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Micole De Vera
Banco de España and IZA

Javier Garcia-Brazales
University of Exeter and LEAP (Bocconi)

Jiayi Lin
Universitat Pompeu Fabra

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

The Long Shadow of Labor Market Entry Conditions: Intergenerational Determinants of Mental Health*

What determines long-term mental health and its intergenerational correlation? Exploiting variation in unemployment rates upon labor market entry across Australian states and cohorts, we provide novel evidence that the mental health of daughters is affected by the labor market entry conditions of their parents. In particular, a one standard deviation shock to the unemployment rate upon parental labor market entry worsens daughters' mental health during adolescence by 11% of a standard deviation. This effect is accompanied by lower levels of satisfaction with their health, financial situation, safety, and overall life. A mediation analysis suggests that a sizable proportion (24%) of the impacts on the descendants' mental health is explained by the worse mental health of their parents at mid-life. We do not detect any systematic impact of parental labor market entry conditions among sons.

JEL Classification: E32, I14, I31, J62

Keywords: recession, mental health, well-being, intergenerational correlation, Australia

Corresponding author:
Micole De Vera
Banco de España
Calle Alcalá, 48
28014 Madrid
Spain
E-mail: micole.devera@bde.es

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1 Introduction

Mental health disorders are widely prevalent and impose large costs (Collins et al., 2011; Greenberg et al., 2015). These costs, including non-pecuniary ones (e.g., lower productivity, negative externalities), have been on the rise for decades and were exacerbated by the Covid-19 pandemic. Moreover, there is growing evidence that the increase in the incidence of poor mental health has been driven by the young (e.g., Blanchflower et al., 2024). More developed economies have acknowledged these facts and have granted mental health a central position in public policy. In 2012, the World Health Assembly coordinated the European Mental Health Action Plan 2013–2020 as a response to the global issue of mental health. In Joe Biden's 2022 State of the Union Address, an emphasis was placed on strategies to tackle the "unprecedented mental health crisis among people of all ages."[1]

Gaining a deeper understanding of the determinants of mental health will help us develop better-targeted policies. While the short-term drivers of mental health are relatively well-understood, knowledge on its long-term determinants is scarce (Adhvaryu et al., 2019). Moreover, while the literature has recently started to measure the degree of intergenerational transmission of mental health, little is still known about its underlying sources (Mazumder, 2024).

In this paper, we explore parental labor market entry conditions as a driver of the intergenerational correlation of mental health. This is motivated by two well-established, but so far disconnected, strands of the literature. First, early childhood is a particularly sensitive period for investment in human capital development and the circumstances experienced by children during this time have long-lasting impacts in adulthood (e.g., Becker and Tomes, 1986; Cunha et al., 2010). Second, "unlucky cohorts" entering the labor market during bad times face adverse outcomes that persist up to midlife (e.g., von Wachter, 2020). Labor market entry conditions of parents affect not only their own mental health but also other outcomes that determine their capability to raise their children and invest

[1] See https://bidenwhitehouse.archives.gov/briefing-room/statements-releases/2022/03/01/fact-sheet-president-biden-to-announce-strategy-to-address-our-national-mental-health-crisis-as-part-of-unity-agenda-in-his-first-state-of-the-union/.

in them. We conjecture that labor market entry conditions, an exogenous shock experienced by parents well-before the conception and birth of their children, can plausibly affect the mental health of both parents and children and, therefore, the intergenerational correlation of mental health.

To investigate these issues, we first measure the effects of adverse parental labor market entry conditions on their children's mental health. We then undertake a systematic study of how parental outcomes (e.g., health, income, risky behaviors, locus of control, etc.) are affected by their own labor market entry conditions to explore potential mechanisms behind the effects on their offspring's mental health. For this, we employ the Household, Income and Labor Dynamics in Australia (HILDA) Survey, a nationally-representative dataset of Australian households that offers comparable measures of mental health linked across two generations and contains complementary information on measures of other relevant life aspects (e.g., income, fertility) over two decades. Our main outcome of interest is the Mental Health Inventory–5 (MHI–5), a 5-element subscale for the mental health portion of the Short Form Health Survey 36 (SF–36) that has been widely validated (e.g., Rumpf et al., 2001; Hoeymans et al., 2004).

Our identification strategy exploits temporal and geographic variation in labor market entry conditions. We overcome the potential threat of endogenous timing of labor market entry by focusing on the labor market conditions experienced by each cohort at ages 18–22. This approach to measuring labor market entry conditions is attractive because it explicitly uses variation in the year of birth, which is plausibly exogenous since parents are unlikely to predict such conditions two decades in advance. Importantly, it does not depend on the exact time of labor market entry, which could be endogenous. This approach has been recently employed in the literature by, for instance, Arellano-Bover (2020) and Berniell et al. (2023).

We find that the daughters of parents that entered the labor market during more unfavorable times have worse mental health at ages 15–20. The impact is economically meaningful: a 1 standard deviation unemployment rate shock during parents' labor market entry corresponds to an increase of 11% of a standard deviation in the index for poor mental health. Moreover, daughters also experience lower satisfaction with their financial situation, safety, community, health, and overall life at adolescence. We do not detect effects of parental labor market entry conditions on sons. This heterogeneity along the gender dimension is consistent with recent evidence that finds that the mental health of girls is more prone to be affected by external circumstances in their environment (Giulietti et al., 2022; Fawaz and Lee, 2022).

Our results are robust to a number of possible threats to internal validity. We highlight a few exercises here. First, they are not dependent on how we measure mental health. In particular, we find quantitatively similar results when we use the Kessler-10 (Kessler et al., 2002), another widely validated tool to measure mental health that is collected by HILDA biennially. Second, we show that our results do not depend on how we measure parental labor market entry conditions. Most notably, they are robust to using national unemployment rate shocks rather than state-specific ones, therefore exploiting only temporal (cross-cohort) variation, which eliminates concerns that our results are driven by internal migration where workers search outside their local labor market for better labor market conditions at the time of entering the labor market. Last, we show that our results are unlikely to be driven by selection related to family formation. We do not find that labor market entry conditions affected partnership formation (who gets married), assortative matching (who they marry), or fertility (who becomes parents).

We further explore mediating factors to the intergenerational effects we document. To guide our analysis, we consider the extensive list of outcomes in the recent survey by von Wachter (2020) as plausible mechanisms and complement this with additional outcomes that are especially pertinent to the context of our study. We find that parents who enter the labor market during adverse conditions are more likely to have worse physical and mental health, have less household income, are more likely to be detached from the labor force, are more likely to be smokers, and are less willing to take financial risks. When measuring these outcomes, we make sure to only include observations that precede the measurement of the children's mental health. Hence, they constitute plausible mechanisms behind the poorer mental health of their children (rather than being outcomes simultaneously determined with child mental health). Using a simple mediation analysis, we identify parental mental health as a key mediator to explain the effect of parental labor market entry conditions on their daughter's mental health. In fact, parental mental health can explain 24% of the intergenerational effect we find.

Overall, our results identify parental labor market entry conditions as a non-biological, market-related shock that may help explain the intergenerational correlation in mental health. This has important implications: (i) the intergenerational correlation in mental health is not purely genetic or hereditary, and (ii) there is scope for social safety net programs to improve mental health outcomes.

Contributions to related literature. We highlight three strands of the literature to which our work contributes.

First, we find that parental labor market entry conditions are a determinant of child mental health. The existing literature on the determinants of child mental health has primarily focused on contemporaneous determinants and in-utero or early childhood determinants. For instance, it has been shown that the well-being of children is affected by contemporaneous parental health shocks (e.g., Glaser and Pruckner, 2023) and parental labor market shocks (e.g., Powdthavee and Vernoit, 2013). However, since development is a dynamic process (e.g., Cunha et al., 2010), circumstances at childhood or in-utero may also have long-run effects on child well-being (Almond et al., 2018). Existing work has indeed identified in-utero or early childhood shocks (Persson and Rossin-Slater, 2018; Adhvaryu et al., 2019; Akbulut-Yuksel et al., 2022; Akee et al., 2023), family background (Currie, 2009), and early-childhood environment (Currie and Almond, 2011) to be important determinants of well-being at later stages of life. Labor market entry conditions, on which our paper focuses, differ from the mechanisms considered in the literature. In particular, labor market entry conditions of parents happen long before the conception or birth of their children and are a precondition of the other determinants that have been studied in the literature.

Second, we find that the effects of labor market entry conditions spillover to the next generation, particularly affecting the mental health of children. The existing literature on the effects of labor market entry conditions has focused primarily on outcomes of the directly-affected generation (von Wachter, 2020). Various life dimensions have been studied in the literature, including income (e.g., Kahn, 2010; Oreopoulos et al., 2012; Altonji et al., 2016), and health and risky health behaviors (e.g., Maclean, 2013; Schwandt and von Wachter, 2020; Maclean, 2015), among others. We are, to the best of our knowledge, the first to explore the impacts of labor market conditions on the outcomes of the succeeding generation. More specifically, we show that parental labor market entry conditions affect children's mental health at adolescence. We further explore the effect of labor market entry conditions on the parents to better understand the underlying mechanisms that drive mental health in the next generation, which we believe to have important implications for policy.

Last, we argue that parental labor market entry conditions may help explain the intergenerational correlation in mental health. In our sample, we find a strong correlation between parental and child mental health. This is consistent with the growing literature that measures intergenerational correlations of mental health in various contexts using both administrative data (Zhou et al., 2023; Bütikofer et al., 2023) and survey data (McLaughlin et al., 2012; Johnston et al., 2013; Bencsik et al., 2023). By relying on an exogenous source of variation in parental mental health, our results further suggest that the intergenerational correlation in mental health is not purely genetic. As with Bütikofer et al. (2024), we identify that institutions and economic conditions also matter in determining the intergenerational correlation in mental health. However, our results go beyond theirs and pinpoint economic conditions even before the child is born as an important mediator.

Outline of the paper. The rest of the paper is structured as follows. In Section 2, we provide a detailed description of the data and variables used in the analysis. In Section 3, we describe our empirical framework and discuss the identification strategy for estimating the impact of parental labor market conditions on child outcomes, report our key results, and probe their robustness to threats to internal validity. In Section 4, we explore potential mediators behind the intergenerational impacts on child outcomes and relate our results to the intergenerational correlation of mental health. Section 5 concludes.

2 Data

Our primary data source is the Household, Income and Labor Dynamics in Australia (HILDA) Survey. HILDA is a nationally-representative longitudinal study of Australian households, modeled after the Panel Study of Income Dynamics in the United States. It is conducted annually by the University of Melbourne and currently spans two decades starting in 2001.[2] This dataset is particularly suitable for our analyses because it provides longitudinal information on a wide range of outcomes for all the members of the household. Most notably, we observe mental health indicators for the offspring and their parents and a detailed set of potential mediators for the parental generation that predate the measurement of their children's mental health.

In this section, we describe the main outcome variables obtained from HILDA, the use of official statistics to construct unemployment rates at labor market entry, our sample selection criteria, and summary statistics of our estimating sample.

2.1 Main Outcomes

The survey design of HILDA is such that all individuals above the age of 15 answer the "adult questionnaire," which elicits individual-level information on health-related outcomes and well-being. We focus on mental health as the primary outcome of interest for the offspring and complement it with a rich set of questions in which the respondent describes his/her level of satisfaction with various aspects of life.

Mental health outcomes. HILDA provides, on a yearly basis, a mental health measure following the MHI–5 scale, which is the mental health subcomponent of the Short Form 36 Health Survey and has been widely validated (Ware et al., 2000; Rumpf et al.,

[2] We employ data up to 2019 to avoid using information during and after the Covid pandemic. Recent papers employing the same dataset are, for instance, Todd and Zhang (2020) and Siminski and Yetsenga (2022).

2001; Hoeymans et al., 2004; Botha et al., 2023). The score goes from 0 to 100 with higher values indicating better mental health. This information is collected for all individuals aged 15 and above. We focus on adolescence, ages 15-20, which is an important time in child development before major life changes. We use the same age criterion for the life satisfaction measures described below.

It is well-known that measuring mental health is difficult because most surveys only attempt to take snapshots of the underlying mental health situation of an individual. These measures may be affected by transient ambient factors at the time of the interview, like weather or pollution (e.g., Power et al., 2015; Burdett et al., 2021). As such, the annual measures we observe in HILDA may only be imperfect measures of the overall persistent mental health of an individual. To deal with measurement error in any year's reported mental health, we average the observations available for each individual between ages 15 and 20 to approximate the latent mental health state (Nybom and Stuhler, 2017). Since these observations pertain to different ages and are elicited across different survey rounds, we first regress the MHI-5 score on survey round fixed effects and a quadratic in age, and then take the within-person average of the resulting residuals. To ease interpretation, we standardize the resulting variable across individuals to have a mean of zero and a standard deviation of one. We also recode the variable so that higher values of the variable indicate worse mental health.

For robustness checks, we employ two alternative measures of mental health. First, we zoom into the five subcomponents of the MHI–5, namely how frequently during the four weeks prior to the survey the respondent felt (1) unhappy, (2) nervous, (3) down, (4) anxious, and (5) unable to cheer up.[3] In particular, we transform the responses to each dimension, which were given in a 6-point scale (none, a little, some of the time, a good bit, most of the time, and all of the time), into indicators taking the value of one if the relevant negative feeling occurred at least "some of the time." These indicators therefore capture the presence of episodes of mental distress. Second, every two years,

[3]For dimensions (1) and (4), the questionnaire actually asks for the frequency of feeling happy and calm. Since the original coding of the variables is such that higher values imply less frequent episodes, we simply rename these variables as "unhappy" and "anxious". For dimensions (2), (3), and (5), which ask about the frequency of feeling nervous, down, and hard to cheer up, we recode these variables such that higher values indicate a higher frequency of unfavorable mental health outcomes.

HILDA elicits an expanded version of the survey tool which corresponds to the Kessler–10 index — another widely employed and validated index (Kessler et al., 2002). We do not take this as our preferred measure of mental health because it is elicited intermittently which means that fewer repeated measurements of an individual's mental health state are available. In any case, the MHI–5 and the Kessler–10 indices are, not surprisingly, very highly correlated (Aulike et al., 2021).

Life satisfaction. After showing that there is a reduced-form impact of parental labor market entry conditions on their offspring's mental health, we will be interested in documenting whether their children's overall life satisfaction is also lower and, if that is the case, which particular aspects of their lives might be driving this lower overall life satisfaction. To do so, we take advantage of another strength of HILDA: the elicitation of satisfaction levels across a large number of life-related dimensions. In particular, HILDA asks respondents to state "how satisfied or dissatisfied you are with some of the things happening in your life" (on a 0–10 scale, with higher values indicating more satisfaction) about the following dimensions: (a) the home you live in; (b) your financial situation; (c) how safe you feel; (d) feeling part of your local community; (e) your health; (f) the neighborhood in which you live; and (g) the amount of free time you have.[4] For all these satisfaction measures, we construct an indicator taking the value of 1 if the stated level of satisfaction is 5 or below, and 0 otherwise. Hence, these variables capture low levels of satisfaction with each particular dimension.

2.2 Measurement of Labor Market Entry Conditions

We collect state-level unemployment rates from the Australian Bureau of Statistics. Given our interest in studying the impact of parental labor market entry conditions, we construct a measure for each parent that averages the unemployment rates that he/she experienced between the ages of 18 and 22, when individuals typically finish formal education and start to work. Focusing on the *predicted timing* of labor market entry rather than on

[4] HILDA also elicits satisfaction with employment opportunities, but we do not explore it for the child generation as they are only aged 15–20.

the actual timing of entry is common practice in the literature (e.g., Arellano-Bover, 2020; Berniell et al., 2023) as it leverages variation coming from the year of birth of the individuals, which is plausibly exogenous, rather than variation from the actual timing of labor market entry, which could be an endogeneous decision.[5] Moreover, it may be regarded as a more conservative approach because if graduation times were completely exogenous, the measurement error introduced by this choice would likely attenuate our estimates (Arellano-Bover, 2020).

