Early Labor Market Origins of Long-Term Mental Health and its Intergenerational Correlation[*]

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Abstract

What drives 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 of persistent effects on mental health two decades after labor market entry. We find that individuals exposed to a one percentage point higher unemployment rate at labor market entry relative to trend have 14% of a standard deviation worse mental health at ages 36–40. We further document an intergenerational impact of labor market entry conditions. Along the extensive margin, females more impacted by labor market entry conditions in terms of mental health increase completed fertility. Along the intensive margin, daughters whose parents experienced a one percentage point higher unemployment rate at entry have 18% of a standard deviation worse mental health during adolescence. Sons' mental health is not impacted.

JEL codes: E32, I14, J13

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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. 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. More recently, 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 in developing 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, little is known about the degree of intergenerational transmission of mental health and, particularly, about the underlying sources of such intergenerational correlations (Bütikofer et al., 2023).

This paper contributes towards these two important questions. First, we measure the long-run effects of adverse labor market entry conditions on mental health and satisfaction with multiple life aspects two decades after entry using a nationally representative sample of Australian individuals. Second, we provide novel evidence on the intergenerational implications of labor market entry conditions. In particular, we ask whether labor market entry conditions of potential parents, which occur well before children are conceived, have persistent effects on their offspring's well-being. Though our focus is on measuring the *overall* intergenerational effects of these early labor market conditions, we explore whether the correlations we find are driven by some salient mechanisms previously identified in the literature such as parental education decisions, worse labor market outcomes and physical health, and changes in household composition.

A key challenge in addressing these questions is the availability of a suitable dataset.

[1]See https://www.whitehouse.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/.

We require a dataset featuring comparable measures of mental health that can be linked across two generations, and contains complementary information on measures of other relevant life aspects (e.g., income, fertility). The Household, Income and Labor Dynamics in Australia (HILDA) satisfies these requirements and provides rich longitudinal information at the individual and household level for a nationally-representative sample of households. Our main outcomes of interest, various measures of mental health, are based on 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), and is often used in mental health-related studies employing HILDA data (e.g., Botha et al., 2023). This measure is available for a parental generation and their children on a yearly basis. We complement our findings with results using the Kessler–10 Psychological Distress Scale (an internationally validated measure of anxiety/depression, Kessler et al., 2002), which is available biennially.

Focusing on individuals born between 1964 and 1980, we find that those who enter the labor market under more unfavorable conditions have worse mental health indicators when they are aged 36–40. In particular, a 1 percentage point (p.p.) unemployment rate shock faced when entering the labor market is associated with a 2–6 p.p. increase in the probability of experiencing more frequent episodes of unhappiness, anxiousness, being down, and difficulty to be cheered up. This corresponds to 14% of a standard deviation difference in the MHI–5 composite measure of mental health. This effect is similar for males and females and is robust to a number of alternative specifications, variable construction, and sample selection. Moreover, we show that these results are not driven by other key outcomes previously identified in the literature to be affected after a bad labor market entry: lower household income, worse physical health, nor by endogenous readjustments in academic achievement.

We then take the analysis one step further and explore possible contributing factors to the adverse mental health effects of unfavorable labor market entry conditions. We look at self-reported satisfaction with various life aspects. Consistent with the previous results, we find that individuals who enter the labor market during an adverse unemployment rate shock are more likely to be unsatisfied with their health at midlife. Moreover, we find that males are also less likely to be satisfied with their financial situation, which we do not find for females. Overall, we document that those who enter the labor market during adverse conditions are more likely to be unsatisfied with life. These results are useful in providing a consistent picture about the poorer mental health uncovered. We do not find statistically significant differences in satisfaction across other life dimensions such as their safety, their neighborhood, or their free time.

Having shown that mental health and life satisfaction at midlife are worse for individuals that are directly affected by unfavorable labor market entry conditions, it is natural to ask whether such conditions spillover to the next generation. This is of particular interest since context and situation during childhood are important determinants of adult outcomes (Almond et al., 2018). There are three particular reasons why spillovers are likely to exist. First, job security and flexibility determine investments in human capital formation of children. Second, poor mental health of parents complements investments in children, for instance, by making time devoted to children less effective. Third, mental well-being of children can be directly affected by their parents' well-being through socialization, a mechanism suggested by the results of Giulietti et al. (2022).

To the best of our knowledge, we are the first ones to explore the effects of labor market entry conditions on the outcomes of the next generation. We find that the persistent effects of adverse labor market entry conditions indeed spillover to the next generation along two margins. First, labor market entry conditions influence fertility. In particular, females whose mental health was initially most affected by unfavorable labor market conditions had more children by the age of 45. We do not find effects for males. From a theoretical point of view, the presence and the direction of the effects on fertility are not obvious ex-ante (Becker, 1973). Unsurprisingly, the few existing papers on the impacts of labor market entry conditions on family formation have found differing effects that are context-specific. For instance, while Currie and Schwandt (2014) find that graduating in bad times lowers completed (at age 40) childbearing in the United States, Hofmann and Hohmeyer (2016) do not find a statistically significant effect in Germany. Our results are similar to those by Choi et al. (2020) who find that South Korean women who entered the labor market during the 1997 Asian Financial Crises increased fertility, while males did not.

Second, we also measure the effects of labor market entry conditions on the children themselves. We find that females whose parents entered the labor market under more unfavorable conditions experience worse mental health in adolescence. In particular, daughters of those cohorts that undergo an unemployment rate shock of 1 p.p. during labor market entry have around 18% of a standard deviation worse mental health at ages 15–20. Moreover, we show that daughters are more likely to be unsatisfied with their health, home, safety and, as a consequence, with their overall life. These novel intergenerational consequences of labor market entry conditions further emphasize the importance of designing policies that attenuate the adverse effects of bad labor market entry conditions. We do not find effects among sons. This heterogeneity in treatment effects is in line with recent evidence from Giulietti et al. (2022) that finds that girls are more prone to suffer from teenage depression and to be affected by external circumstances in their environments.

We then further explore the presence and origins of the intergenerational correlations in mental health. Conditional on having children, we estimate a correlation of about 0.2 between the mental health quality of both parents at midlife and that of their adolescent children. This correlation is stronger between mothers and their daughters. The fact that we first establish that the labor market entry conditions of parents is a common determinant of both parental and child mental health suggests that entry conditions partially explain the intergenerational correlation of mental health we find. In particular, we document through a simple mediation analysis that the reduced-form effect of maternal unemployment rates on the child's mental health is halved and becomes statistically non-significant when introducing maternal mental health into the regression.

Overall, our work makes several contributions. Fundamentally, we propose to think of labor market entry conditions as a novel determinant of mental health *for both generations* and, consequently, act as a potential *driver of the intergenerational correlation* in mental health. Existing work identifying long-run determinants of mental health has focused on in-utero or early childhood events (Persson and Rossin-Slater, 2018; Adhvaryu et al., 2019; Akbulut-Yuksel et al., 2022; Akee et al., 2023), while studies on the determinants of child mental health have revolved around family background (Currie, 2009), parental investments (Cunha et al., 2010), and early-childhood conditions (Currie and Almond, 2011).[2] Labor market entry conditions differ from the mechanisms considered in the literature that focuses on childhood context. For the parental generation, these conditions happen early in their transition from adolescence to adulthood. For the children, the labor market entry conditions of their parents happen long before their conception or birth and are a precondition of the other determinants that have been studied in the literature.

We highlight two additional contributions that this paper makes. First, our results on the long-term impact of labor market entry conditions on the directly affected generation complement the literature on the persistent effects of initial labor market conditions. A number of studies has shown that cohorts entering the labor market under adverse circumstances face earnings losses that remain up to a decade later (Kahn, 2010; Oreopoulos et al., 2012; Altonji et al., 2016).[3] A complementary strand of the literature has extended this analysis beyond labor market outcomes. For instance, Schwandt and Von Wachter (2020) find that the cohorts that entered the labor market during the large recession in the 1980s in the United States experienced higher mortality in midlife, driven by poor physical health. However, the evidence on the impacts on mental health remains scarce. An exception is Maclean (2013), who studies the effects of graduating in bad times on mental health in the United States and finds that entering the labor market in unfavorable times has adverse effects on depressive symptoms at age 40 among males but instead lowers depressive symptoms among females. Our first set of results therefore complements the existing body of work by showing that both males and females entering the labor market during periods of higher unemployment may not only face worse physical health that persists to midlife—two decades after entry—as already shown, but also experience

[2] A complementary literature has studied *contemporaneous* determinants of child well-being. For instance, how job insecurity of parents (Ruiz-Valenzuela, 2020) or parental health shocks (Aaskoven et al., 2022) spillover to school-related outcomes of children.

[3] von Wachter (2020) provides a survey of research measuring the impacts of labor market entry conditions.

worse mental well-being. The fact that some results are context-specific emphasizes the importance of future replications of this exercise beyond Maclean (2013)'s US and our Australia.

Second, and most importantly, our results on intergenerational transmission provide one of the very first evidence on the drivers of intergenerational persistence of health in general and, in particular, of mental health. Moreover, by showing that macroeconomic conditions, an exogenous source of variation in our context, loses predictive power when parental health (an outcome affected by it) is included, we argue that not all of the existing intergenerational correlation can be purely genetic. This type of result on the nature versus nurture debate echoes conclusions on, for instance, the intergenerational transmission of physical health (Lundborg and Majlesi, 2018; Athanasiadis et al., 2022) or of wealth (Black et al., 2019).

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. In Section 4, we document the impacts of labor market entry conditions on midlife mental health and discuss their robustness to various threats to identification. In Section 5, we explore the spillovers to the subsequent generation by measuring the effects on fertility and on their children's mental well-being. Finally, we conclude in Section 6. An appendix contains additional tables and figures.

