

Ubaldi, Michele; Picchio, Matteo

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Michele Ubaldi* and Matteo Picchio

Intergenerational Scars: The Impact of Parental Unemployment on Individual Health Later in Life

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Abstract: This paper studies whether individuals that experienced parental unemployment during their childhood/early adolescence have poorer health once they reach the adulthood. We used data from the German Socio-Economic Panel from 2002 until 2018. Our identification strategy of the causal effect of parental unemployment relied on plant closures as exogenous variation of the individual labor market condition. We combined matching methods and parametric estimation to strengthen the causal interpretation of the estimates. On the one hand, we found a nil effect for parental unemployment on mental health. On the other hand, we detected a negative effect on physical health, which is stronger if parental unemployment occurred in late periods of the childhood and heterogeneous across gender. The negative effect of parental unemployment on physical health may be explained by a higher alcohol and tobacco consumption later in life.

Keywords: parental unemployment; plant closure; mental health; physical health; health behavior

JEL Classification: I10; J62; J65

***Corresponding author: Michele Ubaldi**, Department of Economics and Social Sciences, Marche Polytechnic University, Piazzale Martelli 8, 60121 Ancona, Italy, E-mail: m.ubaldi@pm.univpm.it
<https://orcid.org/0000-0002-5529-7273>

Matteo Picchio, Department of Economics and Social Sciences, Marche Polytechnic University, Ancona, Italy; Department of Economics, Ghent University, Ghent, Belgium; GLO – Global Labor Organization, Essen, Germany; and IZA – Institute of Labor Economics, Bonn, Germany,
E-mail: m.picchio@staff.univpm.it

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1 Introduction

Labor economists, psychologists and social scientists have extensively studied the consequences of unemployment on the lives of the individuals and of their relatives (Jahoda 1982), especially to understand whether unemployment affects both economic and non-economic outcomes (Janlert and Hammarström 2009) and how long these effects last.

Past empirical research provided evidence about the presence of scarring effects on wages, (re-)employment probability, mental health and overall life satisfaction (see e.g. Arulampalam 2001; Chan and Stevens 2001; Drydakis 2015; Green 2011; Jacobson, LaLonde, and Sullivan 1993; Kassenboehmer and Haisken-DeNew 2009; Winkelmann and Winkelmann 1998). For the labor market, the findings were remarkably consistent, regardless of the period and country under analysis, the type of data used and the identification strategy employed (Filomena 2024). Picchio and Ubaldi (2024) conducted meta-analysis on the health effects of unemployment and pointed out a negative effect for laid-off workers, especially on mental health and life satisfaction.

A branch of the literature put special emphasis on the relationship between parents and children, and studied whether and to what extent the unemployment of the former may shape the outcomes of the latter. This relationship may be one of the most important in social sciences, because it may be the principal channel through which the phenomenon of intergenerational mobility occurs (Becker and Tomes 1979, 1986). Our paper contributes to this branch of the literature by studying the impact of parental unemployment on children's health later in life, in young adulthood, in Germany. More in detail, the purpose of our study is to shed light on the long-term effects by answering the following research questions: (i) Does parental unemployment exert a long-term effect on children's health? (ii) If yes, which health dimension is impaired? (iii) Finally, at what extent?

We used data from the German Socio-Economic Panel (SOEP) for the period 2002 to 2018. The SOEP is a rich longitudinal dataset, representative of the adult German population. It contains a wide range of demographic and socio-economic information about the individual and the household. The survey started in 1984 and has been conducted annually ever since. We used the Mental Component Summary (MCS) and Physical Component Summary (PCS) scales as outcome variables (Ware, Kosinski, and Dewey 2000). These measures are widely employed in the economic and psychological literature and nowadays represent a standard in those studies seeking to measure the health effects of unemployment (Marcus 2013; Neuberger et al. 2019; Schmitz 2011; Stauder 2019). They are provided by the SOEP version of the Short Form Health Survey (SF-12v2) questionnaire, which is the shorter and

more practical version of the 36-items Short-Form Health Survey (SF-36). The SF-12v2 is one of the most popular tools used to collect information on individual health and quality of life in large survey samples. The SOEP introduced this questionnaire for the first time in 2002 and ever since every two years. We observed the health outcomes when the individuals were adults (i.e. when they were 18–31 years old).