In addition to the variation coming from the birth year of individuals, we also leverage geographical variation in labor market entry conditions. One limitation of HILDA in this respect is that, in survey rounds 1 to 19 (that is, from 2001 to 2019), it does not elicit information on the geographical location of the individual at ages 18–22, nor on the state of residence prior to those ages. Fortunately, in waves 12, 16, and 20 (2012, 2016, and 2020), HILDA asked for information on the state where the highest level of schooling was completed. This is attractive for our purposes as entry in the labor market is expected to happen right after the highest academic level is achieved. This therefore provides direct information on the labor market conditions faced by these individuals upon entry. Our sample size is significantly reduced if we only include those whose information is available in waves 12, 16, and 20. As such, if information on the graduation location is available, we use it. Otherwise, we rely on the state of residence observed at first entry into the survey to proxy for the state of graduation.[6] As a robustness check, we show that our results are robust to using national unemployment rate shocks instead of shocks that depend on the state of residence at labor market entry.

In Panel (a) of Figure 1, we present the raw time-series variation in unemployment rates at the country-level. As can be seen, the period prior to the year 2000 had the largest fluctuations in the unemployment rate. A component of the changes in unemployment may be predictable from the general business cycle. In our preferred approach, we detrend the unemployment rate series to capture just the changes in the unemployment rate

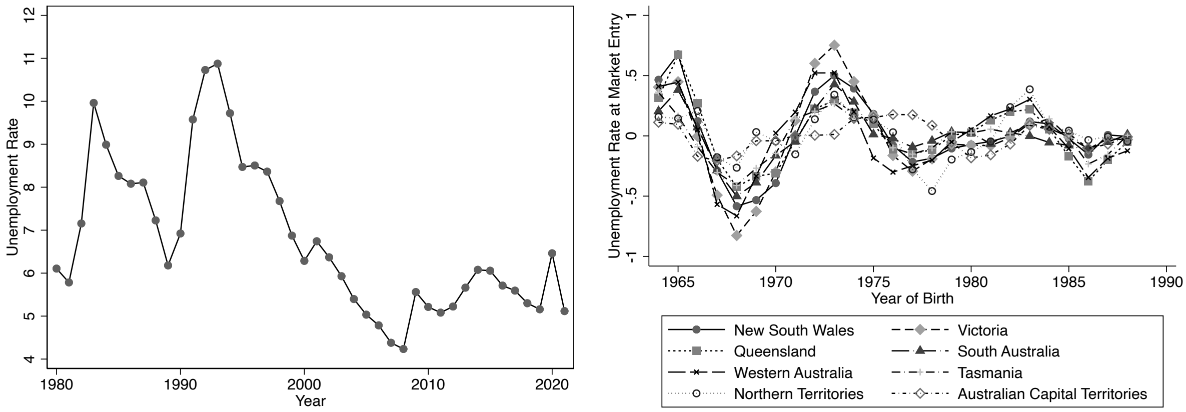
[5] An additional advantage in our case is that we do not need to observe the exact year of graduation, which is not collected in the survey.

[6] We acknowledge that individuals might migrate to a different state in response to the 18–22 unemployment rates. We find that this is uncommon in practice, as 85% of the individuals in our sample completed education in the same state in which we observe them in adulthood. While it may be possible that individuals migrate after age 22, we consider this a margin of adjustment that is affected by our treatment and therefore does not constitute a source of bias.

Figure 1: Variation in unemployment rate and unemployment rate shocks

(a) National unemployment rate, by year

(b) Unemployment rate shocks at labor market entry, by state and cohort



Notes: Panel (a) reports the raw national unemployment rate by year. This time series was obtained from The Organization for Economic Cooperation and Development. Panel (b) reports the state-specific detrended unemployment rate at labor market entry for the cohorts indicated in the horizontal axis. For this, we first detrend the quarterly time series of state-specific unemployment rates using the filter proposed by Hodrick and Prescott (1997), then average the resulting detrended unemployment rates to the yearly frequency. We define labor market entry conditions as the average state-level unemployment rate shocks when the cohort is aged 18–22.

that are not associated with the predictable trend. We believe this detrended series is a more faithful representation of the plausibly exogenous source of variation we are exploiting. In particular, we filter out state-specific trends from the quarterly state-level unemployment rate series using the methodology proposed in Hodrick and Prescott (1997), more commonly referred to as the HP filter.[7] To make it into a variable at the yearly level, we take the annual average of the shocks (cyclical components). In Panel (b) of Figure 1, we focus on the average unemployment rate shocks faced by different cohorts when they were aged 18–22, by state. This is closer to the true variation that we use in our empirical strategy, for which we exploit cohort- and state-specific unemployment rates net of a trend.[8] One can appreciate that, although the average unemployment rate shocks follow similar cohort-trends across states, there are sizable differences in the levels and, more importantly, in the changes. In robustness checks, we show that the results hold when using raw unemployment rates instead of their detrended version.

[7] Following Ravn and Uhlig (2002), we use 1600 for the smoothing parameter corresponding to quarterly data.

[8] In Appendix Figure A1, we provide the corresponding figure with the average unemployment rate, without detrending.

There are no theoretical reasons to inform which of the parents' labor market entry conditions is most relevant for their children's outcomes. As a summary of the labor market entry conditions of both parents, in our preferred specifications, we use the average unemployment shocks of both parents at their predicted time of labor market entry. For completeness, we also report the estimated impacts when we introduce each of the parent's labor market conditions separately.[9] This is not our preferred specification because, due to assortative mating, the labor market entry conditions of the two spouses tend to be highly correlated, which may lead to less stable results due to possible multicollinearity.

2.3 Mediators

It is important to understand the possible mediators of the reduced-form impact of parental labor market entry conditions on their offspring's mental health, if any. Although it is impossible to cover all possible channels, HILDA is attractive in that it offers very rich information on parental outcomes.

von Wachter (2020) surveys the extensive literature on the impacts of an individual's labor market entry conditions on their own short- and medium-run outcomes. We use this summary to systematically guide us on which potential mechanisms may be most relevant to explain the intergenerational effects. In particular, we will explore the impacts, among the parents, of their own labor market entry conditions on the following dimensions: (1) the (log) household annual gross income (in Australian dollars); (2) mental health; (3) physical health; (4) mortality, proxied by an indicator of death during the time-frame of this study; (5) an indicator of whether the person is a smoker; (6) an indicator of whether the person is a heavy drinker; (7) the willingness to take financial risk using available cash; (8) attachment to the labor market; (9) occupational prestige; and (10) locus of control. To account for potential mediators specific to our context, we also include (11) the fraction of total hours devoted by the male and female spouse to housework and playing with children on a typical day that is performed by the female spouse and (12)

[9] Note that, since the child outcomes that we are interested in are independent of parental labor force status, we can study the effects of both fathers and mothers without worrying about selection into labor force participation among females (e.g., Kahn, 2010).

the degree of agreement with the statement that "my work has a positive effect on my children".[10] To ensure that we only consider plausible mediators, we focus on parental outcomes along the above dimensions collected before the first measurement of child mental health (age 15).

2.4 Sample Selection and Summary Statistics

Sample selection. Our interest is in how parental initial labor market conditions impact their offspring's mental health. We focus on children whose mental health status is observed at least once between the ages of 15 and 20. Moreover, we impose that information on all of the mediators described above is available for both parents of the child. In this manner, we can conduct the mediation analysis on the parents of all the children for whom we investigate the mental health impacts of parental labor market entry conditions. We focus on parents born in or after 1964. Our final estimating sample is composed of 508 sons, 493 daughters, and their respective parents.

Representativeness. In Appendix Table A1, we detail how the sample size changes at different steps of our sample selection. Our most demanding restriction on both the child and parent sample is that we need to observe them at appropriate ages (equivalently, they need to be born in certain years). For instance, children need to be observed between ages 15 and 20, while parents included in our analysis of family formation need to be observed at the age of completed fertility.

Though our data requirements are demanding, which leads to our final samples being significantly smaller than the full sample available in HILDA, we show that the distribution of fixed characteristics in our sample is very similar to that of the original sample. In

[10] Mental health is computed in a similar manner as for the offspring, i.e., employing the MHI–5 scale. Physical health is measured by the SF-36 Physical Functioning Scale, which has also been widely validated (Bohannon and DePasquale, 2010). A person is classified as a smoker and as a heavy drinker if he/she reports to smoke cigarettes or any other tobacco products and to drink alcohol at least five days per week, respectively. Willingness to take risks is measured through a questions asking "which of the following statements comes closest to describing the amount of financial risk that you are willing to take with your spare cash?" with options "I take substantial financial risks expecting to earn substantial returns"; "I take above-average financial risks expecting to earn above-average returns"; "I take average financial risks expecting to earn average returns"; and "I am not willing to take any financial risks." Attachment to labor market is measured as being unemployed or out of the labor market. Occupational prestige is measured using the 0–100 AUSEI06 occupational status scale, designed specifically for the Australian context (McMillan et al., 2009). Locus of control is computed employing multiple correspondence analysis for questions on the degree of agreement in a seven-point scale with the statements of: having little control over own life; having no way to solve problems; not being able to change important things in life; feeling helpless; feeling pushed around; believing that the future depends on themselves; and feeling that he/she can do just about anything (when needed, responses are recoded such that higher values on the scale reflect a less internal locus of control).

Appendix Table A2, we focus on the parental sample and show that the characteristics of the parents in our main analysis do not differ from those of the full sample of HILDA parents born in similar years. Specifically, we observe no economically significant differences in the distribution of year of birth, unemployment rate faced at labor market entry, years of education, and whether they are from a migrant family. This is true even when we focus on mothers and fathers separately. These results provide reassurance that, despite our demanding data requirements, our sample likely remains representative of the more general population of parents that we are interested in.

Summary statistics. Table 1 provides some basic statistics of the children in our estimation sample, observed at ages 15 to 20, separated by gender. In terms of mental health, a sizable proportion of our male subsample suffers from frequent episodes of anxiety and nervousness (49.5% and 40.8%, respectively). Other feelings such as unhappiness are common but less prevalent (30.2%). In terms of satisfaction, 4.7% of males report a level of 5 or lower with their health. The proportion is high for the dissatisfaction with their financial situation (28.9%), how much they feel part of a community (22.7%), and with the amount of free time that they have (15.4%). As consistent with past literature, the levels of dissatisfaction and mental health issues are higher among females. The descriptive statistics for the sample of parents is provided in Appendix Table A3.

Turning to our source of exogenous variation, the mean of the raw unemployment rate of either parent between ages 18–22 is around 8.4% with a standard deviation of about 1.2. The detrended version has a mean close to zero, which is expected as it represents shocks. The last row in the table reports the statistics for the variable that averages the value of the paternal and the maternal detrended unemployment rate for each child. As explained, this is our preferred measure of parental labor market entry conditions in the regressions to follow. The standard deviation of the average parental unemployment shock across individuals is 0.31, which we will use to interpret the magnitude of our estimates.

Table 1: Summary statistics (child sample)

	Sons			Daughters		
	Mean	Standard deviation	Count	Mean	Standard deviation	Count
Felt in the last four weeks...						
Unhappy	0.302	0.359	508	0.424	0.381	493
Nervous	0.408	0.385	508	0.524	0.382	493
Down	0.297	0.345	508	0.461	0.383	493
Anxious	0.495	0.383	508	0.648	0.360	493
Hard to cheer up	0.147	0.269	508	0.268	0.342	493
Average bad mental	0.185	0.304	508	0.344	0.372	493
Low satisfaction with life aspects						
Home you live in	0.039	0.136	508	0.058	0.161	493
Financial situation	0.289	0.340	508	0.261	0.314	493
Safety	0.022	0.105	508	0.032	0.121	493
Feeling part of community	0.227	0.329	508	0.233	0.311	493
Your health	0.047	0.150	508	0.104	0.240	493
Your neighborhood	0.076	0.188	508	0.082	0.194	493
Amount of free time	0.154	0.253	508	0.202	0.286	493
Life as a whole	0.015	0.072	508	0.045	0.155	493
Main explanatory variables						
Raw paternal entry unemployment rate	8.381	1.184	508	8.321	1.200	493
Detrended paternal unemployment rate	0.008	0.398	508	-0.025	0.399	493
Raw maternal entry unemployment rate	8.390	1.267	508	8.384	1.292	493
Detrended maternal unemployment rate	-0.046	0.388	508	-0.028	0.386	493
Avg. detrended parental unemployment rate	-0.019	0.309	508	-0.026	0.307	493

Notes: Descriptive statistics from the population aged 15–20 used to estimate the impact of parental labor force entry conditions on mental health and life satisfaction of children. Mental health variables are indicators taking the value of 1 if the person reported to have experienced a given feeling at least "some of the time" in the four weeks prior to the survey. Low satisfaction is defined as reporting a level of satisfaction with a given life aspect of 5 or lower on a 10-point scale. All dimensions are averages across all observations from the same individual before computing the sample moments across all individuals (but, unlike in our econometric specifications, we report them without removing survey round averages and age profiles to ease interpretation). Year of birth of the children ranges from 1989 to 2004.

3 Intergenerational Impacts on Mental Health

3.1 Empirical Strategy

To study the reduced-form impact of parental labor market entry conditions on the outcomes of the next generation, we follow Oreopoulos et al. (2012), who employ variation over time in labor market conditions across US states to estimate the wage effects of labor market conditions at graduation. We estimate the following model (and variations for robustness) separately for sons and daughters (observed at the ages of 15 to 20):

$$y_i = \alpha + \beta \times \mathrm{UR}_{p(i)} + f(c(p(i))) + \lambda_{s(p(i))} + \varepsilon_i, \quad (1)$$

where an outcome of interest y for individual i with parents $p(i)$ is a function of the average unemployment shock of both parents at their labor market entry ($\mathrm{UR}_{p(i)}$) and fixed effects corresponding to the state of labor market entry of the mother (λ_s).[11] We also include $f(c)$, which are functions of the year of birth of both parents to capture cohort-related effects. Below, we discuss the importance of controlling for cohort and how we parametrize these. The main dependent variables are self-reported mental health and the degree of satisfaction with various life aspects. We cluster standard errors at the maternal state at graduation × cohort level.[12]

In our setting, introducing cohort fixed effects is important to strengthen the causal interpretation of our estimates, as it controls for omitted variables. Without cohort fixed effects, we may wrongly attribute differences in outcomes to labor market entry conditions when they might actually be due to broader cohort-specific factors such as changes in educational policy, shifts in labor market institutions, or social norms. Moreover, such inclusion also helps capture effects of the business cycle inasmuch as they constitute a shared experience for the cohort. However, by including cohort-related controls, our identification strategy relies more heavily on cross-sectional across-state variation in labor market entry conditions. While this within-cohort analysis may be appealing from the

[11] We use the state fixed effects corresponding only to the mother as we only have nine cases where the state of the father and mother do not coincide.

[12] We use analytical weights corresponding to the number of observations per child used in constructing the average value of mental health to improve efficiency of the estimates.

point of view of causal interpretation, it also reduces the amount of variation we are exploiting, which may lead to more imprecise estimates of the effects of interest. To resolve this tradeoff, we try various ways to control for these cohort effects. In our preferred specifications, we parameterize the cohort controls as fixed effects corresponding to 5-year cohort bins. In Section 3.3, to complement our main results, we also estimate more flexible cohort trends using yearly cohort-specific fixed effects and fixed effects corresponding to 4-year cohort bins. Moreover, we also try a more parsimonious specification using a quadratic polynomial in the cohort year.

The coefficient of interest, β, captures the change in the outcome induced by a one-percentage point increase in the unemployment rate, relative to the trend, at entry in the labor market of their parents (i.e., as parental labor market entry conditions worsen). Since we use the average unemployment shocks over the ages 18–22 rather than focusing on the unemployment shock at exact labor market entry, the effects we find are best interpreted as intention-to-treat estimates.

As previously mentioned, to deal with noise in self-reported subjective outcomes, our outcome of interest is the within-individual average of the measured outcome between ages 15–20 after partialling out age and business cycle effects.