2 Data

In this paper, we use the Household, Income and Labor Dynamics in Australia (HILDA) survey. HILDA is a rich 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 (2001-2021).[4] This dataset is suitable for our analyses as it contains comparable indicators of mental health for two

[4]We employ data up to 2019 to avoid using information during and after the Covid pandemic. Recent work employing the same dataset is Todd and Zhang (2020) and Siminski and Yetsenga (2022).

linked generations. Moreover, we observe subjective satisfaction with life aspects of both the older (parental) generation and the younger (children) generation. The design of the survey is such that every individual above 15 years of age is distributed the "adult questionnaire" and therefore provides individual-level information on health-related outcomes and well-being.

In this section, we describe in detail the main variables obtained from HILDA, the use of complementary official statistics to construct unemployment rates, our sample selection criteria, and descriptive statistics of our estimating sample.

Parental and child outcomes. HILDA provides information about multiple dimensions of mental health. In particular, there are five survey items eliciting 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.[5] These five elements correspond to the items in the MHI–5 scale, which is the mental health subcomponent of the Short Form 36 Health Survey (Botha et al., 2023) and has been widely validated (Ware et al., 2000). Responses are based on a 6-point scale with options: none, a little, some of the time, a good bit, most of the time, and all of the time. We treat this information in two ways. First, we construct individual indicators taking the value of one if the relevant negative feeling occurred at least "a good bit" of the time. These indicators therefore capture frequent episodes of mental distress and allow us to explore each dimension separately. Second, we construct a composite measure that comprehensively captures (poor) mental health using the same items as the MHI–5. We aggregate these five dimensions through multiple correspondence analysis (MCA).[6] In robustness checks, we exploit the fact that every two survey waves (starting from 2007) HILDA elicits all the items of the Kessler–10 scale, and show that our results are robust to employing this alternative measure of mental health. This is not surprising as both measures have been shown to be strongly

[5]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.

[6]MCA can be thought of as the counterpart of principal component analysis for categorical (particularly, ordinal) data, just like the responses to the questions we have. In our data, the first dimension in the MCA explains 58.1% of the total variation in the responses to the five underlying dimensions.

comparable in HILDA (Aulike et al., 2021).

Importantly, the survey design allows us to have comparable measures of mental health for both parents at midlife and for their children at adolescence since all members of the household above the age of 15 are expected to complete the same questionnaire. We are therefore able to explore the reduced-form effect of bad parental entry labor market conditions on the mental health of the next generation as well as to estimate intergenerational correlations. In that analysis, we focus on children aged 15–20, which corresponds to the period when individuals begin to make important life decisions, but typically still reside with and are financially dependent on their parents.

After showing that there is a reduced-form impact of early labor market conditions on own midlife mental health, we will be interested in documenting whether overall life satisfaction is also lower and, if that is the case, which aspects of life might be factors contributing to this lower overall 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 employment opportunities; (c) your financial situation; (d) how safe you feel; (e) feeling part of your local community; (f) your health; (g) the neighborhood in which you live; (h) the amount of free time you have. For all satisfaction measures, we construct an indicator taking the value of one if stated to be 5 or below, and zero otherwise, hence capturing low levels of satisfaction.

Unemployment rate at labor market entry. We collect state-level monthly unemployment rates from the Australian Bureau of Statistics, which we aggregate to the yearly level. Given our interest in studying the impact of entry conditions, we construct our main explanatory variable as the average unemployment rate when the individual was between the ages of 18 and 22. This is common practice in the literature (e.g., Arellano-Bover, 2020) as it leverages variation coming from the exact year of birth of the individuals, which is plausibly exogenous. Moreover, it does not depend on the exact year of graduation, which could be endogenous.[7] If graduation times were completely exogenous, the measurement error introduced by this is likely to attenuate our estimates (Arellano-Bover, 2020).

One limitation of HILDA 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 are 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. The latter, while employed in the literature, has the limitation that individuals might have migrated to a different state in response to the 18–22 unemployment rates. Reassuringly, we find that 85% of the individuals in our sample completed education in the same state as we observe them in adulthood.[8] As a robustness check, we show that exclusively focusing on those individuals for whom the state of graduation is available does not impact the qualitative findings.

The available state-specific time series of unemployment dates back to 1979. 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. While using raw unemployment rates is attractive for simplicity, a component of the changes in unemployment may, however, be predictable and be part of the general business cycle. We detrend the unemployment rate series to capture just the changes in the unemployment rates that are not associated with the pre-

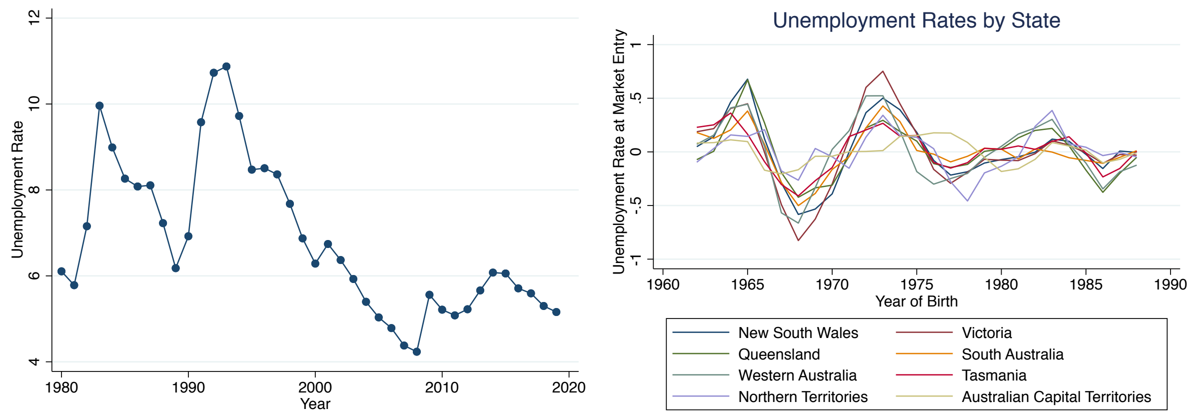
[7] An additional advantage in our case is that we do not need to observe the exact year of graduation, which is not collected in the survey.

[8] Note that 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: Annual unemployment rates: Country-level and by state

(a) By year, at the country-level

(b) Upon labor market entry, by state and cohort



Notes: Annual national unemployment rates obtained from The Organization for Economic Cooperation and Development. Annual state-level unemployment rates are constructed using data from the Australian Bureau of Statistics and detrended following Hodrick and Prescott (1997). Unemployment rate at market entry refers to average state-level unemployment rate when the cohort is aged 18–22.

dictable trend, which allows us to exploit a plausibly more exogenous source of variation. 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. To make it into a variable at the yearly level, we take the annual average of the shocks. In Panel (b) of the same figure, 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.[9] One appreciates from the graph 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.

Controls. While unemployment rates at the time of entry into the labor market are plausibly exogenous (see Section 3 for further discussion and caveats), using additional predetermined controls may be useful to improve statistical efficiency and to explore potential heterogeneity in treatment effects. These include gender, an indicator for whether

[9] In Panel (a) of Appendix Figure A1, we provide the corresponding figure with the average unemployment rate, without detrending.

the father was unemployed for more than six months while the individual was below the age of 14, as well as indicators for whether the mother or the father was born outside Australia. Additionally, we have access to parental education and occupational prestige (the Australian Socieoeconomic Index 2006, AUSEI06), which we employ in robustness checks.[10]

Sample selection. Our interest is in how initial labor market conditions have persistent impacts into midlife, including child development.[11] By midlife we mean ages 36-40, which is about as far in the life-cycle as previous explorations on the effects of entry conditions has gone. In robustness checks, we extend the definition to ages 36–45. As we observe these individuals in their mid-lives, we are able to also focus on the next generation. According to the Australian Institute of Health and Welfare, the average age of maternal first childbearing in Australia is 29 years, with paternal age at first birth slightly above 30.

As commented, in Australia's recent history, the largest variations in unemployment rates were in the period between 1980 and 2000. At the turn of the millennium, unemployment rates stabilized to a low 5%. With this in mind, and aiming to make our sample as comparable as possible by using relatively close cohorts, we are particularly interested in individuals who enter the labor force between the early 1980s and the early 2000s. We focus on the cohorts born between 1964 and 1980. The youngest cohort we observe turns 39 in 2019 while the oldest cohort turns 37 in 2001. This allows us to potentially observe the individuals at least 4 times in the five-year age band that we are interested in.

Lastly, we require our maintained set of controls to be available. We do not drop individuals with missing outcomes (if at least one is available). This explains the small changes in sample sizes across specifications.

Turning to the sample selection among the children's generation, we focus on 15–20 year-old individuals for the mental health outcomes among those whose father we observe at least once while they were 36–40, as previously mentioned. This is to make sure that

[10] A detailed description of this index of occupational prestige can be found in McMillan et al. (2009).

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

we use the children from the same individuals that we employ when looking at parental labor market and mental health outcomes.

Summary statistics. Table 1 provides some basic statistics about our main variables of interest, separated by gender. The average age at which we evaluate the midlife impact on mental health and life satisfaction is 38, based on a sample that spans 17 cohorts. The mean raw unemployment rate between ages 18–22 for this sample is about 8.4% with a standard deviation of 1.2. In our sample there are individuals with an average unemployment rate as low as 4.8% and as high as 11.2%. Its detrended version, which we use in our main specifications, has a mean of about 0.025 and a standard deviation of 0.345. In terms of satisfaction, 7.4% of the male respondents state that their overall life satisfaction is 5 or lower, with subcategories such as financial satisfaction having up to 30% with low levels of satisfaction. In terms of mental health, a sizable proportion of our male subsample suffers from frequent episodes of anxiety and unhappiness (35.1% and 21.8%, respectively). Other feelings such as nervousness, while still widespread, are less frequent (8.7%). As consistent with past literature, the levels of dissatisfaction and mental issues are higher among females.