We built the identification strategy on two stepping stones. First, we used information on the reason for unemployment entry to tackle the endogeneity problem typical of the relation between unemployment and health (Kassenboehmer and Haisken-DeNew 2009). We selected into the treated group only those individuals who experienced parental unemployment due to plant closure when they were children. A plant closure may be regarded to be exogenous with respect to the characteristics of the laid off worker (Brand 2015). However, as pointed out and shown for the US by Hilger (2016), there might be substantial selection on parents' characteristics into plant closure if it is not possible to control for child outcomes before the unemployment event. This leads to the second element of our identification strategy. We applied an approach that combines matching methods and standard outcome regression in order to condition on several observed parents' and child's characteristics, reduce the risk of model dependence and, hence, add further credibility to the causal interpretation of our estimates (Hainmueller 2012; Ho et al. 2007). We defined parental unemployment using three criteria: (i) at least one parent lost his/her job due to a plant closure; (ii) s/he officially registered the unemployment entry at the Federal Employment Agency; (iii) the layoff occurred when the individual was between 0 and 15 years old.

To the best of our knowledge, only three other studies attempted to explore the potential long-term effects of parental unemployment on individuals' health: Brand and Thomas (2014) in the US, Lam and Ambrey (2019) in Australia, and Nikolova and Nikolaev (2021) in Germany. Our study contributes to this body of research in two significant ways. First, we provide new insights into the long-term impact of parental unemployment on both mental and physical health, a topic not yet examined in the context of Germany. Although Nikolova and Nikolaev (2021) also investigated the German case, our study differs in key respects. Whereas their focus was on life satisfaction as an outcome, we delve deeper by examining specific measures of mental and physical health. It is important to note that while life satisfaction and mental health are generally correlated, they represent distinct constructs (Headey, Kelley, and Wearing 1993). Furthermore, our study broadens the scope by including measures of physical health and health behaviors, such as alcohol consumption and smoking.

The second contribution of our study is methodological, as we evaluate the long-term impact of parental unemployment on health by combining an exogenous variation of the individual labor market condition with estimation techniques

that are robust to model dependence. Compared to Brand and Thomas (2014) and Lam and Ambrey (2019), we applied a narrower definition of unemployment, which is based on plant closures as exogenous reason for entering unemployment. Moreover, we collected information on parental unemployment directly from the parents' files, reducing the risk of reporting bias. In addition, in contrast to Brand and Thomas (2014), Lam and Ambrey (2019) and Nikolova and Nikolaev (2021), we combined matching techniques with standard outcome regression to account for various observed characteristics of both parents and children and to mitigate the risk of model dependence, thereby strengthening the causal interpretation of our findings.

We found mixed effects of parental unemployment on individuals' health later in life: a negative effect on physical health and a nil effect on mental health. About physical health, the effect was stronger if parental unemployment occurred in late childhood. Physical health of daughters was negatively affected, whilst sons' physical health was not. Maternal and paternal unemployment exerted similar negative effects on physical health. We also found that parental unemployment induced a higher probability of alcohol and tobacco consumption later in life. About mental health, we found a positive effect of parental unemployment in West Germany and if it occurred in earlier years.

This article is organized as follows. Section 2 presents both theoretical predictions and empirical evidence on the effects of parental unemployment on individual outcomes. Section 3 presents the dataset, the sample selection criteria, the variables and the identification strategy. Section 4 reports and comments on the findings. Section 5 concludes.

2 Literature Review

The economic literature about intergenerational transmission and child development started with the seminal work of Becker and Tomes (1979, 1986). The Beckerian model assumed that individuals' lives may be divided in two periods: childhood and adulthood. The first period is characterized by individuals receiving and transforming parental investments in marketable skills and human capital. The second period is characterized by individuals generating returns by exploiting these skills, for instance, on the labor market (Becker and Tomes 1979, 1986).