Threats to identification. The causal interpretation of β relies on the orthogonality of labor market entry conditions with other determinants of the outcomes of interest. We highlight three of the most salient threats to internal validity and discuss how we address them.

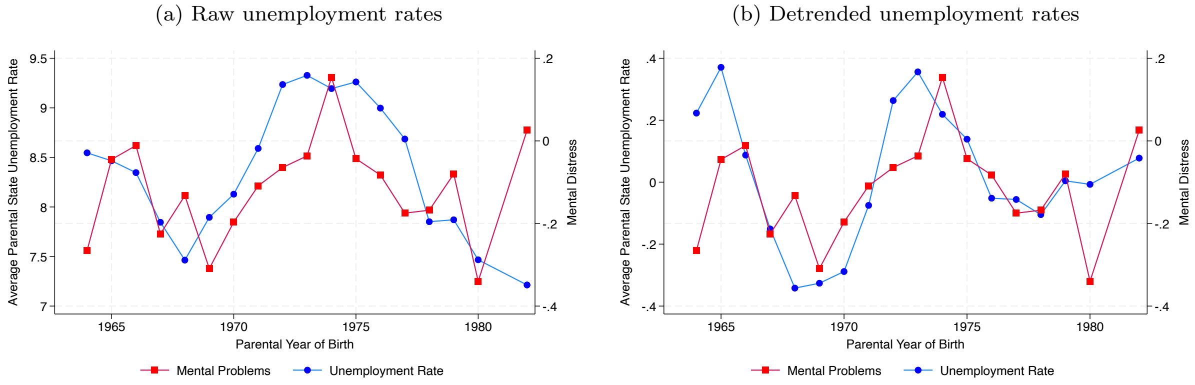
1. Endogenous timing of entry into the labor market: One might be concerned that individuals select *when* they enter the labor market by delaying or prolonging education in response to the economic conditions they face. As mentioned, our measure of labor market entry conditions (unemployment rate shocks at ages 18-22) relies on variation in birth year not in the year of actual entry into the labor market (Arellano-Bover, 2020; Berniell et al., 2023). Birth year is plausibly exogenous as it is unlikely that parents can anticipate the labor market conditions that their

children will face two decades later.

2. Endogenous location of entry into the labor market: Another concern is that individuals select *where* they enter the labor market in response to job availability. Our main specifications use state-specific unemployment rate shocks at ages 18-22, which depend on the state of labor market entry. The underlying assumption is that the state is the relevant local labor market for job search, allowing for individuals to self-select into locations within the state. In a robustness check, we allow the relevant market to be the national labor market by using the national unemployment rate shocks as the measure of labor market entry conditions. Our results are quantitatively similar.

3. Endogenous sample selection: Our outcomes are measured years after the parental generation entered the labor market. A potential concern, then, is that the sample we observe is a result of non-random selection. There are two salient sources of non-random selection. *First*, we might be concerned about selective attrition arising from migration and mortality. Since HILDA continuously tracks individuals irrespective of their location within Australia, internal migration is not a concern. Moreover, we show in Section 4.1 that we do not find effects of parental labor market entry conditions on parental mortality. *Second*, specific to our novel focus on child outcomes, one could be concerned about the selection of parents and children due to family formation. In particular, we may be concerned that labor market entry conditions may affect decisions of family formation such as partnership, assortative mating, and fertility, which in turn affect who we observe as parents and children in our sample. In Section 3.3, we explore this and show that labor market entry conditions do not have effects on partnership formation, assortative mating, or childbearing (measured at age 50).

Figure 2: Parental unemployment rate at graduation and child's mental health



Notes: Unemployment rates are state- and cohort-specific. We employ the raw unemployment rates in Panel (a) and their detrended version in Panel (b). The blue curves (circle markers) plot the average unemployment rate or unemployment rate shock experienced by the two parents at labor market entry (for graphical purposes, we assign the value to the year of birth of the mother on the horizontal axis). The red curve (square markers) is the MHI-5 index of mental health distress (after netting out survey round fixed effects and age profiles) that their children experienced between ages 15 and 20. Parental cohorts with less than 10 observations are not reported.

3.2 Main Results

Mental health. In Figure 2, we graphically show the strong positive relationship between the parental unemployment rates experienced at the predicted time of labor market entry (blue lines) and the extent of mental health issues experienced by their offspring (red lines). Such correlation is present both when using the raw unemployment rate in Panel (a) and its detrended version in Panel (b).

We formalize the above relationship by estimating Equation (1). Table 2 reports the estimated causal effect of parental labor market entry conditions on child mental health, separately by the gender of the child. For completeness, we also show the results first introducing the father's unemployment rate, then the mother's, and finally both of them at the same time. Our preferred specification is the one in Column (4) which uses the average of the two parental unemployment rates to proxy for the labor market entry conditions of parents. We find that parental unemployment rates at labor market entry have a strong detrimental effect on their daughters' mental health in adolescence. In particular, given the 0.31 standard deviation of the average parental unemployment shock, the coefficient of 0.366 means that a 1 standard deviation increase in the unemployment rate relative to its trend is associated with an approximate increase of $0.37 \times 0.31 = 0.1147$ of a standard deviation in the index of poor mental health. This effect is mainly driven by the maternal unemployment rate, although the role of the paternal unemployment rate is sizable in magnitude (but not statistically significant). We do not detect an effect of parental labor market entry conditions on the mental health of sons and the point estimates are significantly smaller in magnitude compared to what we find for daughters.

The gender difference we find in the impacts of labor market entry conditions of parents is an interesting result that was not obvious ex-ante. In Section 4, we will show that the circumstances of parents before their children are aged 15 tend to be worse for those who enter the labor market during more adverse conditions. Gender differences in the psychological, social, or biological mechanisms of how children respond to these more negative situations may help explain possible gender differences. For instance, males are biologically more vulnerable during early ages and are more negatively affected by environmental stressors (Wells, 2000). This may suggest that we should find larger effects for males. Since we do not find this, this biological mechanism is unlikely to be the dominant driver of the results. Rather, we find larger impacts for daughters. This is consistent with psychological mechanisms suggesting that girls may be more sensitive to negative environments. For example, Hankin and Abramson (2001) highlight that girls are more likely to make negative inferences about the causes of adverse events and their implications for self-worth, and are also more prone to rumination, which increases the likelihood of dwelling and recalling negative experiences. These tendencies may amplify daughters' responsiveness to negative environments during childhood, making them more vulnerable to the long-run consequences of parental labor market entry conditions.[13]

Life satisfaction. We explore the effects of parental labor market entry conditions on their children's degree of satisfaction with various life aspects to identify complementary and/or contributing factors to the mental health effects documented above. We estimate linear probability models in the style of Equation (1) where the outcomes are binary

[13]This is also consistent, for instance, with Giulietti et al. (2022) and Fawaz and Lee (2022) who find that girls are more prone than boys to suffer from teenage depression in response to changes in their environment.

Table 2: Intergenerational spillovers on mental health of labor market entry conditions

	Outcome: Bad mental health (z-score)			
	(1)	(2)	(3)	(4)
Panel (a): Sons only				
Father's unemp. rate	-0.139*		-0.147*	
	(0.078)		(0.083)	
Mother's unemp. rate		0.004	0.039	
		(0.085)	(0.091)	
Parental unemp. rate				-0.117
				(0.094)
Observations	508	508	508	508
R-squared	0.075	0.071	0.076	0.073
Panel (b): Daughters only				
Father's unemp. rate	0.217		0.175	
	(0.149)		(0.142)	
Mother's unemp. rate		0.230*	0.191	
		(0.125)	(0.117)	
Parental unemp. rate				0.366*
				(0.187)
Observations	493	493	493	493
R-squared	0.034	0.034	0.039	0.039

*Notes: Regressions of child mental health (measured using MHI-5) on various combinations of paternal and maternal labor market entry conditions, as in Equation (1). "Father's unemp. rate" and "Mother's unemp. rate" refer to the detrended unemployment rate faced by the father and the mother at ages 18-22, respectively. "Parental unemp. rate" refers to the simple average of the father's and the mother's detrended unemployment rates. The outcome is standardized using the mean and standard deviation of 15–20 year old individuals. Standard errors clustered at the maternal state of labor market entry × cohort level. *** p<0.01, ** p<0.05, * p<0.1. The counterpart of this table where standard errors are clustered at the paternal state of labor market entry × cohort level is reported in Appendix Table A4. The results that use the pooled sample including both sons and daughters are reported in Appendix Table A5.*

variables indicating whether the level of satisfaction is less than or equal to 5 in a 10-point scale, averaged over observations during ages 15–20 after partialling out age and business cycle effects.

In Table 3, we find that daughters' poorer mental health is accompanied by a higher likelihood of being dissatisfied with various life aspects. Given a one standard deviation increase in the unemployment rate faced by their parents during labor market entry, we

Table 3: Effects on other aspects of child well-being

Low satisfaction with...	(1) Home	(2) Financial situation	(3) Safety	(4) Community	(5) Health	(6) Neighborhood	(7) Free time	(8) Life
Panel (a): Sons only								
Father's unemp. rate	-0.019	-0.026	-0.030***	0.019	-0.007	-0.043**	-0.041	-0.007
	(0.012)	(0.043)	(0.010)	(0.037)	(0.013)	(0.021)	(0.031)	(0.007)
Mother's unemp. rate	0.011	-0.030	0.009	-0.007	0.007	0.006	0.022	0.021**
	(0.014)	(0.036)	(0.011)	(0.037)	(0.016)	(0.019)	(0.024)	(0.009)
Observations	508	508	508	508	508	508	508	508
R-squared	0.063	0.060	0.056	0.063	0.084	0.062	0.023	0.075
Parental unemp. rate	-0.017	-0.032	-0.028***	0.018	-0.005	-0.042*	-0.036	-0.003
	(0.011)	(0.042)	(0.010)	(0.037)	(0.013)	(0.021)	(0.031)	(0.008)
Observations	508	508	508	508	508	508	508	508
R-squared	0.062	0.059	0.055	0.063	0.084	0.062	0.021	0.065
Panel (b): Daughters only								
Father's unemp. rate	-0.003	0.048	0.006	0.012	0.051**	0.037	0.050	0.008
	(0.019)	(0.039)	(0.015)	(0.036)	(0.026)	(0.024)	(0.034)	(0.012)
Mother's unemp. rate	0.045**	0.069*	0.021*	0.065*	0.062***	0.003	-0.006	0.038***
	(0.018)	(0.037)	(0.012)	(0.034)	(0.021)	(0.025)	(0.038)	(0.014)
Observations	493	493	493	493	493	493	493	493
R-squared	0.082	0.062	0.046	0.047	0.051	0.078	0.043	0.062
Parental unemp. rate	0.043	0.116**	0.027*	0.078*	0.113***	0.039	0.044	0.047***
	(0.027)	(0.046)	(0.016)	(0.044)	(0.026)	(0.024)	(0.045)	(0.017)
Observations	493	493	493	493	493	493	493	493
R-squared	0.075	0.062	0.045	0.045	0.051	0.076	0.041	0.059

*Notes: Regressions replicate those in Table 2's Columns (3) and (4) where the outcome is an indicator taking the value of 1 if the respondent stated that his/her level of satisfaction with the outcome variable is less than or equal to 5 on a 0–10 point scale. Standard errors clustered at the maternal state of labor market entry × cohort level. *** p<0.01, ** p<0.05, * p<0.1. The counterpart of this table where standard errors are clustered at the paternal state of labor market entry × cohort level is reported in Appendix Table A6. The results that use the pooled sample including both sons and daughters are reported in Appendix Table A7.*

find that daughters are $11.3 \times 0.31 = 3.503$ percentage points more likely to report that they are not satisfied with their overall health during adolescence. This result is reassuring as we expect mental health to be an important component of overall health. Moreover, we also find that daughters have higher levels of dissatisfaction with the financial situation of their household. We further find that daughters are less satisfied with their safety and community. We find suggestive evidence that all this translates into a higher likelihood of being dissatisfied with life overall, as shown in Column (8). Similarly to the results for mental health, we do not detect sizable impacts of parental labor market entry conditions on their sons' satisfaction other than in the dimensions of safety and neighborhood, which appear not to translate to overall life satisfaction.

3.3 Robustness Checks

In this section, we probe the robustness of our main results to possible threats to internal validity. We start by assessing the sensitivity of our results to the measurement of mental health, our main outcome of interest. Next, we determine how robust our conclusions are to alternative proxies for parental labor market entry conditions and alternative choices to the empirical specification. Lastly, we address potential concerns about selection and attrition.

Table 4: Effects on mental health indicators of the child

	(1) Felt unhappy	(2) Felt nervous	(3) Felt down	(4) Felt anxious	(5) Cannot cheer up
Panel (a): Sons only					
Parental unemp. rate	0.019	-0.097*	-0.022	-0.031	-0.017
	(0.042)	(0.051)	(0.040)	(0.060)	(0.033)
Observations	508	508	508	508	508
R-squared	0.041	0.057	0.061	0.027	0.087
Panel (b): Daughters only					
Parental unemp. rate	0.193***	0.062	0.075	0.052	0.096
	(0.053)	(0.066)	(0.060)	(0.053)	(0.058)
Observations	493	493	493	493	493
R-squared	0.052	0.033	0.038	0.053	0.054

*Notes: Estimation of the specification in Table 2's Column (4) where the outcomes are indicators of having experienced negative feelings for each of the five components of the MHI-5 in the previous four weeks and the main independent variable is the average of the detrended unemployment rates faced by the two parents at labor market entry. Standard errors clustered at the maternal state of labor market entry × cohort level. *** p<0.01, ** p<0.05, * p<0.1. The results that use the pooled sample including both sons and daughters are reported in Appendix Table A8.*

Alternative measures of mental health. We show in two ways that the mental health impacts we find are not an artifact of our chosen measure of mental health. First, in Table 4, we run the same regression separately for indicators of frequent episodes of poor mental health for each of the 5 components of the MHI-5.[14] We find that daughters whose parents were exposed to higher unemployment rates at their labor market entry are significantly more likely to feel unhappy. In terms of magnitude, a 1 standard deviation unemployment rate shock at labor market entry is associated with a $19.3 \times 0.31 = 5.983$ percentage points increase in the probability of having felt unhappy. While the results appear to be driven primarily by a higher likelihood of unhappiness, the estimated effects on the other dimensions are also consistently positive and economically meaningful, though not measured with enough precision.

Second, in Appendix Table A10, we replicate our analysis using the Kessler-10 scale (Kessler et al., 2002) as our measure of mental health, instead of the MHI-5 employed in our main analysis. We again find economically and statistically significant effects of parental labor market entry conditions only for daughters, which is consistent with our findings using MHI-5.

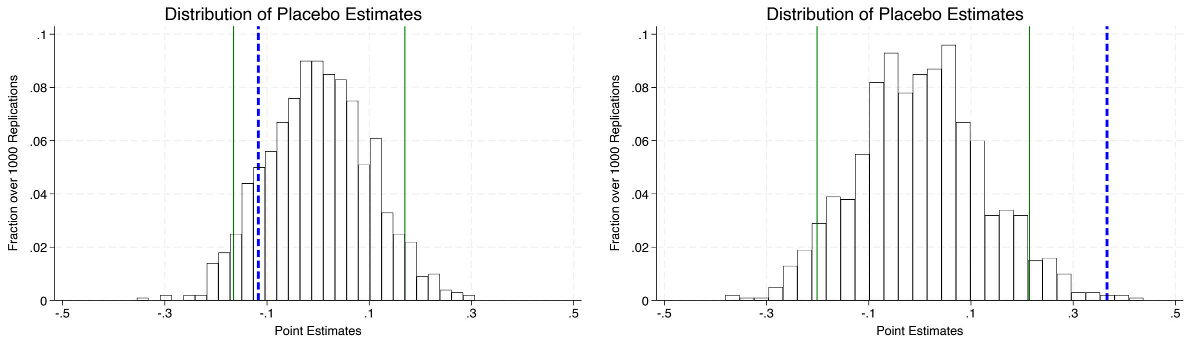
Randomizing labor market entry conditions. To improve our confidence that the results we find are not spurious, we conduct a simple simulation exercise in the spirit of Fisherian randomization inference (Imbens and Wooldridge, 2009). We randomize labor market entry conditions by randomly assigning parental state of labor market entry and year of birth (the two dimensions along which unemployment at labor market entry varies) to each child and then we re-estimate the coefficients corresponding to Column (4) in Table 2. The idea is that, across estimates based on resampled data, we examine the distribution of the point estimate under the null that labor market entry conditions do not affect midlife mental health. Figure 3 displays the empirical distribution of point estimates over 1,000 resampling procedures independently done for both the sons and the daughters subpopulations. For daughters, the point estimate from the actual data (indicated in the graph with the blue discontinuous line) lies comfortably outside the empirical 90% confidence interval, indicated with solid green lines. This suggests that it

[14] In Appendix Table A9, we show the regressions where the unemployment rate shocks of the father and the mother are separately included in the same regression.

would be highly unlikely that we obtained our main results by chance. The point estimate for sons lies within the 90% confidence interval, reaffirming our conclusions in the main analysis.