Table 1: Descriptive statistics

	Males			Females		
	Mean	Standard deviation	Count	Mean	Standard deviation	Count
Felt at least "a good bit"...						
Unhappy	0.218	0.323	2,181	0.234	0.331	2,446
Nervous	0.087	0.222	2,181	0.120	0.260	2,446
Down	0.099	0.230	2,181	0.125	0.250	2,446
Anxious	0.351	0.375	2,181	0.411	0.386	2,446
Hard to cheer up	0.056	0.171	2,181	0.077	0.205	2,446
Average bad mental	0.049	0.165	2,181	0.071	0.198	2,446
Low satisfaction with life aspects						
Home you live in	0.133	0.254	2,306	0.143	0.257	2,496
Employment opportunities	0.173	0.305	2,306	0.244	0.340	2,496
Financial situation	0.302	0.372	2,306	0.340	0.378	2,496
Safety	0.067	0.193	2,306	0.081	0.200	2,496
Feeling part of community	0.293	0.354	2,306	0.251	0.343	2,496
Your health	0.134	0.270	2,306	0.154	0.286	2,496
Your neighborhood	0.098	0.230	2,306	0.107	0.234	2,496
Amount of free time	0.386	0.379	2,306	0.472	0.380	2,496
Life as a whole	0.074	0.205	2,306	0.076	0.201	2,496
Covariates						
Currently employed	0.899	0.255	2,181	0.724	0.384	2,446
Father long-term unemployed	0.136	0.343	2,181	0.148	0.355	2,446
Father non-Australian	0.396	0.489	2,181	0.387	0.487	2,446
Mother non-Australian	0.364	0.481	2,181	0.357	0.479	2,446
Age	37.987	0.708	2,181	37.988	0.696	2,446
Year birth	1971.953	4.953	2,181	1971.795	4.826	2,446
Father occupational prestige	46.570	23.581	2,137	47.229	23.490	2,398
Main explanatory variable						
Raw entry unemployment rate	8.406	1.208	2,181	8.416	1.202	2,446
Detrended entry unemployment rate	0.025	0.345	2,181	0.028	0.350	2,446

Notes: Descriptive statistics from the population aged 36–40 used to estimate the impact of labor force entry condition on mental health and life satisfaction. For each category in bold we require all underlying variables to be available. For the "Covariates" category, we report the statistics for the individuals who have all information available within the mental health category. We allow father occupational prestige to have less observations since it acts only as a control in our robustness checks. All dimensions are first averaged 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). Year of birth ranges from 1964 to 1980. Age from 36 to 40. Raw entry unemployment rate from 4.819 to 11.179 and the detrended one from -0.826 to 0.752.

3 Empirical strategy

We use a similar approach to Oreopoulos et al. (2012), who employ variation in labor market conditions across US states over time to estimate the wage effects of labor market conditions at graduation. We estimate the following model (and variations for robustness) separately for males and females aged 36 to 40:

$$y_i = \alpha + \beta \times \mathrm{UR}_{sc} + X_i'\delta + \gamma_c + \lambda_s + \varepsilon_i, \tag{1}$$

where an outcome of interest y for individual i is a function of the cohort- and state-specific detrended unemployment rate prevailing in his state (s) upon labor market entry (UR_{sc}), cohort controls (γ_c), and state fixed effects (λ_s). We parameterize the cohort controls as a quadratic cohort trend.[12] The main independent variables of interest include: self-reported mental health, satisfaction with various life aspects, childbearing, and child well-being (mental health and life satisfaction). We finally introduce a set of predetermined variables (X_i, enumerated in Section 2) as controls to absorb further variation and increase precision. For inference, we cluster our standard errors at the state at graduation $\times$ 5-year cohort level (Abadie et al., 2017). Intuitively, this allows for arbitrary correlation in the shocks among individuals in the same state and cohort group.

To deal with the noise in self-reported subjective outcomes, we consider individual-specific average values over all observations in the 36–40 age range of the outcome variable of interest as the regressand in the above equation. To focus on the within-cohort variation in entry labor market conditions, we partial out common business-cycle and age effects by first regressing our outcomes of interest on survey round fixed effects and a quadratic polynomial in age, and use the residuals. We employ analytical weights corresponding to the number of observations used in constructing the average value of each outcome of interest.

As discussed in Section 2, the unemployment rate at entry in the labor market of a cohort is measured as the average of the unemployment rate shocks in the state of grad-

[12] As a robustness check, we also estimate a more flexible cohort trend using individual cohort-specific fixed effects.

uation/residence faced between the ages of 18 and 22, when the majority of individuals finish formal education and start their professional careers. The coefficient of interest, β, captures the change in the outcome induced by a one-percentage point variation in the unemployment rate, relative to the trend, at entry in the labor market.[13] Given the cohort profile (γ_c) and state dummies (λ_s), the main identifying variation is within-state, cross-cohort changes in the unemployment rate shocks, net of a national common cohort profile. Since this variation is mostly driven by predetermined characteristics (year of birth), interpreting β as causal seems plausible.

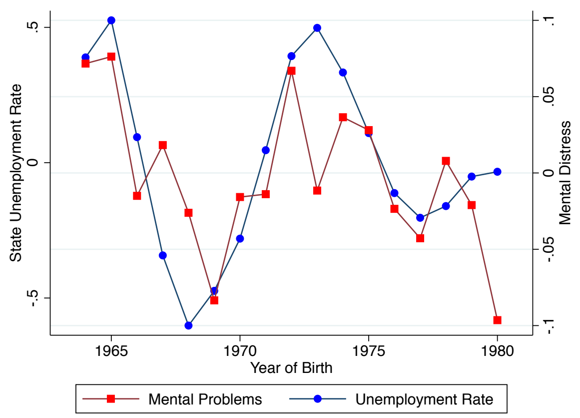
The literature has, nevertheless, emphasized one main threat to internal validity: selective attrition, which could arise, chiefly, through migration and through mortality (von Wachter, 2020). A benefit of HILDA is that it continuously tracks individuals irrespective of their location within Australia. Therefore, sample attrition from migration is unlikely to bias our results in the absence of large international outflows. Our choice of using the detrended unemployment series is also attractive in this respect since we rely on variation that could not be predicted by the individuals based on the prevailing trend, and hence could not have been used as an input for migration decisions. In the robustness section, we will provide further evidence that early labor market conditions do not predict overall exit from the survey. A last form of selective attrition, which is specific to our novel focus on child outcomes, is that labor market conditions could influence the subset of individuals for whom we observe child outcomes if fertility decisions responded to labor market entry conditions. This is a crucial endogenous outcome in itself, as the effects on the next generation might already start from affected individuals having a higher or lower number of children than otherwise. In Section 5, we delve into this and show that indeed complete fertility (that at age 45) increased among females who suffered from bad entry conditions.

[13]As 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. Moreover, as previously discussed, this also alleviates issues on the endogeneity of the timing of labor market entry.

4 Labor market entry conditions and mental health at midlife

4.1 Main results

Figure 2: Unemployment rate at graduation and midlife mental health



Notes: Underlying unemployment rates are state- and cohort-specific and detrended. The blue curve plots the average unemployment rate across individuals from all states faced between ages 18 and 22 by the different cohorts listed in the horizontal axis. The red curve is our MCA-constructed score of mental health distress (after netting out survey round fixed effects and age profiles) that each of the cohorts experienced between ages 36 and 40. The corresponding graph using unemployment rates without detrending is in Panel (b) of Appendix Figure A1.

We first estimate the effects of labor market entry conditions on mental health at midlife. In Figure 2, we document a clear positive relationship between the unemployment rate shocks faced by the various cohorts at ages 18–22 (blue curve) and our composite measure of poor metal health (red curve). This positive correlation suggests that individuals who enter the labor market under unfavorable circumstances (high unemployment rates relative to trend) disproportionately display worse mental health during their midlife.

To formalize this result, we estimate Equation 1 on various mental health related outcomes, first for the whole population and then separately by gender. We report the estimates in Table 2. Our regressions pooling both males and females confirm that, on average, cohorts that enter the labor market with larger unfavorable unemployment shocks have worse mental health at midlife. In Columns (1)–(5) of Table 2, we specifically

Table 2: Impact of adverse labor market entry conditions on own midlife mental health

	(1)	(2)	(3)	(4)	(5)	(6)
	Linear Probability Models					
	Felt unhappy	Felt nervous	Felt down	Felt anxious	Cannot cheer up	Bad mental health (z-score)
Panel (a): Males and females, pooled						
Unemp. rate	0.053***	0.007	0.034***	0.057***	0.014	0.139***
	(0.015)	(0.011)	(0.005)	(0.014)	(0.008)	(0.031)
Observations	4,627	4,627	4,627	4,627	4,627	4,627
R-squared	0.009	0.012	0.010	0.015	0.010	0.016
Panel (b): Males only						
Unemp. rate	0.047***	0.013	0.047***	0.048**	0.019***	0.130***
	(0.011)	(0.011)	(0.013)	(0.019)	(0.006)	(0.021)
Observations	2,181	2,181	2,181	2,181	2,181	2,181
R-squared	0.010	0.007	0.013	0.011	0.007	0.009
Panel (c): Females only						
Unemp. rate	0.059**	0.001	0.022**	0.064***	0.009	0.148**
	(0.023)	(0.017)	(0.010)	(0.023)	(0.012)	(0.055)
Observations	2,446	2,446	2,446	2,446	2,446	2,446
R-squared	0.011	0.015	0.009	0.018	0.015	0.018

*Notes: The estimated model is Equation 1. Outcomes in Columns (1)–(5) are indicators (after removing survey-round specific averages and age profiles) taking the value of 1 if the respondents stated that (s)he experienced the given negative feeling in the column at least "a good bit" of the time in the four weeks prior to the survey round. In Column (6), the outcome is our z-scored MCA-constructed composite variable. Standard errors clustered at the state × cohort level. *** p<0.01, ** p<0.05, * p<0.1.*

explore the effect of labor market entry unemployment rate shocks on the frequency of mental distress. For males, we find that unfavorable labor market entry is associated with increased probabilities of episodes of feeling unhappy, down, anxious, and with more difficulties to cheer up. We find that a one percentage point increase in the unemployment rate while entering the labor market is associated with an increase of 2–5 percentage points in the probability of the various mental health disorders. For females, we find that a one percentage point unfavorable shock to the unemployment rate at labor market entry is associated with a 6 percentage point increase in the probability of feeling unhappy or feeling anxious.[14]

These various outcomes capture complementary dimensions of bad mental health, so the fact that the effects point towards the same direction is indicative of worse overall mental health. In Column (6), we show this to be the case by using our composite measure. This is attractive for gaining statistical power as well as to avoid both relying on multiple comparisons and making a subjective decision on the cutoff for generating the binary variable (Kling et al., 2007; Viviano et al., 2021).[15] We find that, for males, a one percentage-point increase in the unemployment rate while entering the labor market is associated with a 13% of a standard deviation worse mental health relative to the population, based on our composite measure. The results for females, reported in Panel (c), are similar: the point estimate in the regression for our composite measure in Column (6) is 0.148 of a standard deviation.