Parental unemployment may play a relevant role in the human capital formation process. Assessing the sign of the relationship is not trivial because parental unemployment could exert both positive and negative effects. On the one hand, positive effects may arise because unemployment increases the amount of leisure time available for the laid-off parent (Knabe et al. 2010). The laid-off parent may decide to use this additional time for a more intensive parenting activity. Parental

involvement is an essential input in the human capital production function. Through the parenting style, a parent can shape his/her child's preferences (Doepke, Sorrenti, and Zilibotti 2019). Parental involvement also prevents the child to achieve sub-optimal outcomes later in life (Ermisch and Francesconi 2013). Moreover, it promotes the development of soft skills like resilience, which further enhance the stock of human capital (Masten and Narayan 2012; Masten and Palmer 2019). On the other hand, negative effects might arise because families risk to end up in economic and emotional deprivation (Jahoda 1982; Janlert and Hammarström 2009). Unemployment reduces the economic resources available (Aru-lampalam 2001; Jacobson, LaLonde, and Sullivan 1993). This reduction may offset (or at least partially hinder) the parental ability to invest in educational and health goods for the child (Becker and Tomes 1979, 1986; Grossman 1972). Unemployment also causes emotional distress, that in turn may lead to family breaks (Di Nallo et al. 2022; Eliason 2012; Jensen and Smith 1990; Marcus 2013; Mörk, Sjögren, and Svaleryd 2020). Disrupted family structures represent inhospitable environments for the child development. For instance, in the UK Ermisch and Francesconi (2001) and Ermisch, Francesconi, and Pevalin (2004) showed that children that grew up in separated or single-parent families reported poorer educational, behavioral and health outcomes later in life. Francesconi, Jenkins, and Siedler (2010) reported similar findings in Germany. These negative consequences were not fully confirmed by Hilger (2016) in the US: college enrollment, college quality and early career earnings were mildly penalized.

Past empirical research on parental unemployment mostly focused on children's educational and labor market outcomes. Whilst there is consensus on the negative effects on school ambitions and performances, grade completion and tertiary education enrollment (see e.g. Coelli 2011; Kalil and Ziol-Guest 2008; Mörk, Sjögren, and Svaleryd 2020; Rege, Telle, and Votruba 2011; Stevens and Schaller 2011), the findings for the labor market outcomes instead present some degree of heterogeneity. In the US, Oreopoulos, Page, and Stevens (2008) showed that the exposure to the paternal job loss during the years of the adolescence leads the individuals to earn less and rely more on welfare and social aids once they reach the adulthood. For the UK, Macmillan (2014) found that paternal unemployment is also associated with an increase in the duration of the potential joblessness spells experienced by these children. The effect was worse in areas with precarious labor market conditions. Using an instrumental variables approach, Hérault and Kalb (2016) confirmed these findings also in Australia. Finally, individuals that suffered parental unemployment also achieved worst socioeconomic status once they grew old (Karhula, Lehti, and Jani 2017). Nevertheless, Bratberg, Nilsen, and Vaage (2008) and Müller, Riphahn, and Schwientek (2017) did not find similar findings in Norway and Germany. Ekhaugen (2009) posited that most of the negative effect found

is the reflection of a simple intergenerational correlation which disappeared once the unobserved heterogeneity at family level was appropriately controlled for. In this regard, Ekhaugen (2009) compared achievements from siblings pairs once they reached the adulthood and found that the net effect was not statistically different from zero and, if anything, positive.

Also the handful of studies dealing with the health consequences of parental unemployment leaned more towards the negative effects, albeit without providing a clear-cut picture. In the following paragraphs, we categorize studies into two groups: those examining the short- or medium-term effects of parental unemployment on children's health, and those investigating the long-term effects, where children's outcomes are measured later in life, either in young adulthood or midlife.