Figure 3: Randomized inference

(a) Sons only   (b) Daughters only



Notes: Histogram of point estimates of the β coefficient in regressions of the form of Column (4) in Table 2 where the year of birth and the state of each of the two parents are randomly allocated 1,000 times (preserving the initial distribution of these two dimensions), separately for sons and daughters. The discontinuous blue line marks the point estimate obtained in Column (4) of Table 2. The solid green lines mark the empirical 90% confidence interval.

Alternative measures of labor market entry conditions. Just as we probed the robustness of our results to alternative measures of our main dependent variable, we now explore the robustness of our conclusions to alternative measures of our main independent variable: parental labor market entry conditions. In the main analysis, we used the average unemployment shocks of both parents at the state of labor market entry, where the cyclical components were obtained using an HP filter. We consider three alternative measures.

First, we replicate our results using an alternative way to extract the cyclical components. In particular, we take the raw unemployment rates and standardize the series using the state-specific mean and standard deviation. This is an alternative approach to the HP filter where we detrend the unemployment rate series assuming a flat trend over time. Moreover, it makes the deviations more comparable across states as they are expressed in terms of state-specific standard deviations. Such approach has been used by Arellano-Bover (2020), for example. We report the result in Column (1) of Table 5. We

Table 5: Robustness exercises

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Outcome: Bad mental health				
Panel (a): Sons only							
State-specific standardized parental unemp. rate	-0.075						
	(0.079)						
Raw parental unemp. rate		-0.051					
		(0.037)					
Detrended national-level parental unemp. rate			-0.114				
			(0.115)				
Parental unemp. rate				-0.121	-0.366	-0.286*	-0.048
				(0.110)	(0.336)	(0.162)	(0.110)
Observations	508	508	508	438	508	508	508
R-squared	0.072	0.073	0.072	0.105	0.148	0.071	0.057
Panel (b): Daughters only							
State-specific standardized parental unemp. rate	0.332**						
	(0.161)						
Raw parental unemp. rate		0.158*					
		(0.080)					
Detrended national-level parental unemp. rate			0.343*				
			(0.201)				
Parental unemp. rate				0.396*	0.704	0.522*	0.327*
				(0.221)	(0.626)	(0.276)	(0.168)
Observations	493	493	493	414	493	493	493
R-squared	0.040	0.041	0.036	0.055	0.089	0.039	0.033

*Notes: All regressions are variations of Column (4) in Table 2. Regressions in Columns (1) and (2) use as main independent variable the average of the state-specific standardized unemployment rate and the average state-specific raw unemployment rate between the two parents at their expected time of labor market entry, respectively. Column (3) uses as main independent variable the average detrended parental country-level unemployment rate at labor market entry. Column (4) additionally controls for grandparental education, occupational prestige, and indicators for non-Australian origins. Sample size is reduced due to the unavailability of some of these controls for a subset of the individuals employed in Table 2. Column (5) replaces the 5-year cohort indicators by yearly cohort fixed effects. Column (6) replaces the 5-year cohort indicators by 4-year cohort fixed effects. Column (7) replaces the 5-year cohort indicators by quadratic polynomials in the year of birth of parents. Standard errors clustered at the maternal state of labor market entry × cohort level. *** p<0.01, ** p<0.05, * p<0.1. The results that use the pooled sample including both sons and daughters are reported in Appendix Table A11.*

again find that the daughters of parents who faced worse labor market entry conditions have poorer mental health at adolescence.

The literature on the short- and mid-run outcomes of bad labor market entry conditions has traditionally employed raw unemployment rates. In Column (2) of Table 5, we show that replicating our baseline estimation using non-detrended unemployment rates at 18–22 does not change the results. The standard deviation of the average parental non-detrended unemployment rate is about 1.2. Therefore, the point estimate of 0.158

corresponds to an increase of $0.158 \times 1.2 = 0.1896$ standard deviations in the index of poor mental health, which is larger than our baseline estimate. As discussed previously, our preferred specification uses the detrended unemployment rate as it removes the predictable trend of the labor market and focuses on the plausibly exogenous variation around it.

Third, we probe the robustness of our results to the potential endogeneity of the geographical location of parents at the time of labor market entry (i.e., they could choose to migrate to areas of the country with better economic conditions). In our baseline specification, we use state-specific unemployment rate shocks which depend both on the cohort and state at labor market entry. In the case where individuals search for jobs outside their local labor markets during labor market entry, the relevant labor market conditions may be better captured by the national unemployment rate (Bentolila et al., 2022). Using the unemployment rate at the country level exclusively exploits temporal (cross-cohort) variation in labor market conditions and is not affected by concerns of internal migration. Following the same rationale as in our preferred specification, we detrend the country-level yearly unemployment rates using the filter proposed by Hodrick and Prescott (1997), and report the results using the average detrended parental national unemployment rates upon graduation in Column (3). We find very similar results in magnitude and statistical significance.

Controls in main specification. The causal interpretation of our estimate of labor market entry conditions relies on a conditional independence assumption. As argued above, this is likely to hold given that treatment is defined by plausibly exogenous characteristics (year of birth and geographic location upon labor market entry) and that we consider unemployment rate deviations from state-specific trends. In Column (4) of Table 5, we introduce additional sociodemographic controls for education, occupational prestige, and country of origin of the grandparents. We focus on characteristics of the grandparents because they are predetermined and are therefore not affected by labor market entry conditions. Although the sample size is reduced as these variables are missing for some individuals, it is reassuring that the point estimate that we obtain is very close to the one in Table 2's Column (4) for both daughters and sons.

Empirical specification of cohort effects. In the main specification, we account for common national cohort effects through fixed effects corresponding to 5-year cohort bins for each parent. In Column (5) of Table 5, we take a more non-parametric approach and instead include cohort-specific fixed effects for each parent, which is a more data-demanding approach. We obtain estimates that are considerably larger in magnitude yet estimated more imprecisely. In Column (6), we consider 4-year cohort bins and find similar results to our main specification. In Column (7), we instead use a quadratic polynomial to approximate the cohort trends of both parents and also find quantitatively similar results.

Selection: panel attrition. Non-random attrition could arise through migration and/or death of potential parents. Attrition by internal migration is largely alleviated by the sample design of HILDA, which includes nationwide coverage as well as the tracking of split households (which is particularly useful to access child outcomes). A more salient concern is attrition through death. This is specifically motivated by recent work by Schwandt and von Wachter (2020), which shows that individuals graduating in less favorable labor market conditions have increased mortality around midlife, particularly due to diseases related to high-risk behavior. In principle, this would lead to positive selection of individuals that remain in our sample — that is, we would be more likely to observe individuals who have relatively better mental health and other outcomes. Thus, this form of attrition should go against finding worse outcomes for their children. Moreover, Section 4 will formally show that labor market entry conditions do not have an impact on parental mortality.

Selection: family formation. The literature on the effects of labor market entry conditions highlights that selective attrition is a potential threat to identification. Specific to our particular interest, we are concerned that early labor market conditions may affect family formation, which may in turn have implications on the outcomes of the children we

Table 6: Effects on family formation

(a) Partnership formation

	Ever married		Age marriage		Ever separated partner	
	(1)	(2)	(3)	(4)	(5)	(6)
Unemp. rate	-0.056	0.036	-0.365	0.014	0.065	-0.066
	(0.042)	(0.026)	(1.364)	(0.981)	(0.062)	(0.049)
Observations	717	841	568	713	635	718
R-squared	0.008	0.011	0.037	0.020	0.009	0.020
Sample	Males	Females	Males	Females	Males	Females

(b) Assortative matching

	Age gap		Same education level	
	(1)	(2)	(3)	(4)
Unemp. rate	0.218	0.744	0.037	0.091
	(1.063)	(0.735)	(0.079)	(0.095)
Observations	600	531	592	515
R-squared	0.040	0.028	0.013	0.024
Sample	Males	Females	Males	Females

(c) Childbearing

	Any child		No. of children		Age at first child	
	(1)	(2)	(3)	(4)	(5)	(6)
Unemp. rate	0.081	-0.023	0.434	-0.015	-2.051	-0.313
	(0.065)	(0.032)	(0.283)	(0.171)	(1.524)	(1.199)
Observations	717	841	717	841	588	737
R-squared	0.009	0.015	0.020	0.003	0.046	0.024
Sample	Males	Females	Males	Females	Males	Females

*Notes: The sample contains individuals born between 1964 and 1969 that were observed at or after age 50 (i.e., completed fertility). For this reason, we replace our 5-year cohort fixed effects for a quadratic polynomial as in Table 5's Column (7). To be included in the sample, we further require that information on whether the person has had any child is available. We do not impose that other information is available (e.g., age at marriage) which explains changes in sample size. Outcomes in Panel (a): an indicator of the person ever marrying, the age at first marriage, and an indicator for ever having separated from a spouse. Outcomes in Panel (b): the gap in years between the male and the female spouse and an indicator for the level of education of both spouses being the same. Outcomes in Panel (c): an indicator with value 1 if the person had at least one child by the last time the person was observed after age 50, total number of children, and the age of the parent at the time of first childbearing. Standard errors clustered at the state of labor market entry × cohort level. *** p<0.01, ** p<0.05, * p<0.1.*

observe. In particular, labor market entry conditions may affect whether individuals ever get married, who they are married to, and whether they have children. In Table 6, we explore the effects of labor market entry conditions on partnership formation, assortative mating, and childbearing. We find no evidence that labor market entry conditions affect these aspects of family formation, suggesting that our main results are not primarily driven by selection along these dimensions.

In Panel (a) of Table 6, we explore the effects of labor market entry conditions on partnership formation. Prior work on the effects of labor market entry conditions on partnership formation has provided estimates with varying sign and size (e.g., Kondo, 2012; Currie and Schwandt, 2014; Hofmann and Hohmeyer, 2016; Maclean et al., 2016; Choi et al., 2020; Engdahl et al., 2024). In our particular context, we do not find effects of labor market entry conditions on a range of measures of partnership formation. First, we explore the effects of labor market entry on the decision to be married. For this analysis, we focus on individuals we observe at least aged 50. We do not find an economically nor statistically significant effect of labor market entry on individuals ever being married by the age of 50. Second, conditional on being married, we explore the effects of labor market entry conditions on the age at marriage and the event of separating from their partner. We do not find effects of labor market entry on these decisions either.

In Panel (b) of Table 6, we explore the effects of labor market entry conditions on assortative mating or homogamy between partners. We focus on two dimensions of sorting of particular interest in the literature: age (e.g., Atkinson and Glass, 1985; Qian and Preston, 1993; Ciscato and Weber, 2020) and education (e.g., Mare, 1991; Schwartz and Mare, 2005; Hirschl et al., 2024). We do not find statistically significant effects of labor market entry conditions on the age gap between partners nor on the probability that partners are of the same education level.

In Panel (c) of Table 6, we explore the effects of labor market entry conditions on who becomes a parent both at the extensive (any child) and intensive (number of children) margin by age 50. From a theoretical perspective, the presence and direction of the effects on childbearing are ambiguous (Becker, 1973). There is also mixed empirical evidence in the literature as to what is the effect of labor market entry conditions on childbearing: some papers find significant effects (e.g., Currie and Schwandt, 2014; Choi et al., 2020) while others do not (e.g., Hofmann and Hohmeyer, 2016). We do not find any effects of labor market entry conditions on fertility on either the extensive or the intensive margin. Moreover, we do not find effects on the age at which individuals have their first child.

4 Mechanisms and Mediation Analysis

In the previous section, we found a causal relationship between the labor market entry conditions of parents, a shock that occurred before the children were born or conceived, and the mental health of daughters. In this section, we investigate the mechanisms that may link these two situations across generations. To do so, we explore the impacts of labor market entry conditions on various medium-run outcomes of the parental generation deemed to be important determinants of the environment during formative early childhood stages (e.g., Cunha et al., 2010). We then conduct a simple mediation analysis à la Gelbach (2016) to provide suggestive evidence of which of the dimensions might best explain the intergenerational effects that we find.

4.1 Which Outcomes Changed for the Parental Generation?

The existing literature has shown that poorer labor market entry conditions can contemporaneously worsen certain outcomes: income (Borland, 2020), occupational prestige (Lampe et al., 2022), and mental health (Li and Toll, 2021), among others. These circumstances, likely predating the first childbearing, may play a role in determining late childhood outcomes of yet-to-be-born descendants. We complement these results by exploring their persistence at mid-life and, given the constraints of our dataset, explore a wider range of outcomes of the parental generation, *measured at mid-life*, that could be affected by their labor market conditions and that may partly determine their offspring's mental health.

These mid-life outcomes, measured before children reach adolescence, constitute the circumstances surrounding the child during their formative years and may affect adolescent mental health in various ways. *First*, they determine the economic capabilities of parents to invest in their children (Becker and Tomes, 1986; Cunha et al., 2010; Almond et al., 2018). For instance, the literature has studied the effects on children's later life outcomes of parental unemployment (Ermisch et al., 2003; Nikolova and Nikolaev, 2021) and parental death (Garcia-Brazales, 2023) at early childhood. Moreover, these socioeconomic conditions may also affect how children are perceived by their peers, which plausibly affects their mental health (e.g., Tippett and Wolke, 2014). *Second*, the conditions of parents may complement the investments in children (e.g., Guryan et al., 2008; Berger and Font, 2015). For example, time spent with healthy and satisfied parents may be more developmentally beneficial than time spent with stressed caregivers. *Third*, children may internalize their parents' circumstances and use them as references or role models. Persistent exposure to parental hardship or dissatisfaction may influence children's own expectations, emotional states, and coping mechanisms, thereby affecting their mental health (e.g., Conger and Donnellan, 2007).

The above discussion, which is not exhaustive, highlights the existence of many possible pathways through which parental outcomes may affect adolescent mental health. To narrow our focus systematically, we consider dimensions identified by von Wachter (2020) as outcomes that may be affected by own labor market entry conditions. These include: physical health, premature death, risky behaviors (smoking and drinking), income, risk-taking attitudes, locus of control, detachment from the labor force, and occupational prestige. Given our context, we additionally study parental mental health, relative time dedicated to household production, and whether parents think their job affects their children.

We estimate the following regression:

$$y_p = \alpha + \beta \times \mathrm{UR}_p + f(c(p)) + \lambda_{s(p)} + \varepsilon_p. \tag{2}$$

The notation closely follows from Equation (1) but the unit of observation is now the child's parents. The dependent variable of the regression y_p is a summary of parental outcomes of a certain child. In the case of income, mental health, physical health, willingness to take financial risks, occupational prestige, locus of control, and maternal relative time dedicated to home production, it is an average of the outcomes of parents prior to their child being age 15 to ensure our focus is on parental outcomes that are not measured contemporaneously to the child mental health outcomes. For ever dies, smoker, and heavy drinker, we construct a binary variable taking the value of one if parents have died, were smokers, or were heavy drinkers before the child was age 15, respectively. We measure detachment from the labor force as the proportion of observations (prior to their child being 15) for which we observe the individual to be unemployed or out of the labor force. For the measure of whether parents think their job affects children, we rely on the strength of agreement on a seven-point scale with the statement that "my work has a positive effect on my children".