Satisfaction with life aspects at midlife. We look at differences in satisfaction with various life aspects to identify possible contributing factors to the mental health impacts we have documented. We estimate linear probability models in the style of Equation 1 where the outcomes are binary variables indicating that the level of satisfaction is less than or equal to 5 (based on a 10-point scale).

In Panel (a) of Table 3, we report that individuals who faced worse initial labor market conditions are more likely to be unsatisfied with their life, as seen in Column (9). Looking closer, we find that they are particularly unlikely to be satisfied with their health. This is reassuring since this is directly linked to the mental health outcomes previously discussed. Moreover, for males, we find they are also less contented with their financial situation. This is an aspect closely linked to job characteristics, which is in line with the persistent fall in labor earnings emphasized in the existing literature (von Wachter, 2020; Borland, 2020). We also find quantitatively-relevant point estimates that

[14] Li and Toll (2021) find larger effects on males than females. The differences in conclusions may be attributed to differences in the sample as well as differences in the empirical strategy. By focusing on individuals who graduate between 2001–2018, only a few of their individuals of interest are observed in the age range of 36–40 which is the focus of our study. In addition, there was limited variation in the unemployment rate in Australia during this period.

[15] For robustness, we also implement p-value corrections such as Romano and Wolf (2005) that account for simultaneous multiple hypothesis tests. Our results still remain statistically significant under conventional significance levels.

suggest higher dissatisfaction with their community and neighborhood but these are not precisely estimated. We do not find differences in satisfaction with their free time.

Table 3: Labor market entry conditions and satisfaction with various life aspects

	(1) Home	(2) Employment opportunities	(3) Financial situation	(4) Safety	(5) Community	(6) Health	(7) Neighborhood	(8) Free time	(9) Life
Panel (a): Males and females, pooled									
Unemp. rate	0.010	0.018	0.017	0.011	0.023	0.042***	0.022	-0.002	0.025***
	(0.011)	(0.012)	(0.013)	(0.008)	(0.014)	(0.007)	(0.013)	(0.012)	(0.005)
Observations	4,802	4,802	4,802	4,802	4,802	4,802	4,802	4,802	4,802
R-squared	0.005	0.023	0.013	0.014	0.020	0.011	0.007	0.018	0.007
Panel (b): Males only									
Unemp. rate	0.006	0.012	0.036**	0.014	0.018	0.037***	0.017	-0.006	0.021**
	(0.013)	(0.015)	(0.016)	(0.009)	(0.018)	(0.009)	(0.011)	(0.012)	(0.009)
Observations	2,306	2,306	2,306	2,306	2,306	2,306	2,306	2,306	2,306
R-squared	0.007	0.016	0.014	0.015	0.021	0.014	0.011	0.008	0.008
Panel (c): Females only									
Unemp. rate	0.013	0.023*	0.000	0.009	0.027	0.047***	0.026	0.002	0.029***
	(0.017)	(0.013)	(0.019)	(0.012)	(0.019)	(0.017)	(0.019)	(0.019)	(0.010)
Observations	2,496	2,496	2,496	2,496	2,496	2,496	2,496	2,496	2,496
R-squared	0.006	0.010	0.010	0.015	0.017	0.010	0.008	0.005	0.008

*Notes: All outcomes were indicators taking the value of 1 if the average satisfaction with a given dimension is below or equal to 5 (in a 10-point scale) prior to netting out survey round fixed effects and cohort trends. Standard errors clustered at the state × cohort level. *** p<0.01, ** p<0.05, * p<0.1.*

4.2 Robustness checks

We perform a series of alternative regressions to assess the robustness of our main results. Here, we focus on the composite measure of mental health as our main outcome but in Appendix Tables A1–A5 we also present the same robustness checks for the five binary variables that capture the frequency at which different mental health issues occur.

Alternative measures of unemployment rate. Given that the unemployment rate upon labor market entry is our main independent variable, we explore the stability of our results to using alternative measures. First, we take the raw unemployment rates and construct the corresponding state-specific standardized time series. This is an alternative approach to Hodrick and Prescott (1997) to 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. Column (1) in Table 4 confirms the stability of the results, specifically for the pooled and male subsample (note that the interpretation of the coefficient is different since we are now using a standardized independent variable).

The literature on the short- and mid-run outcomes of bad labor market entry conditions has traditionally employed raw unemployment rates. In Column (2), we show that replicating our baseline estimation using non-detrended unemployment rates at 18–22 yields similar results. This is not our preferred specification because we argue that the detrended unemployment rate series is the more plausibly exogenous variation that we want to leverage in estimating our main effects. To some extent, we also alleviate the issues regarding individuals endogenously reacting to early-career labor market conditions as we focus on deviations from the predictable trend.

A final alternative construction of the unemployment rate, as mentioned in Section 3, is to focus exclusively on those individuals for whom we know their exact state of graduation. While this is not our preferred approach since we end up with smaller sample sizes, we find in unreported regressions that the estimates are similar in magnitude to our main specification and remain statistically significant.

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. As mentioned before, the controls we include are there to absorb any residual variation. In Column (3), we present the estimates when we do not include these controls. Meanwhile, in Column (4), we include additional controls for paternal education and paternal occupational prestige. In both cases, we find that the estimates are very similar to those in our preferred specification, which is reassuring.

Table 4: Labor market entry conditions and own midlife mental health: Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
	Outcome: Bad mental health (z-score)					
Panel (a): Males and females, pooled						
Standardized unemp. rate	0.087***					
	(0.029)					
Unfiltered unemp. rate		0.039***				
		(0.014)				
Unemp. rate			0.143***	0.142***	0.123***	0.349***
			(0.033)	(0.037)	(0.027)	(0.080)
Observations	4,627	4,627	4,627	3,970	5,268	4,627
R-squared	0.011	0.011	0.007	0.018	0.011	0.019
Panel (b): Males only						
Standardized unemp. rate	0.102***					
	(0.019)					
Unfiltered unemp. rate		0.051***				
		(0.013)				
Unemp. rate			0.136***	0.139***	0.118***	0.232*
			(0.021)	(0.026)	(0.023)	(0.119)
Observations	2,181	2,181	2,181	1,885	2,496	2,181
R-squared	0.010	0.010	0.006	0.014	0.011	0.014
Panel (c): Females only						
Standardized unemp. rate	0.075					
	(0.051)					
Unfiltered unemp. rate		0.029				
		(0.025)				
Unemp. rate			0.151***	0.149**	0.129**	0.446***
			(0.053)	(0.064)	(0.052)	(0.130)
Observations	2,446	2,446	2,446	2,085	2,772	2,446
R-squared	0.016	0.015	0.010	0.022	0.014	0.025

*Notes: The estimated model is Equation 1. All columns replicate Column (6) of Table 2. Column (1) uses unemployment rates standardized at the state level. Column (2) employs the raw (non-detrended) unemployment rates. Column (3) does not include any individual controls (other than state fixed effects and the cohort polynomial). Column (4) uses the same set of controls as in the main specification and adds paternal education and occupation prestige (which explains the decrease in sample size). Column (5) makes use of individuals aged 36–45. Column (6) substitutes the cohort polynomial for cohort fixed effects. Standard errors clustered at the state × cohort level. *** p<0.01, ** p<0.05, * p<0.1.*

Alternative definition of midlife: Ages 36–45. We expand our definition of midlife from ages 36–40 to ages 36–45. As shown in Column (5), results are robust. We choose to focus on outcomes at 36–40 in our main specifications to maximize our sample while limiting issues that may arise from unbalancedness in ages observed across cohorts.

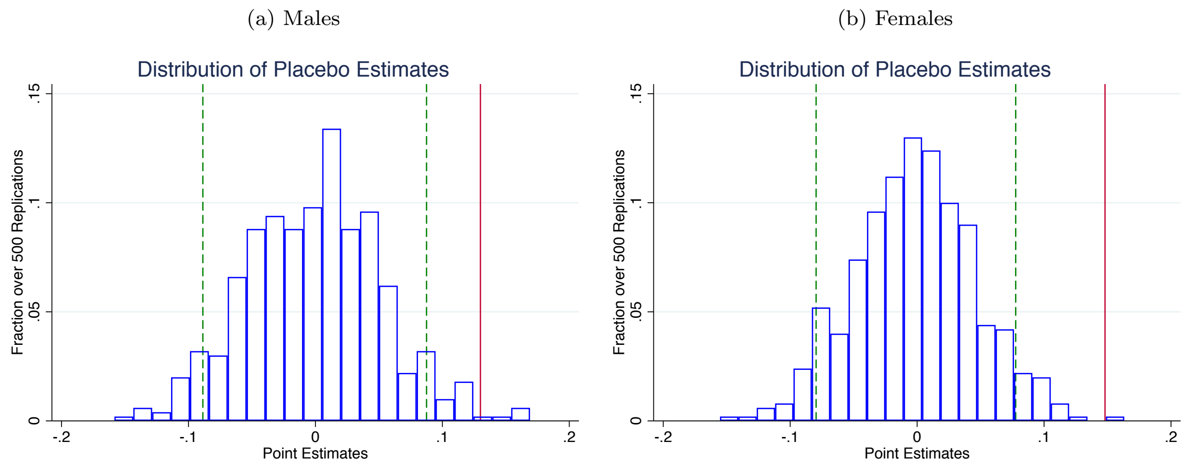
Treatment of cohort effects. In the main specification, we account for common national cohort effects through a quadratic cohort trend. In Column (6) of Table 4, we take a non-parametric approach and instead include cohort-specific fixed effects, which is a more data-demanding approach. We find larger (and significant) effects, but their estimation is more imprecise.

