'Anna, 2021). Controls include basic parental and child demographics (age, race, and gender), socio-economic indicators (household assets, and parental employment and educational outcomes), prenatal and perinatal health (height and weight at birth, exposure to alcohol and drugs intra-utero, prenatal care, and delivery conditions), early life stressors (indicators capturing family environment, parent-child relationship, and exposure to bullying and violence), parental and child mental health indicators, and child cognitive development (spatial, working memory, reading, writing, and math skills).

Table (A2) Effects of parental job loss on children's mental health

	Internalizing psychopathology (1)	Externalizing psychopathology (2)	CBCL total score (3)	1(Any mental illness) (4)
Event-time				
-1	-0.016	-0.022	0.027	-0.010
	(0.078)	(0.066)	(0.058)	(0.027)
0	0.175	0.169	0.226	0.068
	(0.050)	(0.048)	(0.060)	(0.021)
1	0.007	0.044	-	0.013
	(0.082)	(0.082)	-	(0.031)
Mean at baseline	-	-	-	0.260

Note: This table shows the effects of parental job loss on children's internalizing and externalizing psychopathology assessed by the DAWBA bands (columns 1 and 2, respectively), overall psychopathology assessed by the CBCL score (column 3), and probability of being diagnosed with any mental disorder (column 4). Standard errors (in parenthesis) are computed with an individual-level clustered bootstrap. The internalizing, externalizing, and CBCL scores are standardized to a distribution with zero mean and a unit standard deviation. This procedure is applied for each age-bin $\times$wave combination. Estimates at event-time 0 measure the impact of parental job loss at the subsequent wave after the event. Analogously, estimates at event-time +1 assess the effects two waves after. Estimates at event-time -1 are placebo effects, which only exploit variation that precedes parental job losses. The CBCL instrument was not collected in the last wave, so we do not present effects on event-time 1 for the CBCL scores. We control for a wide range of baseline covariate-specific trends using doubly-robust methods (Callaway and Sant'Anna, 2021). Controls include basic parental and child demographics (age, race, and gender), socio-economic indicators (household assets, and parental employment and educational outcomes), prenatal and perinatal health (height and weight at birth, exposure to alcohol and drugs intra-utero, prenatal care, and delivery conditions), early life stressors (indicators capturing family environment, parent-child relationship, and exposure to bullying and violence), parental and child mental health indicators, and child cognitive development (spatial, working memory, reading, writing, and math skills).

Table (A3) Treatment effects of parental job loss on children's mental health – alternative scales

	Internalizing psychopathology [SDQ]	Externalizing psychopathology [SDQ]	CBCL internalizing score	CBCL externalizing score
	(1)	(2)	(3)	(4)
Event time				
-1	0.030	0.008	0.046	0.013
	(0.067)	(0.059)	(0.065)	(0.061)
0	0.145	0.195	0.192	0.195
	(0.045)	(0.043)	(0.068)	(0.064)
1	-0.004	0.102	-	-
	(0.084)	(0.075)	-	-

Note: This table shows the effects of parental job loss on children's internalizing and externalizing psychopathology assessed by the SDQ and CBCL (columns 1, 2, 3, and 4, respectively). Standard errors (in parenthesis) are computed with an individual-level clustered bootstrap. All scores are standardized to a distribution with zero mean and a unit standard deviation. This procedure is applied for each age-bin $\times$ wave combination. Estimates at event-time 0 measure the impact of parental job loss at the subsequent wave after the event. Analogously, estimates at event-time +1 assess the effects two waves after. Estimates at event-time -1 are placebo effects, which only exploit variation that precedes parental job losses. The CBCL instrument was not collected in the last wave, so we do not present effects on event-time 1 for the CBCL scores. We control for a wide range of baseline covariate-specific trends using doubly-robust methods (Callaway and Sant'Anna, 2021). Controls include basic parental and child demographics (age, race, and gender), socio-economic indicators (household assets, and parental employment and educational outcomes), prenatal and perinatal health (height and weight at birth, exposure to alcohol and drugs in-utero, prenatal care, and delivery conditions), early life stressors (indicators capturing family environment, parent-child relationship, and exposure to bullying and violence), parental and child mental health indicators, and child cognitive development (spatial, working memory, reading, writing, and math skills).