Table 7: Mediation: Impacts on parental outcomes

	(1) Log household income	(2) Bad mental health	(3) Bad physical health	(4) Ever dies
Unemp. rate	-0.234***	0.227**	0.213**	0.024
	(0.083)	(0.088)	(0.096)	(0.017)
Observations	1,001	1,001	1,001	1,001
R-squared	0.074	0.030	0.067	0.035
	(5) Current smoker	(6) Current heavy drinker	(7) Financial risk aversion	(8) Detached from labor force
Unemp. rate	0.093*	0.011	0.131*	0.029**
	(0.056)	(0.033)	(0.067)	(0.012)
Observations	1,001	1,001	1,001	1,001
R-squared	0.071	0.042	0.056	0.060
	(9) Occupational prestige	(10) Locus of control	(11) Maternal relative home production	(12) Job affects children
Unemp. rate	-4.018	0.018	0.015	0.060
	(2.908)	(0.097)	(0.022)	(0.132)
Observations	1,001	1,001	1,001	1,001
R-squared	0.043	0.021	0.030	0.017

*Notes: Estimation of Equation (2) for a sample composed of the parents of the 508 (sons) + 493 (daughters) = 1,001 children in the main estimating sample. Outcomes are the average value of the given variable for the two parents measured while (i) parents are less than 60 years of age and (ii) the child is less that 15 years of age. The details on the construction of the outcomes are documented in Section 2. Standard errors clustered at the maternal state of labor market entry × cohort level. *** p<0.01, ** p<0.05, * p<0.1.*

Table 7 reports the estimates of Equation (2) separately for each of the twelve outcomes of interest. In Column (1), we find that the collective household income of parents who enter the labor market during worse times is lower, on average.[15] In Columns (2) and (3), we find that the parents who entered the labor market under worse conditions are more likely to suffer from poorer mental and physical health, respectively. We do not detect effects on premature death, as seen in Column (4). Furthermore, parents who enter the labor market under worse conditions are less willing to take financial risks (Column (7)). With regards to other risk-taking behavior, we find higher take-up of smoking, but not of drinking (Columns (5) and (6), respectively). Column (8) shows that parents are more likely to be detached from the labor force. Although the coefficient is not statistically significant, Column (9) suggests that, if employed, the prestige of their occupation is lower. We do not find effects on parent's locus-of-control (Column (10)). In Column (11), we find that, among parents who enter the labor market in worse conditions, the mother does not devote more nor less time to home production relative to their partner. Lastly, in Column (12), we do not find evidence that parents think their job affects their children. Appendix Table A12 replicates the analysis only employing the parents of daughters, who are our focus of interest since it is only for daughters for whom we found an impact on mental health in Table 2. The results hold.

We show that the effects described above are not specific to the parents of daughters. In Appendix Table A13, we replicate the analysis for the parents of the sample of sons. As expected, we find similar effects as for the daughters' sample. Moreover, in Appendix Table A14, we replicate the analysis for all the individuals born after 1964, regardless of whether they eventually have children or not. The results reinforce the presence of negative effects on household income and mental health. Moreover, these results provide additional support to our discussion in Section 2.4 that our sample is likely representative of the overall population of parents born in the appropriate cohorts. Therefore, the effects we find are not necessarily specific to the sample of parents we consider.

[15] Total household income includes non-labor earnings such as business and capital income. While the literature has mainly focused on labor income alone, we believe that total household income is more relevant for a child's circumstances.

4.2 Mediation Analysis

How much do the effects of labor market entry conditions on parental mid-life outcomes help explain the poorer mental health of their daughters' that we document? In Appendix Table A15, we start in Column (1) with our preferred estimate of the impact of parental labor market entry conditions on daughters' mental health (i.e., the one in Column (4) of Table 2), and then additionally control in Column (2) for the mediators studied in Section 4.1. The estimate falls from 0.366 to 0.161, which suggests that the parental mid-life outcomes we study explain about 56% of the intergenerational effect we have documented.

We follow Gelbach (2016) to apportion the explained fraction of our estimated effect to the individual mechanisms we consider. This decomposition exercise begins with our main estimate of the effect of parental labor market entry conditions on child outcomes, estimated using Equation (1), which we call the "short" regression. Correspondingly, we call this estimate β^{short} for exposition. We then consider a model, which we call the "long" regression, where we augment the regression with the mediators we consider; that is,

$$y_i = \alpha^{\text{long}} + \beta^{\text{long}} \times \text{UR}_{p(i)} + f^{\text{long}}(c(p(i))) + \lambda^{\text{long}}_{s(p(i))} + \sum_{k=1}^{K} \delta^k m^k_{p(i)} + \nu_i, \tag{3}$$

where m^k corresponds to the kth mediator of which there are K in total. The difference $\beta^{\text{short}} - \beta^{\text{long}}$ is the part of the estimated treatment effect that can be explained by the mediators we consider. Gelbach (2016) proposes a way to allocate parts of this explained difference to each of the mechanisms using omitted variable bias formulas. Informally, the contribution of a specific mechanism to explain the treatment effect is the product of two quantities: (i) the effect of labor market entry conditions on the mechanism, estimated in the previous subsection using Equation (2) and reported in Appendix Table A12; and (ii) the partial effect of the mechanism on the outcome, δ^k, estimated using Equation (3) and reported in Appendix Table A15. The latter component highlights that the contribution of one mediator to explaining the intergenerational effects of labor market entry conditions focuses on the contribution beyond what is explained by the other mediators considered. In other words, if a mediator does not have a direct marginal effect on the outcome conditional on all the other mediators we consider, that mediator does not contribute to explaining the intergenerational effects we find.

Table 8: Mediation analysis: Breakdown of relative importance of channels in worsened daughters' mental health

	(1) Coefficient/ Contribution	(2) Standard Error	(3) % of short
Short regression	0.366*	0.187	100
Long regression	0.161	0.148	44
Parental outcome:			
Bad mental health	0.088*	0.051	24
Bad physical health	0.014	0.017	4
Death	0.068	0.089	19
Smoking	0.030	0.027	8
Heavy drinking	-0.000	0.003	−0
Income	-0.027	0.018	−7
Willingness financial risk with cash	0.035	0.030	10
Unemployment spells & out of labor market	0.042	0.028	12
Occupational prestige	-0.037	0.030	−10
Locus of control	-0.001	0.004	−0
Maternal relative home production	-0.002	0.005	−1
Job affects children	-0.006	0.013	−2
Total Explained ($\beta^{\text{short}} - \beta^{\text{long}}$)	0.205*	0.108	56

*Notes: Sample composed by the subsample of (493) daughters. Gelbach (2016) decomposition of the role of the various mechanisms for explaining the gap in daughter's mental health by parental labor market entry conditions. "Total Explained" represents the difference in the estimate of the variable "parental unemp. rate" between the full and the base models (the base model corresponds to the fourth column for females in Table 2). Standard errors reported in Column (2) are clustered at the maternal state of labor market entry × cohort level. Column (3) reports the fraction of the intergenerational effects that can be explained by each mediator. The sum of the percentages for the long regression and those for each of the mediators may not add up to 100 due to rounding. Similarly, the sum of individual contributions of the mediators may not sum to the total explained part. *** p<0.01, ** p<0.05, * p<0.1*

The results of this mediation analysis are reported in Table 8. Parental mental health emerges as the variable that explains most of the effect of parental labor market entry conditions on child mental health. In particular, it can explain about 24% of the intergenerational effect. This is due to the combination of the sizable effects that we find for (i) parental labor market entry conditions on parental mental health, and (ii) parental health on child mental health conditional on other possible mediators such as parental income or risky behavior. Parental death is the second best candidate to explain the effect of parental labor market entry conditions on child mental health, explaining 19% of our estimated effect, although the estimated contribution is not statistically significant. Overall, our results suggest that parental labor market entry conditions affect the mental health of daughters at adolescence primarily through worsened parental mental health.

Limitations of the mediation analysis. The Gelbach (2016) decomposition analysis may not necessarily be causal for two reasons. *First*, Gelbach (2016)'s framework is agnostic about the causal direction of the variables contemplated as mediators. We therefore rely on timing to make sure that the mediators we include are causal. In particular, the mediating variables are constructed using only parental outcomes before the child turns 15, which is the earliest we measure our child outcomes. As such, the outcomes we claim as mediators clearly happen before the outcomes we are measuring, which reinforces them as plausible mediators. *Second*, the proper attribution of the explained portion to the various dimensions requires that we are able to observe all relevant mediators. That is, we may be concerned that the contributions we estimate capture the effects operating through mediators that we do not include but are correlated with the included ones. Possible mediators that are a threat to our exercise are those that satisfy three conditions: (i) are correlated with the mediators in our analysis, (ii) are affected by labor market entry conditions, and (iii) have a direct effect on explaining child mental health above and beyond the mediators we already consider. As mentioned, we have limited the possible threats by considering the outcomes that have been identified in the literature as being affected by labor market entry conditions (von Wachter, 2020). Coincidentally, they are also the variables that have been systematically explored in the literature as factors that potentially affect child mental health. While we think this assuages the concern that there are additional relevant omitted variables, we acknowledge that we cannot completely ignore this concern.

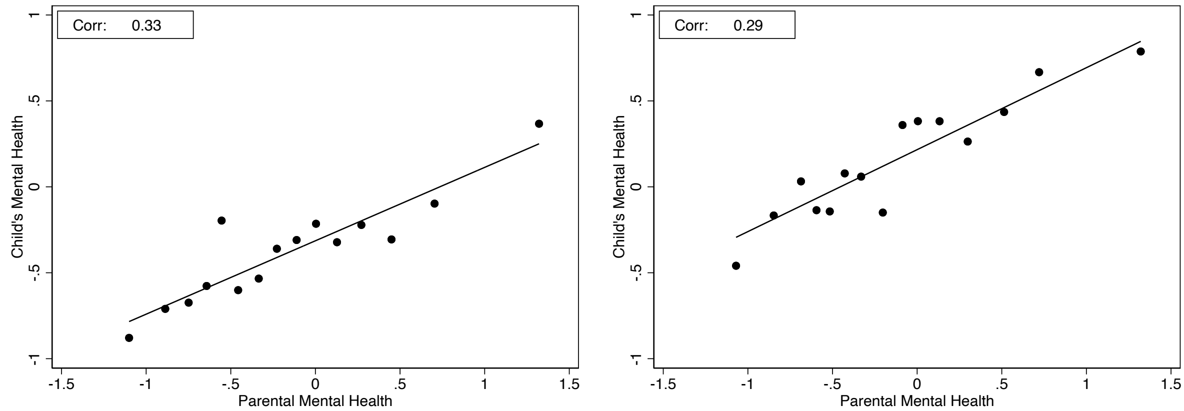
4.3 Discussion: Implications for the Intergenerational Correlation of Mental Health

In the previous subsection, we find that parental mental health is an important mediator to explain the effect of parental labor market entry conditions on the mental health of their daughters. As mentioned, this is mediated by the effects of parental mental health on child mental health. This naturally connects with the intergenerational correlation of mental health, which we explore in this section.

Figure 4: Intergenerational correlations of poor mental health

(a) Parents and sons

(b) Parents and daughters



Notes: Binned scatter plots of the relationship between the average parental mental health up to the child being 15 (first taking the residuals after controlling for business cycle and age profile, and then standardized) and the mental health of the child when aged 15–20 (after following a similar treatment as for the parents). The underlying correlation coefficient is shown in the upper-left corner of the graphs. In Appendix Figure A2, we report the partial correlations of child mental health with the two parents individually.

A growing literature has estimated a strong and significant intergenerational correlation of mental health in various settings using both administrative and survey data (e.g., McLaughlin et al., 2012; Johnston et al., 2013; Bencsik et al., 2023; Zhou et al., 2023; Bütikofer et al., 2023). In Figure 4, we show that the average mental health of both parents and the mental health of their children are also correlated in our sample. Our estimated correlations are around 0.30. In Appendix Figure A2, we report partial correlations that measure the correlation of one parent and their child, netting out the mental health of the other parent. Overall, we do not find substantive differences in the correlation of children's mental health with that of their mothers or fathers.[16]

While we have begun to better measure the intergenerational correlation of mental health, there is scarce evidence on the causal mechanisms that underpin this correlation (Mazumder, 2024). Our results show that labor market entry conditions of parents may explain part of the intergenerational correlations in mental health. We believe this has two important implications for our understanding of the intergenerational correlation of mental health. *First*, intergenerational transmission of mental health is not purely explained by genetics or nature alone, and that nurture and the environment also play a key role. Moreover, we stress the importance of accounting for potential heterogeneity in treatment effects, especially along gender. These conclusions echo similar points made by Lundborg and Majlesi (2018) and Athanasiadis et al. (2022) for physical health, and Black et al. (2019) for wealth. *Second*, our results suggest that there is scope for labor market policies to improve mental health outcomes. In particular, our findings suggest that by developing policies and programs that alleviate or protect against the adverse effects of bad labor market entry conditions, we might improve mental health outcomes for future generations.

5 Conclusion

Understanding the long-term determinants of mental health is a crucial yet less understood question. In this paper, we leverage geographical and time series variation in unemployment rates at ages 18–22 among a representative sample of Australians to show that poor labor market entry conditions have a negative impact on the mental health of their yet-to-be-born daughters. This result is robust to the use of alternative measures of mental health and specifications. Moreover, we find that daughters of parents who enter the labor market under worse conditions have lower levels of satisfaction with their own health and overall life situation.

The richness of our data and the long time series available allow us to explore which of the dimensions previously documented to be affected by labor market entry conditions

[16]If anything, we find the correlation between mothers and sons to be stronger than for the other pairs.

may plausibly drive the novel intergenerational impacts that we document. We find support that poorer parental mental health is an important contributor, and that aspects such as lower household income are unlikely to drive the results.

Our results therefore highlight that the negative impacts of bad labor entry conditions go beyond persistent adverse effects in the outcomes of the directly affected cohorts (von Wachter, 2020). We find that the effects of unfavorable labor market entry conditions spill over to the next generation, their offspring. This is consistent with the literature on human capital formation where the circumstances that children grow up in have effects on their long-run outcomes.

Our findings may be useful for academics and policy makers alike. We contribute novel evidence on the long-term determinants of mental health, not only for the individuals who directly experienced variation in our shock of interest, but also for their children, even if they were not yet born nor conceived. This complements the growing and influential literature that has emphasized in-utero and early-life events as key drivers of adult outcomes. In this paper, we take one step back and track how a particularly meaningful and plausibly exogenous situation, parental labor market entry conditions, ends up influencing in-utero and early-life situations and, as a consequence, early adult outcomes of the next generation. Moreover, while there is some work documenting the presence of intergenerational correlations in mental health, we provide one of the first causal roots rationalizing its presence and showing that it cannot be solely driven by genetics. These results support the importance of social safety net programs such the European Mental Health Action Plan to insure individuals from the mental consequences of poor labor market conditions. Our analyses further suggest that particular care should be taken with the mental health of women.

We recognize that the impact of parental labor market entry conditions on subsequent generations is likely shaped by the broader institutional context, particularly labor market structures, social safety nets, and welfare policies. As such, our findings reflect conditions specific to our study setting, and the strength or existence of similar intergenerational effects may differ elsewhere. This highlights the importance of comparative research across diverse institutional landscapes to better understand how policy environments can amplify or mitigate these intergenerational dynamics.