Randomizing labor market entry conditions. To improve our confidence that the results we find are not spurious, we conduct a simple simulation exercise. We randomize labor market entry conditions by randomly assigning state of labor market entry and year of birth (the two dimensions along which unemployment at labor market entry varies) to the individuals and then we re-estimate the coefficient corresponding to Column (6) of Table 2. This exercise is in the spirit of Fisherian randomization inference where, by resampling, we examine the distribution of the point estimate under the null that labor market entry conditions do not affect midlife mental health (Imbens and Wooldridge, 2009). Figure 3 displays the histogram of point estimates over 500 replications for the male and female subpopulations separately. One can appreciate that the point estimates from the actual data (indicated in the graph with the red solid line) lie comfortably outside the empirical 90% confidence interval, indicated with discontinuous green lines. This suggests that it would be highly unlikely that we obtained our main results by chance.

Alternative measures of mental health: Kessler–10. In Appendix Table A6, we replicate Column (6) in Table 2 employing as outcome for mental distress the Kessler–10 scale, which is only available biannually. The correlation between our preferred outcome and the Kessler–10 scale is 0.84. Our results hold quantitatively while standard errors are slightly larger, which is partially attributable to the smaller sample size available.

Ruling out that the effects are driven by other affected outcomes. As discussed in the introduction, von Wachter (2020) reviews existing evidence that labor market entry conditions impact a range of relevant outcomes. Although the validity of the reduced-form

Figure 3: Randomized inference



Notes: Histogram of point estimates of Column (6) in Table 2 under 500 different random allocations of each individual's state and year of birth. The continuous red line indicates our baseline estimate. The dashed lines indicate the empirical 90% confidence interval.

impact of early conditions on mental health is independent from whether these effects are mediated by other impacts, the policy implications and the relevance of our mental health outcome as a "stand-alone" outcome would be changed. In Appendix Table A7, we replicate Column (6) in Table 2 controlling for (1) household income, (2) own level of education, (3) household size, and (4) physical health. All of them are outcomes that could have been impacted by labor market entry conditions and, in turn, affect mental health. The main point estimates decrease only slightly suggesting that the mechanisms salient in the literature are not enough to explain our results.

5 Intergenerational spillovers of labor market entry conditions

In the previous section, we have shown that unfavorable labor market entry conditions have mental health impacts that persist up to midlife. This complements the large literature that has found persistent effects in earnings and physical health among the cohorts directly affected by the entry conditions. In this section, we take this analysis one step further and ask whether early labor market circumstances have long-term effects that spillover to the subsequent generation either through adjustments in fertility or, conditional on childbearing, through impacts on the mental well-being of their children.

5.1 Labor market entry conditions and fertility

First, we focus on fertility at age 45 (i.e., completed fertility) along two margins: (i) the probability of having any child and (ii) the number of children. Table 5 reports the estimates from Equation 1 on these two outcomes. Focusing on Columns (1) and (4), we find that, on average, labor market entry conditions do not affect the probability of having children nor the total number of children.

There are reasons to believe, however, that the long-term effects of labor market entry conditions are path dependent and may therefore be a function of how affected an individual was at the onset (i.e., right after labor market entry). Consistently with this idea, we show that the females that were most affected by labor market entry conditions in terms of mental health were more likely to have a higher number of children, albeit not more likely to have any children. More specifically, in Columns (2) and (5), we present the estimates allowing for an interaction of entry unemployment rate shocks and our composite measure of mental health. As a first approximation, under the assumption that mental health is highly persistent, the composite measure of mental health that we have been using in our analyses proxies for the mental health right after labor market entry. For females, we find a positive interaction term in Column (5) suggesting that those who enter the labor market during unfavorable circumstances and had worse mental health tend to have more children. Ideally, we would instead want to measure the interaction using mental health right after labor market entry. For a smaller group of individuals we can do this, since we observe them between the ages of 22 and 28. For this subset of people, we reconstruct our mental health measure at those ages. In Columns (3) and (6), we show the results allowing the interaction with this measure. With this substantially smaller sample, the qualitative results on the fertility of females stand. For males, we do not find any level nor heterogeneous treatment effects among males or, if any, the effects might even be that of the opposite: they are less likely to have any children, and have less children, on average.

This set of results is consistent with recent evidence from South Korea where females affected by worse entry conditions due the 1997 Asian financial crisis have more children, whereas males do not change their decisions (Choi et al., 2020). It is also in line with the result in Table 3 of females being less satisfied with their employment opportunities, which suggests that the substitution effect (lower opportunity costs of childbearing) is indeed likely to dominate the income effect of bad labor market entry among females.

Table 5: Effects on fertility

	Any child			Number of children		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel (a): Males only						
Unemp. rate	-0.022	-0.019	-0.039	-0.115	-0.093	0.541
	(0.018)	(0.019)	(0.240)	(0.079)	(0.086)	(0.790)
z-score bad mental health		-0.021**			-0.026	
		(0.008)			(0.040)	
Unemp. rate × z-mental		-0.033			-0.088	
		(0.024)			(0.108)	
z-score bad mental health (below age 28)			-0.055*			-0.200***
			(0.028)			(0.063)
Unemp. rate × z-mental (below age 28)			-0.159*			-0.045
			(0.087)			(0.309)
Observations	2,631	2,496	481	2,631	2,496	481
R-squared	0.019	0.019	0.067	0.025	0.022	0.079
Panel (b): Females only						
Unemp. rate	-0.020	-0.009	0.118	0.014	-0.009	0.047
	(0.027)	(0.027)	(0.119)	(0.103)	(0.100)	(0.415)
z-score bad mental health		-0.014*			0.032	
		(0.007)			(0.035)	
Unemp. rate × z-mental		-0.007			0.221***	
		(0.019)			(0.071)	
z-score bad mental health (below age 28)			-0.015			0.063
			(0.015)			(0.095)
Unemp. rate × z-mental (below age 28)			0.024			0.502**
			(0.033)			(0.183)
Observations	2,868	2,772	552	2,868	2,772	552
R-squared	0.017	0.018	0.064	0.029	0.030	0.059

*Notes: Regressions follow Equation 1 where the outcome is either the total number of children or an indicator with value 1 if the person had at least one child by the last time she was observed at ages 36–45. Since there is variation in the last age a person is observed, we additionally control for age-at-last-observation fixed effects. Columns (3) and (6) employ the same measure of mental health but that variable is constructed using information only up to age 28. This explains the reduction in sample size. Standard errors clustered at the state × cohort level. *** p<0.01, ** p<0.05, * p<0.1.*

5.2 Parental labor market entry conditions and children's mental health

The previous subsection has shown that labor market entry conditions already operate on the next generation through the extensive margin of childbearing. In this section we ask, conditional on having a child, whether the outcomes of their offspring are different. Table 6 shows that sons are not affected by their father's nor mother's labor market entry conditions. This is not the case for daughters. As Columns (4)–(6) show, we find that daughters whose father or mother entered in worse conditions display worse mental health in adolescence. For completeness, we present results where we introduce into the regression only the labor market entry conditions of one parent but we focus our interpretations on the regressions that include both. In particular, daughters whose parent enters the labor market with a 1 p.p. unemployment rate shock have around 18% of a standard deviation worse mental health, though the effect of the father's labor market entry conditions are not statistically significant.[16] In Appendix Table A8, we show that the estimated effects in Table 6 do not change after controlling for endogenous outcomes of the parental generation (household income, education, household size, and physical health). Furthermore, in Appendix Table A9, we show that these results are driven by more frequent feelings of unhappiness, nervousness, anxiety, and of difficulties to be cheered up.

The gender differences in the mental health effects we find are consistent with recent evidence from Giulietti et al. (2022) showing that girls are more prone to suffer from teenage depression and to be affected by their environment, compared to boys.

Satisfaction with life aspects at adolescence. Given the effects on children's mental health, and similarly to our approach for the parental generation, we proceed to look at child's satisfaction with various life aspects to gain insights on the possible underlying determinants of the worse mental health outcomes. In Table 7, we show patterns con-

[16] These results should be interpreted as *relative to their peers* in the child generation. The outcome is standardized relative to people of age 15–20 so the magnitude of the effect is not directly comparable with the effects found for the parental generation.

Table 6: Intergenerational spillovers on mental health of labor market entry conditions

	Sons			Daughters		
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome: Bad mental health (z-score)						
Father's unemp. rate	-0.031		-0.053	0.236*		0.179
	(0.091)		(0.087)	(0.124)		(0.122)
Mother's unemp. rate		0.059	0.075		0.228**	0.182**
		(0.105)	(0.105)		(0.087)	(0.081)
Observations	516	516	516	528	528	528
R-squared	0.042	0.043	0.044	0.034	0.035	0.040

*Notes: Regressions of child mental health (composite measure) on various combinations of paternal and maternal unemployment rates. The outcome is standardized using the mean and standard deviation of 15–20 year old individuals. We additionally control for quadratic cohort trends based on the paternal and maternal year of birth and state of residence. Standard errors clustered at the state × maternal cohort level. *** p<0.01, ** p<0.05, * p<0.1.*

sistent with those in Table 6. We find that sons are not that affected while daughters are largely affected: they are more likely to be unhappy about their home, safety, and health. We also find large adverse effects on daughters' satisfaction with their financial situation and community though these effects are not estimated precisely. This translates into daughters being more likely to feel unsatisfied with their life overall.