Table (A4) Treatment effects of parental job loss on children's mental health – clinical ratings of specific mental disorders

	1(Anxiety)	1(Depression)	1(Conduct/Oppositional)	1(ADHD)
	(1)	(2)	(3)	(4)
Event-time				
-1	-0.001	0.031	-0.022	-0.019
	(0.029)	(0.019)	(0.020)	(0.021)
0	0.045	0.036	0.011	-0.001
	(0.020)	(0.016)	(0.014)	(0.013)
1	0.013	0.037	0.003	0.007
	(0.031)	(0.028)	(0.024)	(0.024)
Mean at baseline	0.109	0.068	0.029	0.109

Note: This table shows the effects of parental job loss on the probability of being rated as having anxiety (column 1), depression (column 2), conduct disorders (column 3) or ADHD (column 4) by a trained psychiatrist based on answers to the DAWBA instrument. Standard errors (in parenthesis) are computed with an individual-level clustered bootstrap. Estimates at event-time 0 measure the impact of parental job loss at the subsequent wave after the event. Analogously, estimates at event-time +1 assess the effects two waves after. Estimates at event-time -1 are placebo effects, which only exploit variation that precedes parental job losses. We control for a wide range of baseline covariate-specific trends using doubly-robust methods (Callaway and Sant'Anna, 2021). Controls include basic parental and child demographics (age, race, and gender), socio-economic indicators (household assets, and parental employment and educational outcomes), prenatal and perinatal health (height and weight at birth, exposure to alcohol and drugs intra-utero, prenatal care, and delivery conditions), early life stressors (indicators capturing family environment, parent-child relationship, and exposure to bullying and violence), parental and child mental health indicators, and child cognitive development (spatial, working memory, reading, writing, and math skills).

Table (A5) Treatment effects of parental job loss on children's educational attainment

	Educational attainment
	(1)
Event-time	
-1	0.032
	(0.068)
0	-0.062
	(0.048)
1	-0.050
	(0.094)

Note: This table shows the effects of parental job loss on educational attainment. Standard errors (in parenthesis) are computed with an individual-level clustered bootstrap. Educational attainment was standardized to a distribution with zero mean and a unit standard deviation. This procedure is applied for each age-bin $\times$wave combination. Estimates at event-time 0 measure the impact of parental job loss at the subsequent wave after the event. Analogously, estimates at event-time +1 assess the effects two waves after. Estimates at event-time -1 are placebo effects, which only exploit variation that precedes parental job losses. We control for a wide range of baseline covariate-specific trends using doubly-robust methods (Callaway and Sant'Anna, 2021). Controls include basic parental and child demographics (age, race, and gender), socio-economic indicators (household assets, and parental employment and educational outcomes), prenatal and perinatal health (height and weight at birth, exposure to alcohol and drugs intra-utero, prenatal care, and delivery conditions), early life stressors (indicators capturing family environment, parent-child relationship, and exposure to bullying and violence), parental and child mental health indicators, and child cognitive development (spatial, working memory, reading, writing, and math skills).

Table (A6) Treatment effects of parental job loss on exposure to abuse and neglect and family composition

	Exposure to abuse and neglet [Children questionnaire]	Exposure to abuse and neglet [Parent questionnaire]	1(Parents living together)
	(1)	(2)	(3)
Event-time			
-1	-0.078	-0.052	-0.004
	(0.074)	(0.067)	(0.020)
0	0.153	0.152	0.010
	(0.049)	(0.047)	(0.014)
1	0.051	-0.014	0.001
	(0.075)	(0.070)	(0.026)
Mean at baseline	-	-	0.518

Note: This table shows the effects of parental job loss on children's exposure to abuse and neglect (columns 1 and 2), and the probability of parents living together (column 3). Standard errors (in parenthesis) are computed with an individual-level clustered bootstrap. The two indexes measuring exposure to abuse and neglect, according to the children and parent questionnaire, are standardized to a distribution with zero mean and a unit standard deviation. This procedure is applied for each age-bin $\times$wave combination. Estimates at event-time 0 measure the impact of parental job loss at the subsequent wave after the event. Analogously, estimates at event-time +1 assess the effects two waves after. Estimates at event-time -1 are placebo effects, which only exploit variation that precedes parental job losses. We control for a wide range of baseline covariate-specific trends using doubly-robust methods (Callaway and Sant'Anna, 2021). Controls include basic parental and child demographics (age, race, and gender), socio-economic indicators (household assets, and parental employment and educational outcomes), prenatal and perinatal health (height and weight at birth, exposure to alcohol and drugs intra-utero, prenatal care, and delivery conditions), early life stressors (indicators capturing family environment, parent-child relationship, and exposure to bullying and violence), parental and child mental health indicators, and child cognitive development (spatial, working memory, reading, writing, and math skills).