References

Adhvaryu, Achyuta, James Fenske, and Anant Nyshadham (2019) "Early life circumstance and adult mental health," *Journal of Political Economy*, 127 (4), 1516–1549, https://www.journals.uchicago.edu/doi/epdf/10.1086/701606. (return to page 1, 4)

Akbulut-Yuksel, Mevlude, Erdal Tekin, and Belgi Turan (2022) "World War II Blues: The Long–lasting Mental Health Effect of Childhood Trauma," Working Paper 30284, National Bureau of Economic Research, 10.3386/w30284. (return to page 4)

Akee, Randall, William Copeland, and Emilia Simeonova (2023) "Child Mental Health, Family Circumstance, and Long-Term Success: The Effect of Household Income," *Journal of Human Resources*, https://jhr.uwpress.org/content/wpjhr/early/2023/08/02/jhr.1222-12709R2.full.pdf. (return to page 4)

Almond, Douglas, Janet Currie, and Valentina Duque (2018) "Childhood Circumstances and Adult Outcomes: Act II," *Journal of Economic Literature*, 56 (4), 1360–1446, 10.1257/jel.20171164. (return to page 4, 31)

Altonji, Joseph G, Lisa B Kahn, and Jamin D Speer (2016) "Cashier or consultant? Entry labor market conditions, field of study, and career success," *Journal of Labor Economics*, 34 (S1), S361–S401, https://www.journals.uchicago.edu/doi/epdf/10.1086/682938. (return to page 5)

Arellano-Bover, Jaime (2020) "The Effect of Labor Market Conditions at Entry on Workers' Long-Term Skills," *The Review of Economics and Statistics*, 1–45, 10.1162/rest_a_01008. (return to page 2, 9, 16, 24)

Athanasiadis, Georgios, Joeri J Meijsen, Dorte Helenius et al. (2022) "A comprehensive map of genetic relationships among diagnostic categories based on 48.6 million relative pairs from the Danish genealogy," *Proceedings of the National Academy of Sciences*, 119 (6), e2118688119, https://www.pnas.org/doi/full/10.1073/pnas.2118688119. (return to page 38)

Atkinson, Maxine P. and Becky L. Glass (1985) "Marital Age Heterogamy and Homogamy, 1900 to 1980," *Journal of Marriage and Family*, 47 (3), 685–691, http://www.jstor.org/stable/352269. (return to page 29)

Aulike, Ingrid A, Annette J Dobson, Jacob Egwunye, David M Fitzgerald, and Gita D Mishra (2021) "Assessing agreement between the K10 and MHI-5 measures of psychological wellbeing," *Applied Research in Quality of Life*, 16, 1753–1766, https://link.springer.com/article/10.1007/s11482-020-09843-0. (return to page 8)

Becker, Gary S. (1973) "A Theory of Marriage: Part I," *Journal of Political Economy*, 81 (4), 813–846, http://www.jstor.org/stable/1831130. (return to page 29)

Becker, Gary S. and Nigel Tomes (1986) "Human Capital and the Rise and Fall of Families," *Journal of Labor Economics*, 4 (3, Part 2), S1–S39, 10.1086/298118. (return to page 1, 31)

Bencsik, Panka, Timothy J. Halliday, and Bhashkar Mazumder (2023) "The intergenerational transmission of mental and physical health in the United Kingdom," *Journal of Health Economics*, 92, 102805, https://doi.org/10.1016/j.jhealeco.2023.102805. (return to page 5, 37)

Bentolila, Samuel, Florentino Felgueroso, Marcel Jansen, and Juan F. Jimeno (2022) "Lost in recessions: youth employment and earnings in Spain," *SERIEs*, 13 (1), 11–49, 10.1007/s13209-021-00244-6. (return to page 26)

Berger, Lawrence M. and Sarah A. Font (2015) "The Role of the Family and Family-Centered Programs and Policies," *The Future of Children*, 25 (1), 155–176, http://www.jstor.org/stable/43267767. (return to page 31)

Berniell, Inés, Leonardo Gasparini, Mariana Marchionni, and Mariana Viollaz (2023) "Lucky women in unlucky cohorts: Gender differences in the effects of initial labor market conditions in Latin America," *Journal of Development Economics*, 161, 103042, https://doi.org/10.1016/j.jdeveco.2022.103042. (return to page 2, 9, 16)

Black, Sandra E, Paul J Devereux, Petter Lundborg, and Kaveh Majlesi (2019) "Poor Little Rich Kids? The Role of Nature versus Nurture in Wealth and Other Economic Outcomes and Behaviours," *The Review of Economic Studies*, 87 (4), 1683–1725, 10.1093/restud/rdz038. (return to page 38)

Blanchflower, David, David Bell, and Alex Bryson (2024) "The Declining Mental Health of the Young in the UK,"Technical report, National Bureau of Economic Research, 10.3386/w32879. (return to page 1)

Bohannon, Richard W and Louis DePasquale (2010) "Physical Functioning Scale of the Short-Form (SF) 36: internal consistency and validity with older adults," *Journal of Geriatric Physical Therapy*, 33 (1), 16–18, 10.1097/JPT.0b013e3181d0735e. (return to page 12)

Borland, Jeff (2020) "Scarring effects: A review of Australian and international literature," *Australian Journal of Labour Economics*, 23 (2), 173–188, https://search.informit.org/doi/10.3316/informit.469140968965412. (return to page 30)

Botha, Ferdi, Richard W Morris, Peter Butterworth, and Nick Glozier (2023) "The kids are not alright: differential trends in mental ill-health in Australia,"Technical report, Melbourne Institute of Applied Economic and Social Research, The University ..., https://lifecoursecentre.org.au/wp-content/uploads/2023/02/2023-02-LCC-Working-Paper-Both-et-al._Final.pdf. (return to page 7)

Burdett, Ashley, Apostolos Davillas, and Ben Etheridge (2021) "Weather, mental health, and mobility during the first wave of the COVID-19 pandemic," *Health Economics*, 30 (9), 2296–2306, https://doi.org/10.1002/hec.4371. (return to page 7)

Bütikofer, Aline, Rita Ginja, Krzysztof Karbownik, and Fanny Landaud (2023) "(Breaking) intergenerational transmission of mental health," *Journal of Human Resources*, 10.3368/jhr.1222-12711R2. (return to page 5, 37)

Bütikofer, Aline, Antonio Dalla-Zuanna, and Kjell G. Salvanes (2024) "Breaking the Links: Natural Resource Booms and Intergenerational Mobility," *The Review of Economics and Statistics*, 1–18, 10.1162/rest_a_01256. (return to page 5)

Choi, Eleanor Jawon, Jaewoo Choi, and Hyelim Son (2020) "The long-term effects of labor market entry in a recession: Evidence from the Asian financial crisis," *Labour Economics*, 67, 101926, https://doi.org/10.1016/j.labeco.2020.101926. (return to page 29, 30)

Ciscato, Edoardo and Simon Weber (2020) "The role of evolving marital preferences in growing income inequality," *Journal of Population Economics*, 33 (1), 307–347, 10.1007/s00148-019-00739-4. (return to page 29)

Collins, Pamela Y., Vikram Patel, Sarah S. Joestl et al. (2011) "Grand Challenges in Global Mental Health," *Nature*, 475 (7354), 27–30, 10.1038/475027a. (return to page 1)

Conger, Rand D. and M. Brent Donnellan (2007) "An Interactionist Perspective on the Socioeconomic Context of Human Development," *Annual Review of Psychology*, 58 (Volume 58, 2007), 175–199, https://doi.org/10.1146/annurev.psych.58.110405.085551. (return to page 31)

Cunha, Flavio, James J. Heckman, and Susanne M. Schennach (2010) "Estimating the Technology of Cognitive and Noncognitive Skill Formation," *Econometrica*, 78 (3), 883–931, https://doi.org/10.3982/ECTA6551. (return to page 1, 4, 30, 31)

Currie, Janet (2009) "Healthy, Wealthy, and Wise: Socioeconomic Status, Poor Health in Childhood, and Human Capital Development," *Journal of Economic Literature*, 47 (1), 87–122, 10.1257/jel.47.1.87. (return to page 4)

Currie, Janet and Douglas Almond (2011) "Chapter 15 - Human capital development before age five," in Card, David and Orley Ashenfelter eds. *Handbook of Labor Economics*, 4, 1315–1486: Elsevier, https://doi.org/10.1016/S0169-7218(11)02413-0. (return to page 4)

Currie, Janet and Hannes Schwandt (2014) "Short- and long-term effects of unemployment on fertility," *Proceedings of the National Academy of Sciences*, 10.1073/pnas.1408975111. (return to page 29, 30)

Engdahl, Mattias, Mathilde Godard, and Oskar Nordström Skans (2024) "Early Labor Market Prospects and Family Formation," *Journal of Human Resources*, 59 (5), 1564–1598, 10.3368/jhr.1220-11387R1. (return to page 29)

Ermisch, John, Marco Francesconi, and David J. Pevalin (2003) "Parental Partnership and Joblessness in Childhood and their Influence on Young People's Outcomes," *Journal of the Royal Statistical Society Series A: Statistics in Society*, 167 (1), 69–101, 10.1111/j.1467-985X.2004.00292.x. (return to page 31)

Fawaz, Yarine and Junhee Lee (2022) "Rank comparisons amongst teenagers and suicidal ideation," *Economics & Human Biology*, 44, 101093, 10.1016/j.ehb.2021.101093. (return to page 3, 19)

Garcia-Brazales, Javier (2023) "Orphanhood and Child Development: Evidence From India," *Demography*, 60 (2), 517–537, 10.1215/00703370-10584073. (return to page 31)

Gelbach, Jonah B. (2016) "When Do Covariates Matter? And Which Ones, and How Much?" *Journal of Labor Economics*, 34 (2), 509–543, 10.1086/683668. (return to page 30, 34, 35, 36)

Giulietti, Corrado, Michael Vlassopoulos, and Yves Zenou (2022) "Peers, gender, and long-term depression," *European Economic Review*, 144, 104084, https://doi.org/10.1016/j.euroecorev.2022.104084. (return to page 3, 19)

Glaser, Felix and Gerald J. Pruckner (2023) "A hard pill to swallow? Parental health shocks and children's mental health," *Health Economics*, 32 (12), 2768–2800, https://doi.org/10.1002/hec.4752. (return to page 4)

Greenberg, Paul E, Andree-Anne Fournier, Tammy Sisitsky, Crystal T Pike, and Ronald C Kessler (2015) "The economic burden of adults with major depressive disorder in the United States (2005 and 2010)," *The Journal of Clinical Psychiatry*, 76 (2), 5356, https://pubmed.ncbi.nlm.nih.gov/25742202/. (return to page 1)

Guryan, Jonathan, Erik Hurst, and Melissa Kearney (2008) "Parental Education and Parental Time with Children," *Journal of Economic Perspectives*, 22 (3), 23–46, 10.1257/jep.22.3.23. (return to page 31)

Hankin, Benjamin L. and Lyn Y. Abramson (2001) "Development of gender differences in depression: An elaborated cognitive vulnerability–transactional stress theory.," *Psychological Bulletin*, 127 (6), 773–796, 10.1037/0033-2909.127.6.773. (return to page 19)

Hirschl, Noah, Christine R. Schwartz, and Elia Boschetti (2024) "Eight Decades of Educational Assortative Mating: A Research Note," *Demography*, 61 (5), 1293–1307, 10.1215/00703370-11558914. (return to page 29)

Hodrick, Robert J. and Edward C. Prescott (1997) "Postwar U.S. Business Cycles: An Empirical Investigation," *Journal of Money, Credit and Banking*, 29 (1), 1–16, http://www.jstor.org/stable/2953682. (return to page 10, 26)

Hoeymans, Nancy, Anna A Garssen, Gert P Westert, and Peter FM Verhaak (2004) "Measuring mental health of the Dutch population: a comparison of the GHQ-12 and the MHI-5," *Health and Quality of Life Outcomes*, 2, 1–6, https://link.springer.com/article/10.1186/1477-7525-2-23. (return to page 2, 7)

Hofmann, Barbara and Katrin Hohmeyer (2016) "The effect of the business cycle at college graduation on fertility," *Economics of Education Review*, 55, 88–102, https://doi.org/10.1016/j.econedurev.2016.09.004. (return to page 29, 30)

Imbens, Guido W. and Jeffrey M. Wooldridge (2009) "Recent Developments in the Econometrics of Program Evaluation," *Journal of Economic Literature*, 47 (1), 5–86, 10.1257/jel.47.1.5. (return to page 23)

Johnston, David W., Stefanie Schurer, and Michael A. Shields (2013) "Exploring the intergenerational persistence of mental health: Evidence from three generations," *Journal of Health Economics*, 32 (6), 1077–1089, https://doi.org/10.1016/j.jhealeco.2013.09.001. (return to page 5, 37)

Kahn, Lisa B. (2010) "The long-term labor market consequences of graduating from college in a bad economy," *Labour Economics*, 17 (2), 303–316, https://doi.org/10.1016/j.labeco.2009.09.002. (return to page 5, 11)

Kessler, Ronald C, Gavin Andrews, Lisa J Colpe, Eva Hiripi, Daniel K Mroczek, S-LT Normand, Ellen E Walters, and Alan M Zaslavsky (2002) "Short screening scales to monitor population prevalences and trends in non-specific psychological distress," *Psychological Medicine*, 32 (6), 959–976, https://pubmed.ncbi.nlm.nih.gov/12214795/. (return to page 3, 8, 23)

Kondo, Ayako (2012) "Gender-specific labor market conditions and family formation," *Journal of Population Economics*, 25 (1), 151–174, 10.1007/s00148-011-0367-7. (return to page 29)

Lampe, Bryn, Catherine de Fontenay, Jessica Nugent, and Patrick Jomini (2022) "Climbing the Jobs Ladder Slower: Young People in a Weak Labour Market," *Australian Economic Review*, 55 (1), 40–70, https://doi.org/10.1111/1467-8462.12444. (return to page 30)

Li, Ang and Mathew Toll (2021) "Effects of graduating during economic downturns on mental health," *Annals of Epidemiology*, 55, 41–49, https://doi.org/10.1016/j.annepidem.2020.12.005. (return to page 30)

Lundborg, Petter and Kaveh Majlesi (2018) "Intergenerational transmission of human capital: Is it a one-way street?" *Journal of Health Economics*, 57, 206–220, https://doi.org/10.1016/j.jhealeco.2017.12.001. (return to page 38)

Maclean, Johanna Catherine (2013) "The health effects of leaving school in a bad economy," *Journal of Health Economics*, 32 (5), 951–964, https://doi.org/10.1016/j.jhealeco.2013.07.003. (return to page 5)

——— (2015) "The Lasting Effects of Leaving School in an Economic Downturn on Alcohol Use," *ILR Review*, 68 (1), 120–152, 10.1177/0019793914556243. (return to page 5)

Maclean, Johanna Catherine, Reginald Covington, and Asia Sikora Kessler (2016) "Labor market conditions at school-leaving: long-run effects on marriage and fertility," *Contemporary Economic Policy*, 34 (1), 63–88, https://doi.org/10.1111/coep.12113. (return to page 29)

Mare, Robert D. (1991) "Five Decades of Educational Assortative Mating," *American Sociological Review*, 56 (1), 15–32, http://www.jstor.org/stable/2095670. (return to page 29)

Mazumder, Bhashkar (2024) "Chapter 11: What do we know about the intergenerational transmission of health," in Kilpi-Jakonen, Elina, Jo Blanden, Jani Erola, and Lindsey Macmillan eds. *Research Handbook on Intergenerational Inequality*, 150 – 163, Cheltenham, UK: Edward Elgar Publishing, 10.4337/9781800888265.00018. (return to page 1, 38)

McLaughlin, Katie A., Anne M. Gadermann, Irving Hwang et al. (2012) "Parent psychopathology and offspring mental disorders: Results from the WHO World Mental Health Surveys," *British Journal of Psychiatry*, 200 (4), 290–299, 10.1192/bjp.bp.111.101253. (return to page 5, 37)

McMillan, Julie, Adrian Beavis, and Frank L Jones (2009) "The AUSEI06: A new socioeconomic index for Australia," *Journal of Sociology*, 45 (2), 123–149, https://journals.sagepub.com/doi/10.1177/1440783309103342. (return to page 12)

Nikolova, Milena and Boris N. Nikolaev (2021) "Family matters: The effects of parental unemployment in early childhood and adolescence on subjective well-being later in life," *Journal of Economic Behavior & Organization*, 181, 312–331, https://doi.org/10.1016/j.jebo.2018.05.005. (return to page 31)