Selection and attrition. One important threat to identification to consider is selective attrition. We discuss two potential sources of selection and attrition biases. First, specific to our analyses on the intergenerational impact of entry labor market conditions, we might be concerned about selection on who becomes a parent. In Section 5.1, we already discussed differences in fertility induced by labor market entry conditions as an outcome of interest in itself. Second, non-random attrition could arise through migration and/or death of potential parents. Attrition by 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 under unfavorable

Table 7: 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 unemp. rate	0.002	-0.017	-0.028***	-0.003	0.008	-0.013	-0.033	-0.019**
	(0.012)	(0.037)	(0.009)	(0.048)	(0.015)	(0.031)	(0.029)	(0.008)
Mother unemp. rate	-0.019	-0.020	0.011	0.006	0.004	-0.012	0.026	0.025**
	(0.014)	(0.035)	(0.016)	(0.029)	(0.024)	(0.023)	(0.026)	(0.011)
Observations	548	548	548	548	548	548	548	548
R-squared	0.043	0.053	0.033	0.042	0.064	0.054	0.021	0.112
Panel (b): Daughters only								
Father unemp. rate	-0.020	0.061	-0.008	0.030	0.032	0.025	0.025	-0.009
	(0.018)	(0.048)	(0.015)	(0.038)	(0.032)	(0.031)	(0.028)	(0.014)
Mother unemp. rate	0.069***	0.054	0.036***	0.053	0.090***	0.026	0.021	0.057***
	(0.018)	(0.039)	(0.008)	(0.033)	(0.014)	(0.024)	(0.031)	(0.012)
Observations	545	545	545	545	545	545	545	545
R-squared	0.082	0.046	0.053	0.039	0.065	0.069	0.035	0.043

*Notes: Regressions replicate those in Columns (3) and (6) of Table 6. Standard errors clustered at the state × maternal cohort level. *** p<0.01, ** p<0.05, * p<0.1.*

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 mental health and worse outcomes for their children. We nevertheless explore whether there are systematic differences in attrition by early career unemployment rates. For this, we construct an indicator taking the value of 1 if a person attrites from the sample before age 45, and zero otherwise. For this exercise, we focus on people born between 1964 and 1974.[17] We find that unemployment rates upon entry do not predict exit from the survey (point estimate of 0.020 and standard error of 0.039).

[17]Given that the last survey round used is from 2019, 1974 is the last year for which we observe outcomes at age 45.

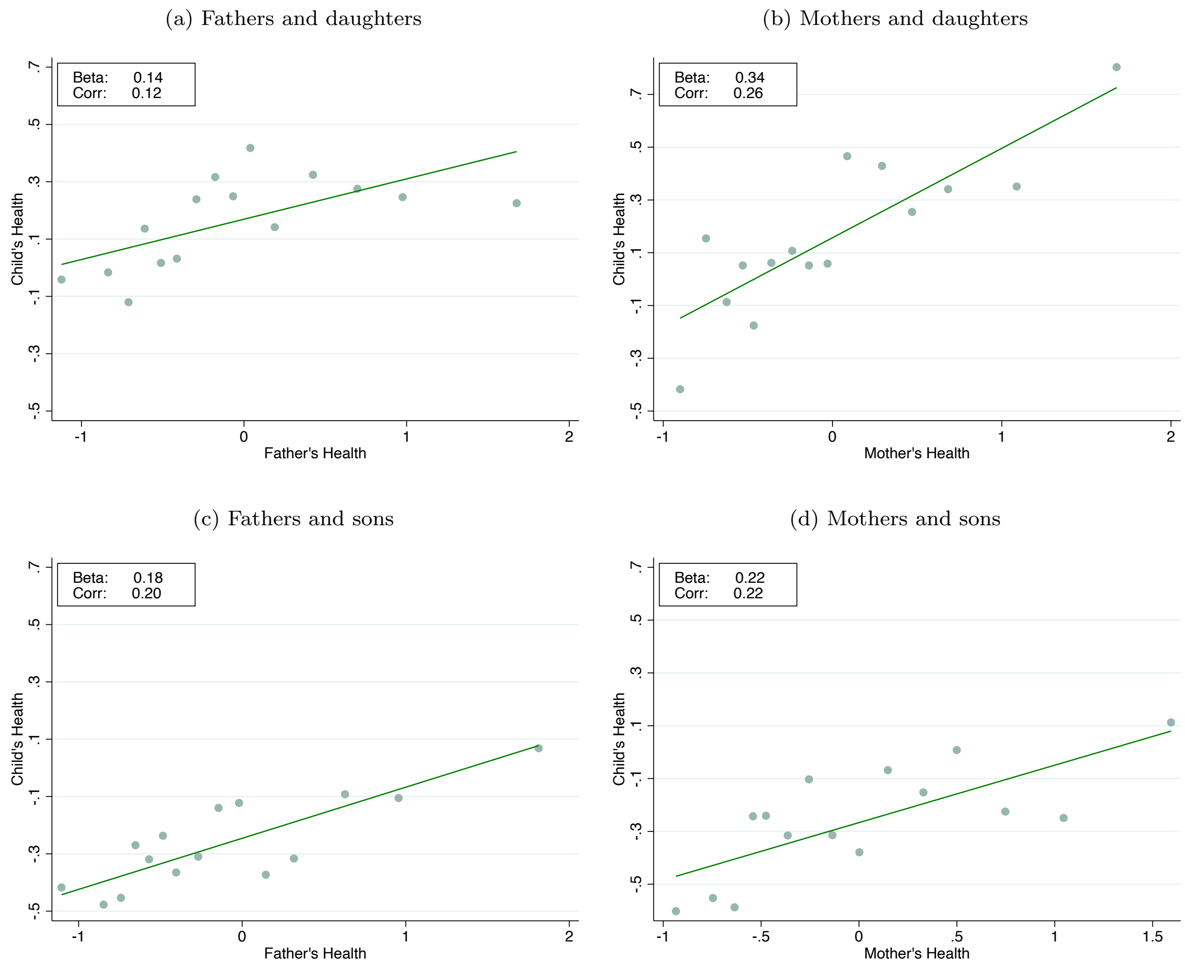
5.3 Discussion: Implications for the intergenerational correlation of mental health

So far we have documented that labor market entry conditions have a long-term impact both on the cohorts that directly experience the shock and on their children. This suggests that these conditions constitute an exogenous source of variation that may explain part of the existing intergenerational correlations in mental health.

We start by showing that the mental health of the parents is indeed correlated with that of their offspring. One should note that the raw correlations of the mental health of just one parent and the child may be misleading as paternal and maternal mental health may themselves be correlated either by assortative mating (e.g., Guner et al., 2018) or through correlated shocks that the couples experience. We report in Appendix Figure A2 that the mental health measures of both parents are indeed correlated (coefficient of 0.22). The raw correlations between mental health of parents and children are in Appendix Figure A3. In Figure 4, we report instead partial correlations where we measure the correlation of one parent and their child, netting out the mental health of the other parent. The partial correlation of sons' mental health with that of his mother and father seem to be similar at around 0.20. On the other hand, the intergenerational partial correlations of the daughters' mental health is significantly stronger for the mothers' health (0.26) than for the fathers' (0.12).

We then proceed to undertake a mediation analysis in Table 8. More specifically, we are interested in observing how the magnitude and significance of our estimates for the effects of maternal and paternal unemployment rates change as our main mediating factor, namely parental mental health, is added to the regressions. Column (5) should coincide with the estimates in Columns (3) and (6) of Table 6. Panel (b) of Table 8 documents that the point estimate of the effect of the maternal unemployment rate is halved and is statistically non-significant as maternal mental health is added, both in Columns (2) and (6). This suggests that most of the effect of the maternal unemployment rates on child mental health was operating through poor maternal mental health. In the case of paternal unemployment rates, we see a similar halving of the point estimate. Consistent

Figure 4: Intergenerational partial correlations of bad mental health



Notes: Binned scatter plots of the relationship between a father's/mother's mental health during his/her 36–40 years of age (first residualized for business cycle and age profile, and then standardized) and the mental health of the child in his/her 15–20 (after similar treatment to the parent). For each graph, we net out the other parent's mental health. We also report the underlying correlation coefficient and the estimated OLS coefficient. The version without netting the other parent's mental health is provided in Appendix Figure A3. Correlations of the maternal and paternal mental health measures are presented in Appendix Figure A2.

with previous results, the male subsample is unaffected by parental labor market entry conditions. This is also in line with the presence of a social channel operating in the formation of the mental health of females (Giulietti et al., 2022). In particular, we identify this social channel as strongly connecting daughters with their mothers.

Though mediation analyses should generally be interpreted with care as the true effect of the mediators can be conflated with omitted variable bias, our results suggest that part of the intergenerational correlation in mental health, particularly among daughters and their mothers, could be traced to a common root: exogenous shocks to labor market entry conditions of the parents. This result highlights that the 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. These conclusions echo similar points made by Lundborg and Majlesi (2018) and Athanasiadis et al. (2022) for physical health.

Measurement error. A concern in this exercise is how the measurement of mental health affects our estimates of the intergenerational coefficient. Mental health is intrinsically hard to measure and 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. The outcomes we use aggregate information from multiple aspects of mental health (as in the MHI-5 or Kessler-10) and also averages over time. By combining information from various measures and averaging over time, we attempt to capture the persistent component of mental health of an individual. This idea is commonly practiced in the measurement of the intergenerational elasticity of lifetime income (Nybom and Stuhler, 2017).

Table 8: Mental health: mediation

	(1)	(2)	(3)	(4)	(5)	(6)
	Bad mental health of child (z-score)					
Panel (a): Sons only						
Father's unemp. rate			-0.031	-0.073	-0.053	-0.092
			(0.091)	(0.075)	(0.087)	(0.065)
Father's z-score bad mental health				0.201***		0.162***
				(0.039)		(0.040)
Mother's unemp. rate	0.059	-0.022			0.075	-0.005
	(0.105)	(0.096)			(0.105)	(0.110)
Mother's z-score bad mental health		0.242***				0.225***
		(0.059)				(0.059)
Observations	516	516	516	497	516	497
R-squared	0.043	0.098	0.042	0.086	0.044	0.134
Panel (b): Daughters only						
Father's unemp. rate			0.236*	0.209	0.179	0.083
			(0.124)	(0.134)	(0.122)	(0.108)
Father's z-score bad mental health				0.192***		0.120**
				(0.053)		(0.046)
Mother's unemp. rate	0.228**	0.078			0.182**	0.089
	(0.087)	(0.058)			(0.081)	(0.057)
Mother's z-score bad mental health		0.401***				0.371***
		(0.050)				(0.052)
Observations	528	528	528	494	528	494
R-squared	0.035	0.142	0.034	0.062	0.040	0.156

*Notes: Baseline child's mental health regressions where the interest is in how the point estimates of maternal and paternal unemployment rates change as measures of maternal and paternal mental health are added. Standard errors clustered at the state × maternal cohort level *** p<0.01, ** p<0.05, * p<0.1.*

6 Conclusion

Understanding the long-term determinants of mental health is a crucial yet little understood question. In this paper, we employ geographical and time series variation in unemployment rates at ages 18–22 among a representative sample of Australian individuals to show that midlife mental health is significantly worse for those who entered the labor market during less favorable macroeconomic conditions. We find this to be the case for multiple forms of mental distress, including feeling unhappy, anxious, and down. Using a composite measure of mental health, we find that a 1 p.p. increase in the unemployment rate upon entry is associated with a fall of 14% of a standard deviation of our outcome, and that this effect is of the same magnitude for males and females.

In parallel, we find that higher unemployment rates at labor market entry are associated with lower levels of satisfaction with one's own health and overall life at midlife. For males, we also find that they are less satisfied with their financial situation. Though satisfaction with these life aspects contributes to an individual's state of mental well-being, we cannot distinguish whether mental health may also affect views of the world and thus also affect self-reported satisfaction. Still, our results provide evidence that adverse labor market entry conditions have persistent effects on these aspects at midlife. This highlights that the negative impacts of bad labor entry conditions go beyond persistent falls in earnings and in physical health as currently shown in the literature (von Wachter, 2020).

We take our analysis one step further and ask whether labor market entry conditions also impact the subsequent generation. We answer this question focusing on two margins. First, we find that the females who were most affected by entering the labor market during unfavorable times tend to have more children. We do not find this among males. This echoes the experience of South Korean women who entered the labor market during the Asian Financial Crisis as studied by Choi et al. (2020). Second, we find that the daughters of parents who entered the labor market during adverse conditions have worse mental health at adolescence. They are also more likely to be unsatisfied with their health, home, and safety. We find evidence that a channel through which daughters are affected by their parents' labor market entry conditions is through their mothers' mental health. This is consistent with recent evidence from Giulietti et al. (2022) showing that female teenagers' mental health is most susceptible to their environment and social influences.

Overall, our results suggest that adverse labor market entry conditions have undesirable long-term effects that persist across generations. Individuals who enter the labor market during unfavorable times have worse mental health at midlife. The women who were disproportionately affected tend to have more children. The adolescent daughters, whose mental health seems to be more heavily influenced by their mothers, also have worse mental health and are more likely to be unsatisfied with various life aspects. These spillovers that seem to compound the detrimental effects of poor labor market entry conditions resonate the importance of policies to address them.

Our results may be useful for academics and policy makers alike. In terms of the former, we contribute novel evidence on the long-term determinants of mental health, not only for the individuals who directly experienced variation in our treatment but also for their children, even if they were not yet born nor conceived. This complements the extant 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 such presence and showing that it cannot be solely driven by genetics. In terms of the latter, our findings reinforce the policy perspective, conceptualized in programs such as the European Mental Health Action Plan, that individuals should be insured from the mental consequences of poor labor market conditions. Our analyses suggest that particular care should be taken with females' mental health formation.

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A Appendix: Additional figures and tables

Table A1: Indicator felt unhappy: Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
Panel (a): Males only						
Std. unemp. rate	0.044***					
	(0.011)					
Unfiltered unemp. rate		0.021***				
		(0.006)				
Unemp. rate			0.047***	0.042***	0.047***	0.018
			(0.011)	(0.013)	(0.011)	(0.042)
Observations	2,181	2,181	2,181	1,885	2,181	2,181
R-squared	0.012	0.012	0.008	0.010	0.010	0.018
Panel (b): Females only						
Std. unemp. rate	0.041**					
	(0.017)					
Unfiltered unemp. rate		0.015*				
		(0.009)				
Unemp. rate			0.058**	0.054**	0.059**	0.222***
			(0.022)	(0.026)	(0.023)	(0.043)
Observations	2,446	2,446	2,446	2,085	2,446	2,446
R-squared	0.011	0.009	0.006	0.014	0.011	0.021

*Notes: Replication of Columns (1)–(6) of Table 4 for the indicator of frequent feelings of unhappiness. *** p<0.01, ** p<0.05, * p<0.1.*

Table A2: Indicator felt nervous: Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
Panel (a): Males only						
Std. unemp. rate	0.015*					
	(0.009)					
Unfiltered unemp. rate		0.008				
		(0.005)				
Unemp. rate			0.014	0.016	0.013	0.061*
			(0.011)	(0.012)	(0.011)	(0.030)
Observations	2,181	2,181	2,181	1,885	2,181	2,181
R-squared	0.008	0.008	0.003	0.013	0.007	0.015
Panel (b): Females only						
Std. unemp. rate	-0.009					
	(0.010)					
Unfiltered unemp. rate		-0.005				
		(0.004)				
Unemp. rate			0.003	0.009	0.001	0.003
			(0.017)	(0.018)	(0.017)	(0.032)
Observations	2,446	2,446	2,446	2,085	2,446	2,446
R-squared	0.015	0.015	0.009	0.023	0.015	0.021

*Notes: Replication of Columns (1)–(6) of Table 4 for the indicator of frequent feelings of nervousness. *** p<0.01, ** p<0.05, * p<0.1.*

Table A3: Indicator felt down: Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
Panel (a): Males only						
Std. unemp. rate	0.035***					
	(0.007)					
Unfiltered unemp. rate		0.016***				
		(0.003)				
Unemp. rate			0.048***	0.055***	0.047***	0.042
			(0.013)	(0.015)	(0.013)	(0.038)
Observations	2,181	2,181	2,181	1,885	2,181	2,181
R-squared	0.013	0.013	0.012	0.020	0.013	0.015
Panel (b): Females only						
Std. unemp. rate	0.015*					
	(0.008)					
Unfiltered unemp. rate		0.005				
		(0.004)				
Unemp. rate			0.023**	0.024*	0.022**	0.107***
			(0.010)	(0.013)	(0.010)	(0.027)
Observations	2,446	2,446	2,446	2,085	2,446	2,446
R-squared	0.009	0.008	0.004	0.010	0.009	0.014

*Notes: Replication of Columns (1)–(6) of Table 4 for the indicator of frequent state of feeling down. *** p<0.01, ** p<0.05, * p<0.1.*

Table A4: Indicator felt anxious: Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
Panel (a): Males only						
Std. unemp. rate	0.031**					
	(0.014)					
Unfiltered unemp. rate		0.013				
		(0.008)				
Unemp. rate			0.048**	0.049**	0.048**	0.095*
			(0.019)	(0.018)	(0.019)	(0.056)
Observations	2,181	2,181	2,181	1,885	2,181	2,181
R-squared	0.010	0.010	0.010	0.014	0.011	0.019
Panel (b): Females only						
Std. unemp. rate	0.034					
	(0.021)					
Unfiltered unemp. rate		0.012				
		(0.010)				
Unemp. rate			0.061***	0.057**	0.064***	0.216***
			(0.022)	(0.026)	(0.023)	(0.060)
Observations	2,446	2,446	2,446	2,085	2,446	2,446
R-squared	0.016	0.015	0.010	0.021	0.018	0.025

*Notes: Replication of Columns (1)–(6) of Table 4 for the indicator of frequent anxious feelings. *** p<0.01, ** p<0.05, * p<0.1.*

Table A5: Indicator hard to cheer up: Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
Panel (a): Males only						
Std. unemp. rate	0.012**					
	(0.005)					
Unfiltered unemp. rate		0.005**				
		(0.003)				
Unemp. rate			0.020***	0.021**	0.019***	0.022
			(0.006)	(0.008)	(0.006)	(0.021)
Observations	2,181	2,181	2,181	1,885	2,181	2,181
R-squared	0.006	0.006	0.005	0.017	0.007	0.009
Panel (b): Females only						
Std. unemp. rate	0.002					
	(0.010)					
Unfiltered unemp. rate		0.000				
		(0.004)				
Unemp. rate			0.011	0.013	0.009	0.042
			(0.012)	(0.011)	(0.012)	(0.028)
Observations	2,446	2,446	2,446	2,085	2,446	2,446
R-squared	0.015	0.015	0.008	0.025	0.015	0.018

*Notes: Replication of Columns (1)–(7) of Table 4 for the indicator of frequent feelings of finding it hard to cheer up. *** p<0.01, ** p<0.05, * p<0.1.*

Table A6: Kessler–10: Robustness

	(1)	(2)	(3)
	Outcome: Kessler–10 (z-score)		
Unemp. rate	0.146***	0.140**	0.146
	(0.047)	(0.053)	(0.096)
Sample	All	Males	Females
Observations	3,527	1,663	1,864
R-squared	0.019	0.012	0.023

*Notes: Replication of Column (6) of Table 2 for the residualized Kessler–10 measure of mental health. Sample size decreases because the Kessler–10 measures are only available biyearly and starting from 2007. *** p<0.01, ** p<0.05, * p<0.1.*