Nybom, Martin and Jan Stuhler (2017) "Biases in Standard Measures of Intergenerational Income Dependence," *Journal of Human Resources*, 52 (3), 800–825, 10.3368/jhr.52.3.0715-7290R. (return to page 7)

Oreopoulos, Philip, Till von Wachter, and Andrew Heisz (2012) "The Short- and Long-Term Career Effects of Graduating in a Recession," *American Economic Journal: Applied Economics*, 4 (1), 1–29, 10.1257/app.4.1.1. (return to page 5, 15)

Persson, Petra and Maya Rossin-Slater (2018) "Family ruptures, stress, and the mental health of the next generation," *American Economic Review*, 108 (4-5), 1214–52, https://www.aeaweb.org/articles?id=10.1257/aer.20141406. (return to page 4)

Powdthavee, Nattavudh and James Vernoit (2013) "Parental unemployment and children's happiness: A longitudinal study of young people's well-being in unemployed households," *Labour Economics*, 24, 253–263, https://doi.org/10.1016/j.labeco.2013.09.008. (return to page 4)

Power, Melinda C, Marianthi-Anna Kioumourtzoglou, Jaime E Hart, Olivia I Okereke, Francine Laden, and Marc G Weisskopf (2015) "The relation between past exposure to fine particulate air pollution and prevalent anxiety: observational cohort study," *BMJ*, 350, 10.1136/bmj.h1111. (return to page 7)

Qian, Zhenchao and Samuel H. Preston (1993) "Changes in American Marriage, 1972 to 1987: Availability and Forces of Attraction by Age and Education," *American Sociological Review*, 58 (4), 482–495, http://www.jstor.org/stable/2096072. (return to page 29)

Ravn, Morten O. and Harald Uhlig (2002) "On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations," *The Review of Economics and Statistics*, 84 (2), 371–376, 10.1162/003465302317411604. (return to page 10)

Rumpf, Hans-Jürgen, Christian Meyer, Ulfert Hapke, and Ulrich John (2001) "Screening for mental health: validity of the MHI-5 using DSM-IV Axis I psychiatric disorders as gold standard," *Psychiatry Research*, 105 (3), 243–253, https://www.sciencedirect.com/science/article/pii/S0165178101003298. (return to page 2, 6)

Schwandt, Hannes and Till M von Wachter (2020) “Socioeconomic decline and death: Midlife impacts of graduating in a recession,”Technical report, National Bureau of Economic Research, https://www.nber.org/system/files/working_papers/w26638/w26638.pdf. (return to page 5, 27)

Schwartz, Christine R. and Robert D. Mare (2005) “Trends in educational assortative marriage from 1940 to 2003,” *Demography*, 42 (4), 621–646, 10.1353/dem.2005.0036. (return to page 29)

Siminski, Peter and Rhiannon Yetsenga (2022) “Specialization, Comparative Advantage, and the Sexual Division of Labor,” *Journal of Labor Economics*, https://www.journals.uchicago.edu/doi/pdf/10.1086/718430. (return to page 6)

Tippett, Neil and Dieter Wolke (2014) “Socioeconomic Status and Bullying: A Meta-Analysis,” *American Journal of Public Health*, 104 (6), e48–e59, 10.2105/AJPH.2014.301960, PMID: 24825231. (return to page 31)

Todd, Petra E and Weilong Zhang (2020) “A dynamic model of personality, schooling, and occupational choice,” *Quantitative Economics*, 11 (1), 231–275, https://qeconomics.org/ojs/index.php/qe/article/view/716. (return to page 6)

von Wachter, Till (2020) “The Persistent Effects of Initial Labor Market Conditions for Young Adults and Their Sources,” *Journal of Economic Perspectives*, 34 (4), 168–94, 10.1257/jep.34.4.168. (return to page 1, 3, 5, 11, 31, 36, 39)

Ware, JE, KK Snow, and M Kosinski (2000) “SF-36 version 2 health survey: manual and interpretation guide,” *Linc RI Qual Metr Inc*, https://www.researchgate.net/publication/247503121_SF36_Health_Survey_Manual_and_Interpretation_Guide. (return to page 6)

Wells, Jonathan C.K. (2000) “Natural Selection and Sex Differences in Morbidity and Mortality in Early Life,” *Journal of Theoretical Biology*, 202 (1), 65–76, https://doi.org/10.1006/jtbi.1999.1044. (return to page 19)

Zhou, Mengping, Henrik Larsson, Brian M. D’Onofrio, Mikael Landén, Paul Lichtenstein, and Erik Pettersson (2023) “Intergenerational Transmission of Psychiatric Conditions and Psychiatric, Behavioral, and Psychosocial Outcomes in Offspring,” *JAMA Network Open*, 6 (12), e2348439–e2348439, 10.1001/jamanetworkopen.2023.48439. (return to page 5, 37)

A Appendix: Additional Tables and Figures

Table A1: Sample size when selection criteria are implemented

	(1) All	(2) Females	(3) Males
Panel (a): Children sample			
Initial sample (age 15 to 20)	9,202	4,627	4,575
Both parents available in HILDA	5,193	2,549	2,644
Parents born in 1964 or after	1,259	627	632
Available information on child's satisfaction	1,257	625	632
Available information on parental mediators	1,001	493	508
	(1) All	(2) Females	(3) Males
Panel (b): Family formation sample			
Initial sample	23,362	11,645	11,717
Born in 1964 or after	22,294	11,112	11,182
Observed at complete fertility	1,666	889	777
Available information on childbearing	1,558	841	717
	(1) All	(2) Females	(3) Males
Panel (c): Representativeness comparison sample			
Initial sample	23,362	11,645	11,717
Born in 1964 or after	22,294	11,112	11,182
Have a child	9,075	5,006	4,069
Child potentially observed at ages 15–20	4,588	2,651	1,937

Notes: The table presents the changes in sample size resulting from the application of each sample selection criterion. Panel (a) refers to the creation of the sample for the outcomes of the children, i.e., the sample in Tables 2, 3, 4, 5, and 8. Note that, as explained in the text, we define children as individuals aged between 15 and 20. Available information on child's satisfaction refers to the availability of the outcome variables in Table 3. Available information on parental mediators refers to the availability of the outcome variables in Table 7. Panel (b) refers to the creation of the sample for the exploration of family formation patterns for the individuals observed at complete fertility (age 50), i.e., the sample in Table 6. Panel (c) refers to the creation of the sample used to explore the representativeness of the parental sample in Table 7, as described in Section 2.4.

Table A2: Sample representativeness

	Estimating sample							Representativeness comparison sample						
	(1) p10	(2) p25	(3) p50	(4) p75	(5) p90	(6) Mean	(7) Obs.	(8) p10	(9) p25	(10) p50	(11) p75	(12) p90	(13) Mean	(14) Obs.
Panel (a): All parents														
Year birth	1965	1967	1970	1973	1976	1970.103	2,002	1965	1967	1970	1974	1979	1970.982	4,588
Unemp. rate	-0.533	-0.334	-0.003	0.284	0.501	-0.023	2,002	-0.501	-0.289	-0.001	0.303	0.465	0.009	4,572
Years of education	11	12	13	16	16	13.735	2,002	11	11	13	14	16	13.145	4,583
Father is non-Australian	0	0	0	1	1	0.347	2,002	0	0	0	1	1	0.382	4,532
Panel (b): Fathers														
Year birth	1965	1966	1969	1972	1975	1969.393	1,001	1965	1966	1970	1974	1978	1970.732	1,937
Unemp. rate	-0.568	-0.310	-0.001	0.362	0.465	-0.008	1,001	-0.533	-0.289	0.005	0.317	0.465	0.009	1,930
Years of education	11	13	13	16	16	13.777	1,001	11	11	13	14	16	13.101	1,934
Father is non-Australian	0	0	0	1	1	0.357	1,001	0	0	0	1	1	0.391	1,910
Panel (c): Mothers														
Year birth	1966	1968	1970	1974	1977	1970.814	1,001	1965	1967	1970	1975	1979	1971.165	2,651
Unemp. rate	-0.533	-0.334	-0.041	0.224	0.501	-0.037	1,001	-0.501	-0.289	-0.001	0.295	0.465	0.009	2,642
Years of education	11	12	13	16	16	13.692	1,001	11	11	13	14	16	13.177	2,649
Father is non-Australian	0	0	0	1	1	0.337	1,001	0	0	0	1	1	0.375	2,622

Notes: The table presents various features of the distribution of a set of fixed characteristics (year of birth, unemployment rate shock experienced upon labor market entry, years of education achieved, and an indicator for whether the person's father was non-Australian). The features reported are the mean and the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution. Columns (1)–(7) report these features for the parental sample in Table 7. There are 2,002 parents corresponding to 1,001 fathers and 1,001 mothers. Columns (8)–(14) report the same features for the full sample of parents constructed in Table A1's Panel (c). Panels (b) and (c) focus on the sample of males and females, respectively.

Table A3: Summary statistics (parental sample)

	Sons			Daughters		
	Mean	Standard deviation	Count	Mean	Standard deviation	Count
Panel (a): Father, felt in the last four weeks...						
Unhappy	0.385	0.322	508	0.414	0.328	493
Nervous	0.168	0.239	508	0.203	0.267	493
Down	0.224	0.268	508	0.234	0.261	493
Anxious	0.548	0.339	508	0.578	0.334	493
Hard to cheer up	0.115	0.177	508	0.118	0.184	493
Average bad mental	0.154	0.232	508	0.161	0.229	493
Panel (b): Mother, felt in the last four weeks...						
Unhappy	0.402	0.323	508	0.395	0.320	493
Nervous	0.265	0.296	508	0.250	0.304	493
Down	0.287	0.281	508	0.302	0.275	493
Anxious	0.639	0.319	508	0.643	0.318	493
Hard to cheer up	0.148	0.220	508	0.159	0.225	493
Average bad mental	0.210	0.273	508	0.219	0.278	493
Panel (c): Father, low satisfaction with life aspects						
Home you live in	0.128	0.195	508	0.128	0.187	493
Employment opportunities	0.131	0.225	508	0.135	0.213	493
Financial situation	0.255	0.287	508	0.284	0.293	493
Safety	0.055	0.132	508	0.048	0.120	493
Feeling part of community	0.212	0.265	508	0.245	0.284	493
Your health	0.099	0.198	508	0.128	0.218	493
Your neighborhood	0.070	0.142	508	0.082	0.156	493
Amount of free time	0.391	0.300	508	0.442	0.312	493
Life as a whole	0.050	0.133	508	0.064	0.143	493
Panel (d): Mother, low satisfaction with life aspects						
Home you live in	0.155	0.215	508	0.148	0.200	493
Employment opportunities	0.224	0.259	508	0.219	0.259	493
Financial situation	0.301	0.313	508	0.300	0.289	493
Safety	0.084	0.166	508	0.079	0.160	493
Feeling part of community	0.210	0.261	508	0.194	0.250	493
Your health	0.125	0.227	508	0.129	0.224	493
Your neighborhood	0.084	0.164	508	0.080	0.157	493
Amount of free time	0.486	0.310	508	0.492	0.307	493
Life as a whole	0.054	0.128	508	0.045	0.110	493

Notes: Descriptive statistics of the fathers and mothers of the children in the main analysis. Panels (a) and (b) report measures of mental health of fathers and mothers, respectively. Panels (c) and (d) report measures of satisfaction with life aspects of fathers and mothers, respectively. The first block of columns reports statistics of the parents of sons. The second block of columns reports statistics of the parents of daughters.

Table A4: Intergenerational spillovers on mental health of labor market entry conditions: Robustness to clustering at the paternal state at graduation × cohort level

	Outcome: Bad mental health (z-score)			
	(1)	(2)	(3)	(4)
Panel (a): Sons only				
Father's unemp. rate	-0.139*		-0.147*	
	(0.078)		(0.082)	
Mother's unemp. rate		0.004	0.039	
		(0.084)	(0.089)	
Parental unemp. rate				-0.117
				(0.099)
Observations	508	508	508	508
R-squared	0.075	0.071	0.076	0.073
Panel (b): Daughters only				
Father's unemp. rate	0.217**		0.175	
	(0.107)		(0.113)	
Mother's unemp. rate		0.230*	0.191	
		(0.130)	(0.137)	
Parental unemp. rate				0.366***
				(0.135)
Observations	493	493	493	493
R-squared	0.034	0.034	0.039	0.039

*Notes: Replication of Table 2 with standard errors clustered at the paternal state of labor market entry × cohort level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.*

Table A5: Intergenerational spillovers on mental health of labor market entry conditions (pooled sample)

	Outcome: Bad mental health (z-score)			
	(1)	(2)	(3)	(4)
Father's unemp. rate	0.029		0.005	
	(0.090)		(0.091)	
Mother's unemp. rate		0.114	0.113	
		(0.070)	(0.072)	
Parental unemp. rate				0.116
				(0.103)
Observations	1,001	1,001	1,001	1,001
R-squared	0.105	0.107	0.107	0.106

*Notes: Regressions replicate those in Table 2 for the pooled sample of sons and daughters. Standard errors clustered at the maternal state of labor market entry × cohort level. *** p<0.01, ** p<0.05, * p<0.1.*

Table A6: Effects on other aspects of child well-being: Robustness to clustering at the paternal state at graduation × cohort level

Low satisfaction with...	(1) Home .	(2) Financial situation	(3) Safety	(4) Community	(5) Health	(6) Neighborhood	(7) Free time	(8) Life
Panel (a): Sons only								
Father's unemp. rate	-0.019*	-0.026	-0.030***	0.019	-0.007	-0.043**	-0.041	-0.007
	(0.011)	(0.033)	(0.009)	(0.027)	(0.014)	(0.021)	(0.029)	(0.007)
Mother's unemp. rate	0.011	-0.030	0.009	-0.007	0.007	0.006	0.022	0.021***
	(0.013)	(0.037)	(0.013)	(0.036)	(0.017)	(0.022)	(0.026)	(0.008)
Observations	508	508	508	508	508	508	508	508
R-squared	0.063	0.060	0.056	0.063	0.084	0.062	0.023	0.075
Parental unemp. rate	-0.017	-0.032	-0.028***	0.018	-0.005	-0.042**	-0.036	-0.003
	(0.011)	(0.031)	(0.009)	(0.026)	(0.014)	(0.021)	(0.029)	(0.008)
Observations	508	508	508	508	508	508	508	508
R-squared	0.062	0.059	0.055	0.063	0.084	0.062	0.021	0.065
Panel (b): Daughters only								
Father's unemp. rate	-0.003	0.048	0.006	0.012	0.051**	0.037	0.050**	0.008
	(0.015)	(0.037)	(0.016)	(0.039)	(0.021)	(0.026)	(0.022)	(0.013)
Mother's unemp. rate	0.045**	0.069	0.021	0.065	0.062**	0.003	-0.006	0.038**
	(0.022)	(0.044)	(0.013)	(0.044)	(0.030)	(0.020)	(0.037)	(0.018)
Observations	493	493	493	493	493	493	493	493
R-squared	0.082	0.062	0.046	0.047	0.051	0.078	0.043	0.062
Parental unemp. rate	0.043*	0.116**	0.027	0.078	0.113***	0.039	0.044	0.047**
	(0.024)	(0.048)	(0.020)	(0.049)	(0.035)	(0.025)	(0.039)	(0.023)
Observations	493	493	493	493	493	493	493	493
R-squared	0.075	0.062	0.045	0.045	0.051	0.076	0.041	0.059

*Notes: Replication of Table 3 with standard errors clustered at the paternal state of labor market entry × cohort level. *** p<0.01, ** p<0.05, * p<0.1.*

Table A7: Effects on other aspects of child well-being (pooled sample)