Table A7: Inclusion of other outcomes as controls: Robustness

	(1)	(2)	(3)	(4)	(5)
	Outcome: Bad mental health (z-score)				
Panel (a): Males and females, pooled					
Unemp. rate	0.131***	0.143***	0.140***	0.112***	0.111***
	(0.029)	(0.030)	(0.031)	(0.023)	(0.022)
Observations	4,627	4,627	4,627	4,615	4,615
R-squared	0.060	0.031	0.024	0.161	0.182
Panel (b): Males only					
Unemp. rate	0.119***	0.135***	0.136***	0.116***	0.111***
	(0.024)	(0.022)	(0.020)	(0.021)	(0.022)
Observations	2,181	2,181	2,181	2,175	2,175
R-squared	0.057	0.019	0.025	0.130	0.159
Panel (c): Females only					
Unemp. rate	0.142***	0.149***	0.146**	0.108**	0.107***
	(0.048)	(0.048)	(0.054)	(0.044)	(0.039)
Observations	2,446	2,446	2,446	2,440	2,440
R-squared	0.059	0.043	0.021	0.184	0.205

*Notes: Replication of Column (6) of Table 2 introducing additional (potentially endogenous) controls. Column (1) includes (log) household gross yearly income. Column (2) includes the highest (categorical) level of education achieved by the respondent. Column (3) includes the number of household members. Column (4) controls for the physical functioning subcomponent of the Short Form 36 Health Survey. Sample size slightly decreases in Column (4) due to the physical functionality variable not being available. Column (5) jointly controls for the four additional controls. *** p<0.01, ** p<0.05, * p<0.1.*

Table A8: Intergenerational spillovers on mental health: Robustness to inclusion of other outcomes as controls

	Sons			Daughters		
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome: Bad mental health (z-score)						
Father's unemp. rate	-0.044		-0.063	0.239*		0.179
	(0.086)		(0.083)	(0.134)		(0.127)
Mother's unemp. rate		0.052	0.069		0.232**	0.186**
		(0.102)	(0.102)		(0.086)	(0.077)
Observations	510	510	510	520	520	520
R-squared	0.094	0.094	0.095	0.065	0.066	0.071

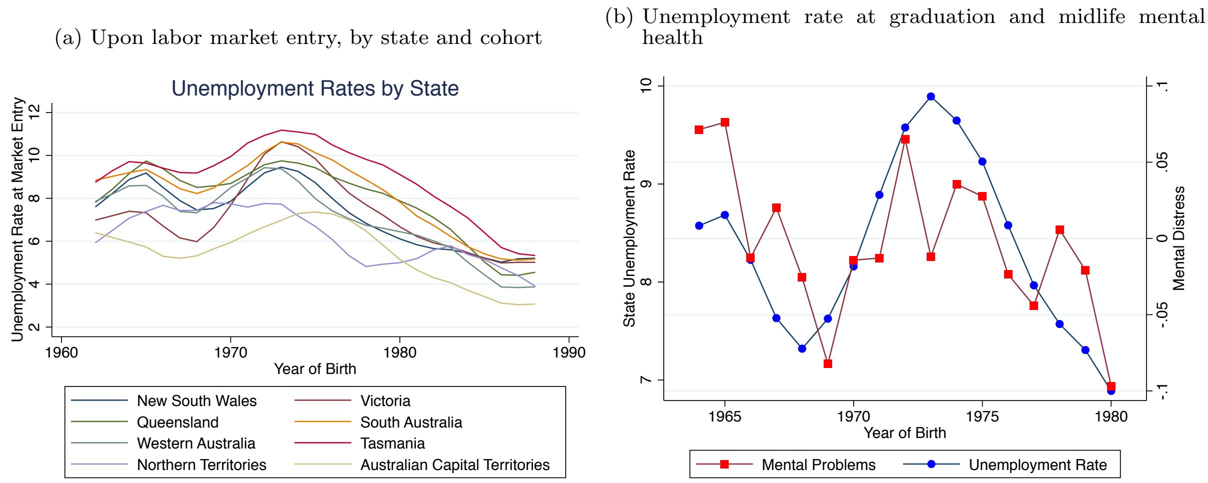
*Notes: This Table replicates Table 6 controlling in all columns for the same additional dimensions as in Table A7's Column (5): average parental income, education, physical health, and household size. *** p<0.01, ** p<0.05, * p<0.1.*

Table A9: 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					
Father's unemp. rate	-0.034	-0.048	-0.007	-0.034	-0.009
	(0.032)	(0.044)	(0.020)	(0.026)	(0.018)
Mother's unemp. rate	0.029	0.046	0.030	-0.002	0.012
	(0.037)	(0.035)	(0.031)	(0.041)	(0.031)
Observations	516	516	516	516	516
R-squared	0.052	0.019	0.051	0.024	0.049
Panel (b): Daughters only					
Father's unemp. rate	0.012	0.103***	0.055	-0.035	0.054
	(0.034)	(0.035)	(0.045)	(0.054)	(0.034)
Mother's unemp. rate	0.085**	-0.005	0.029	0.062*	0.068***
	(0.040)	(0.028)	(0.025)	(0.036)	(0.024)
Observations	528	528	528	528	528
R-squared	0.050	0.048	0.032	0.036	0.069

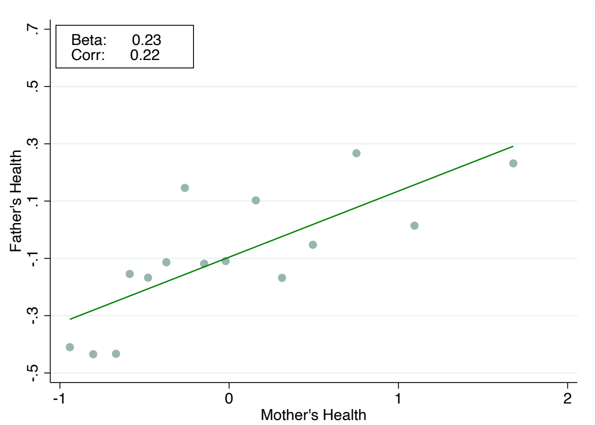
*Notes: Replication of Table 6 for the indicators of frequent negative feelings. *** p<0.01, ** p<0.05, * p<0.1.*

Figure A1: Graphs relating to the average unemployment rate at ages 18–22



Notes: Unemployment rate at market entry refers to average state-level unemployment rate when the cohort is aged 18–22. In Panel (a), we plot this average over cohorts. In Panel (b), we plot how it relates to mental health at midlife. The blue curve plots the average unemployment rate across individuals from all states faced between ages 18 and 22 by the different cohorts listed in the horizontal axis. The red curve is our MCA-constructed score of mental health distress (after netting out survey round fixed effects and age profiles) that each of the cohorts experienced between ages 35 and 40.

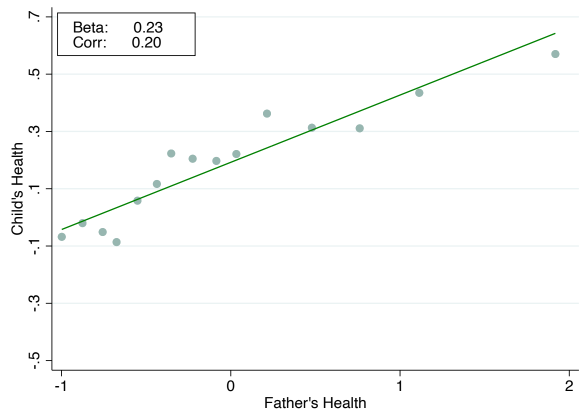
Figure A2: Correlation of paternal and maternal mental health



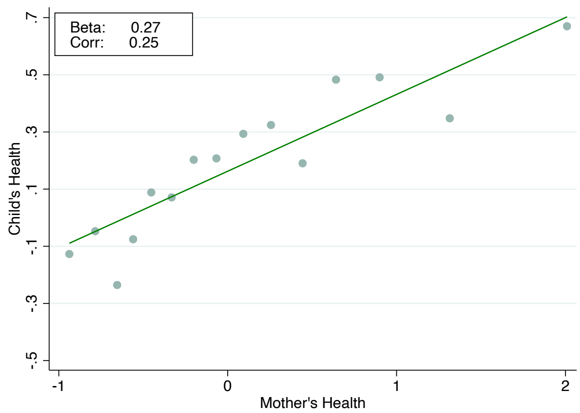
Notes: Binned scatter plot of the relationship between the paternal and maternal mental health at age 36–40 (first residualized for business cycle and age profile, and then standardized). We also report the underlying correlation coefficient and the estimated OLS coefficient.

Figure A3: Intergenerational correlations of bad mental health

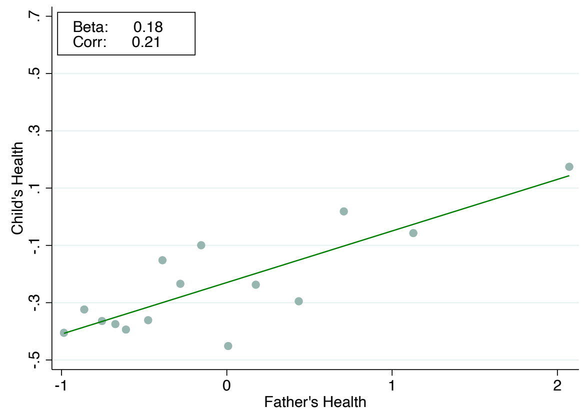
(a) Fathers and daughters



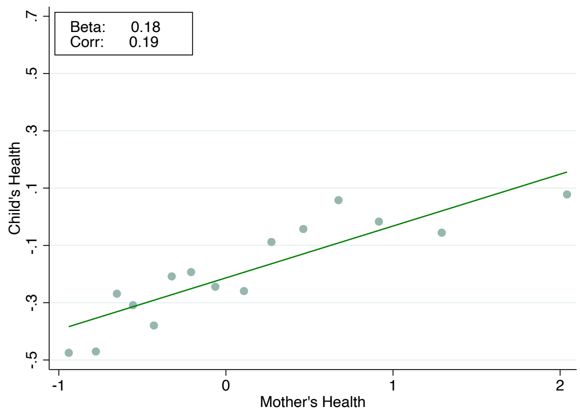
(b) Mothers and daughters



(c) Fathers and sons



(d) Mothers and sons



Notes: Similar exercise to Figure 4 without netting out the other parent's mental health.