Low satisfaction with...	(1) Home .	(2) Financial situation	(3) Safety	(4) Community	(5) Health	(6) Neighborhood	(7) Free time	(8) Life
Father's unemp. rate	-0.014	0.009	-0.014*	0.015	0.017	-0.007	-0.000	-0.000
	(0.010)	(0.029)	(0.008)	(0.026)	(0.015)	(0.015)	(0.025)	(0.007)
Mother's unemp. rate	0.029**	0.022	0.014**	0.031	0.041***	0.006	0.007	0.029***
	(0.011)	(0.031)	(0.007)	(0.027)	(0.015)	(0.016)	(0.023)	(0.008)
Observations	1,001	1,001	1,001	1,001	1,001	1,001	1,001	1,001
R-squared	0.044	0.030	0.030	0.040	0.031	0.055	0.009	0.036
Parental unemp. rate	-0.008	0.014	-0.011	0.022	0.026	-0.005	0.001	0.006
	(0.010)	(0.027)	(0.008)	(0.025)	(0.016)	(0.016)	(0.024)	(0.008)
Observations	1,001	1,001	1,001	1,001	1,001	1,001	1,001	1,001
R-squared	0.037	0.029	0.027	0.039	0.024	0.054	0.009	0.026

*Notes: Regressions replicate those in Table 3 for the pooled sample of sons and daughters. Standard errors clustered at the maternal state of labor market entry × cohort level. *** p<0.01, ** p<0.05, * p<0.1.*

Table A8: Effects on mental health indicators of the child (pooled sample)

	(1) Felt unhappy	(2) Felt nervous	(3) Felt down	(4) Felt anxious	(5) Cannot cheer up
Parental unemp. rate	0.105***	-0.014	0.025	0.006	0.038
	(0.034)	(0.040)	(0.035)	(0.041)	(0.033)
Observations	1,001	1,001	1,001	1,001	1,001
R-squared	0.048	0.055	0.086	0.069	0.073

*Notes: Regressions replicate those in Table 4 for the pooled sample of sons and daughters. Standard errors clustered at the maternal state of labor market entry × cohort level. *** p<0.01, ** p<0.05, * p<0.1.*

Table A9: Effects on mental health indicators of the child: Inclusion of each parent's unemployment rate separately

	(1) Felt unhappy	(2) Felt nervous	(3) Felt down	(4) Felt anxious	(5) Cannot cheer up
Panel (a): Sons only					
Father's unemp. rate	-0.022	-0.065	-0.050	-0.011	-0.051**
	(0.040)	(0.049)	(0.033)	(0.046)	(0.025)
Mother's unemp. rate	0.044	-0.031	0.031	-0.020	0.038
	(0.043)	(0.036)	(0.036)	(0.055)	(0.033)
Observations	508	508	508	508	508
R-squared	0.043	0.058	0.065	0.027	0.095
Panel (b): Daughters only					
Father's unemp. rate	0.091**	0.082*	0.027	0.040	0.039
	(0.041)	(0.045)	(0.047)	(0.049)	(0.041)
Mother's unemp. rate	0.102**	-0.019	0.048	0.013	0.057
	(0.040)	(0.050)	(0.045)	(0.041)	(0.038)
Observations	493	493	493	493	493
R-squared	0.052	0.038	0.038	0.054	0.054

*Notes: Extension of Table 4 where we introduce each parent's unemployment rate separately. *** p<0.01, ** p<0.05, * p<0.1.*

Table A10: Kessler–10: Robustness

Outcome: Kessler–10 (z-score)	(1) Sons	(2) Daughters
Father's unemp. rate	-0.114	0.328**
	(0.082)	(0.145)
Mother's unemp. rate	0.040	0.070
	(0.092)	(0.123)
Observations	495	481
R-squared	0.076	0.052
Parental unemp. rate	-0.081	0.400*
	(0.090)	(0.214)
Observations	495	481
R-squared	0.074	0.048

*Notes: Panel (a) replicates Column (3) of Table 2 for the residualized Kessler–10 measure of mental health. Sample size decreases because the Kessler–10 measures are only available bienially and beginning from 2007. Panel (b) proceeds similarly to Column (4) of Table 2. Standard errors clustered at the maternal state of labor market entry × cohort level. *** p<0.01, ** p<0.05, * p<0.1.*

Table A11: Robustness exercises (pooled sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Outcome: Bad mental health						
State-specific parental unemp. rate	0.106						
	(0.083)						
Raw parental unemp. rate		0.044					
		(0.042)					
Detrended national-level parental unemp. rate			0.109				
			(0.109)				
Parental unemp. rate				0.113	0.267	0.106	0.131
				(0.120)	(0.376)	(0.181)	(0.097)
Observations	1,001	1,001	1,001	852	1,001	1,001	1,001
R-squared	0.107	0.106	0.106	0.108	0.136	0.105	0.103

*Notes: Regressions replicate those in Table 5 for the pooled sample of sons and daughters. Standard errors clustered at the maternal state of labor market entry × cohort level. *** p<0.01, ** p<0.05, * p<0.1.*

Table A12: Mediation: Impacts on parental outcomes (daughters only)

	(1) Log household income	(2) Bad mental health	(3) Bad physical health	(4) Ever dies
Unemp. rate	-0.243***	0.239**	0.165*	0.045
	(0.078)	(0.120)	(0.098)	(0.028)
Observations	493	493	493	493
R-squared	0.079	0.040	0.101	0.059
	(5) Current smoker	(6) Current heavy drinker	(7) Financial risk aversion	(8) Detached from labor force
Unemp. rate	0.095	-0.006	0.099	0.033**
	(0.072)	(0.036)	(0.111)	(0.015)
Observations	493	493	493	493
R-squared	0.077	0.054	0.051	0.068
	(9) Occupational prestige	(10) Locus of control	(11) Maternal relative home production	(12) Job affects children
Unemp. rate	-5.839*	0.050	0.014	0.113
	(3.292)	(0.127)	(0.024)	(0.185)
Observations	493	493	493	493
R-squared	0.057	0.034	0.066	0.020

*Notes: Replication of Table 7 focusing exclusively on the parents of the subsample of daughters, which is the only one for which we have detected a statistically-significant impact of parental labor market entry conditions on mental health. Standard errors clustered at the maternal state of labor market entry × cohort level. *** p<0.01, ** p<0.05, * p<0.1.*

Table A13: Mediation: Impacts on parental outcomes (sons only)

	(1) Log household income	(2) Bad mental health	(3) Bad physical health	(4) Ever dies
Unemp. rate	-0.213*	0.217	0.258**	0.003
	(0.118)	(0.132)	(0.121)	(0.013)
Observations	508	508	508	508
R-squared	0.089	0.036	0.068	0.063
	(5) Current smoker	(6) Current heavy drinker	(7) Financial risk aversion	(8) Detached from labor force
Unemp. rate	0.088	0.034	0.157*	0.026*
	(0.059)	(0.046)	(0.079)	(0.014)
Observations	508	508	508	508
R-squared	0.091	0.058	0.081	0.091
	(9) Occupational prestige	(10) Locus of control	(11) Maternal relative home production	(12) Job affects children
Unemp. rate	-3.067	-0.024	0.019	-0.008
	(3.516)	(0.137)	(0.026)	(0.149)
Observations	508	508	508	508
R-squared	0.059	0.023	0.053	0.053

*Notes: Replication of Table 7 focusing exclusively on the parents of the subsample of sons. Standard errors clustered at the maternal state of labor market entry × cohort level. *** p<0.01, ** p<0.05, * p<0.1.*

Table A14: Impacts on *all* individuals born in or after 1964

	(1) Log household income	(2) Bad mental health	(3) Bad physical health	(4) Ever dies
Unemp. rate	-0.051**	0.115***	-0.070**	-0.003
	(0.020)	(0.029)	(0.033)	(0.003)
Observations	10,447	10,447	10,419	10,447
R-squared	0.023	0.004	0.004	0.003
	(5) Current smoker	**(6) Current heavy drinker**	**(7) Financial risk aversion**	**(8) Detached from labor force**
Unemp. rate	0.012	-0.008	0.049**	0.002
	(0.014)	(0.010)	(0.024)	(0.007)
Observations	10,136	10,135	10,173	10,447
R-squared	0.008	0.005	0.017	0.005
	(9) Occupational prestige	**(10) Locus of control**		
Unemp. rate	-0.977	0.037		
	(0.884)	(0.029)		
Observations	10,256	8,754		
R-squared	0.023	0.005		

*Notes: Replication of Table 7 for the full sample of individuals born in or after 1964, regardless of whether they eventually had children or not. We do not include results for "maternal relative home production" and "job affects children" because these outcomes are exclusively for parents. Standard errors clustered at the state of labor market entry × cohort level. *** p<0.01, ** p<0.05, * p<0.1.*

Table A15: Coefficients from the "short" and "long" regressions (daughters only)

Regression...	(1) Short	(2) Long
Parental unemp. rate	0.366* (0.187)	0.161 (0.148)
Bad mental health		0.368*** (0.101)
Bad physical health		0.087 (0.095)
Death		1.504 (1.255)
Smoking		0.320 (0.171)
Heavy drinking		0.073 (0.236)
Income		0.111 (0.069)
Willingness financial risk with cash		0.127 (0.102)
Indicator no cash		0.275 (0.235)
Unemployment spells & out of labor market		1.279** (0.538)
Occupational prestige		0.006* (0.003)
Locus of control		-0.016 (0.084)
Maternal relative home production		-0.153 (0.279)
Job affects children		-0.054 (0.055)

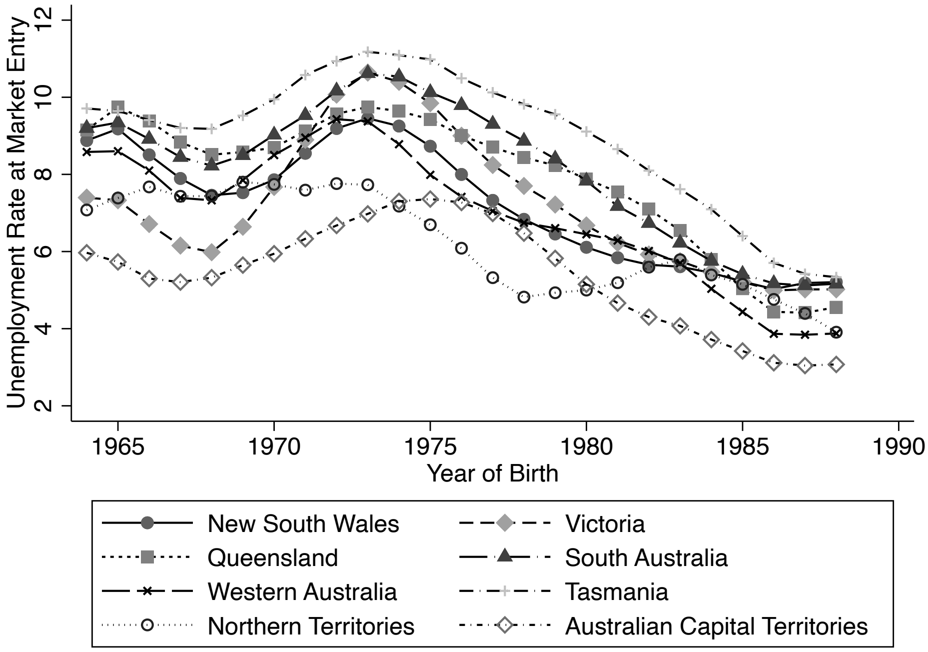
*Notes: Column (1) replicates Table 2's Column (4), i.e., provides the "short" coefficient of interest and its standard error in parenthesis. Column (2) reports the relevant coefficients from Equation (3), namely β^{long} and δ^k for each of the mediators considered. Standard errors clustered at the maternal state of labor market entry $\times$ cohort level. *** p<0.01, ** p<0.05, * p<0.1*

Table A16: Mediation analysis: Robustness to only measuring mediators based on the mother

	(1) Coefficient	(2) Standard Error	(3) % of short
Short regression	0.412**	0.192	100
Long regression	0.270	0.169	66
Parental outcome:			
Bad mental health	0.099*	0.059	24
Bad physical health	0.011	0.015	3
Death	-0.020	0.023	−5
Smoking	0.013	0.019	3
Heavy drinking	0.000	0.017	0
Income	-0.033*	0.020	−8
Willingness financial risk with cash	0.039	0.036	9
Unemployment spells & out of labor market	0.060	0.043	15
Occupational prestige	0.001	0.011	0
Locus of control	0.000	0.003	0
Maternal relative home production	-0.034	0.033	−8
Job affects children	0.007	0.012	2
Total Explained ($\beta^{\text{short}} - \beta^{\text{long}}$)	0.142	0.099	34

*Notes: Replication of Table 8 where all the mediators are measured exclusively using maternal responses (instead of the average between the father and the mother). Sample size is reduced to 444. Standard errors clustered at the maternal state of labor market entry × cohort level. *** p<0.01, ** p<0.05, * p<0.1*

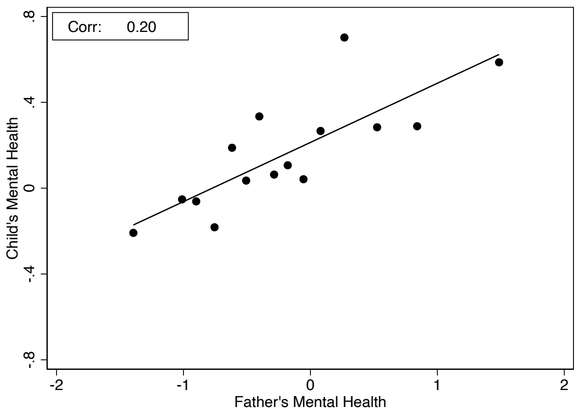
Figure A1: Unemployment rates upon labor market entry, by state and cohort (raw)



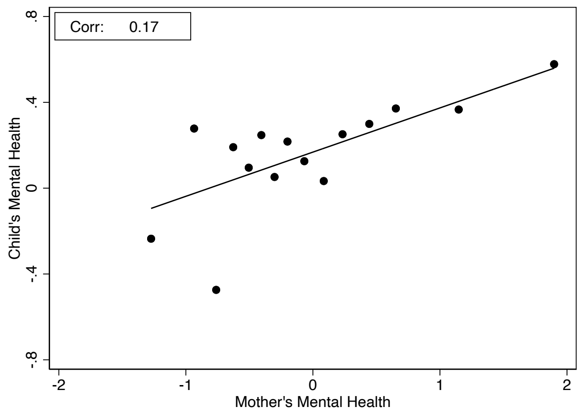
Notes: Unemployment rate at labor market entry refers to average state-level unemployment rate when the cohort is aged 18–22.

Figure A2: Intergenerational partial correlations of poor mental health

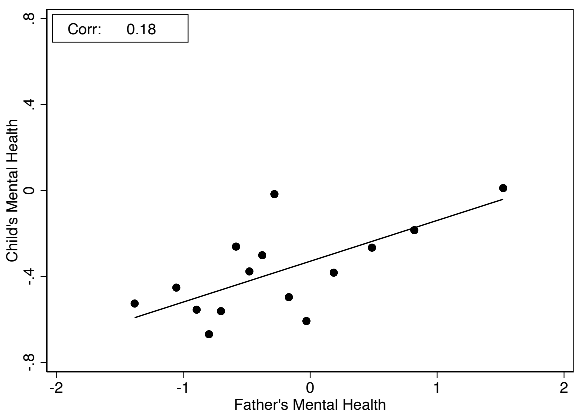
(a) Fathers and daughters



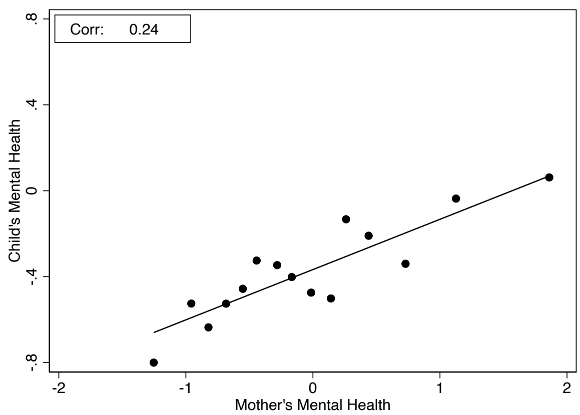
(b) Mothers and daughters



(c) Fathers and sons



(d) Mothers and sons



Notes: Similar exercise to Figure 4 looking at the partial correlation between the mental health of a given parent and that of the child (after netting out the other parent's mental health).