Regarding the short- or medium-term effects of parental unemployment, Mörk, Sjögren, and Svaleryd (2020) found that in Sweden parental joblessness did not impair the mental health of the offspring in the childhood. Powdthavee and Vernoit (2013) reported mixed evidence on the happiness of the British adolescents, with paternal unemployment exerting a positive effect and maternal unemployment a negative one. Pieters and Rawlings (2020) found that in China, whereas paternal joblessness was associated with poorer dietary habits and increased odds of low-weight births, maternal unemployment generated an improvement in the dietary habits. Lindo (2011) reported similar findings on birth weight in Germany. In particular, the author found that those children born after a paternal job displacement were more likely to report a 5 % lower weight. Moreover, in Ireland, Briody (2021) found that children living in a household with at least one unemployed parent were more likely to consume unhealthy food and exercise less. These associations were particularly strong in the case of paternal unemployment.

Regarding the long-term effects of parental unemployment, Brand and Thomas (2014) examined how job displacement among single mothers influences the outcomes of their children in the US. Using propensity score matching estimators, they discovered that a single mother's job displacement leads to increased depressive symptoms in her child during young adulthood. Similarly, Lam and Ambrey (2019) explored the impact of a father's unemployment during childhood on mental health in midlife (45–65 years of age). Employing the five-item Mental Health Inventory (MHI-5) to assess mental health and using random effect models, they found that paternal unemployment is associated with poorer mental health outcomes for children later in life. In another study, Nikolova and Nikolaev (2021) investigated the effect of parental job loss on children's life satisfaction in Germany. By leveraging plant closures as an exogenous source of job displacement and applying random effect regressions, they found that unemployment exerts a negative effect only if parental unemployment occurred in early childhood or early adolescence (i.e. 0–5 and 11–15 years of age).

Finally, unemployment increases the likelihood for the laid-off worker of engaging in risky behaviors, such as smoking or drinking (Mörk, Sjögren, and Svaleryd 2020; Reine, Novo, and Hammarström 2013; Schunck and Rogge 2010). Past empirical research showed that these behaviors are likely to transmit from parents to children, representing another potential threat in children's human capital accumulation process (Bantle and Haisken-DeNew 2002; Göhlmann, Schmidt, and Tauchmann 2010; Schmidt and Tauchmann 2011; Yu 2003). This is something we tried to shed light on by examining the impact of parents' layoff on children's risky behaviors later in life, like smoking or drinking.

3 Data and Method

3.1 Data, Sample Selection Criteria and Treatment Definition

We obtained our sample by combining two datasets: (i) the German Socio-Economic Panel (SOEP-Core v36, EU edition), a household panel survey representative of the adult German population (Wagner, Frick, and Schupp 2007);¹ (ii) the Federal Employment Agency statistics. The SOEP represents the main building block. Started in 1984, the survey is carried out annually. In 2021, more than 30,000 adult individuals participated in the panel.² The SOEP presents several useful features. First, once a household is selected, all members are interviewed and they may remain in the sample even if they separate from the original household. If an individual gets married or starts a cohabitation, also the partner and the future kids join the sample.³ This longitudinal structure allows to track individuals over time, regardless of complex family dynamics. Individuals exit the sample only if they die, move abroad or decide to quit.⁴ Second, the SOEP collects retrospective information. By combining both retrospective and currently acquired information,

1 We used the EU edition of the SOEP dataset. The EU edition represents the standard edition of the SOEP data distribution and may be obtained after signing the standard data distribution contract with DIW Berlin. This edition includes 100 % of all observations present in the sample and contains geospatial information up to German federal states. The DIW Berlin makes available other more detailed editions of the SOEP dataset that include geospatial information up to postal codes. These editions are available under more restrictive conditions. For more details, visit <https://companion.soeep.de/index.html> (last accessed August 28, 2024).

2 According to the SOEP, a person is considered adult only after s/he turned 17.

3 Either one of the parents or a legal guardian answers the survey questions on behalf of non-adults.

4 In the SOEP, panel attrition is not a major problem. The percentage of successful follow-ups is above 95 % in all years. Furthermore, participation rates are usually beyond 85 % (Siegers, Steinhauer, and Dührsen 2021). The SOEP is continuously integrated with refreshment samples to maintain the representativeness of the German population (Goebel et al. 2019).

a researcher can recreate the full history of each SOEP member. Third, the SOEP covers a vast range of topics, such as health and consumption habits, well-being, labor conditions, political affiliations, income, etc.

We started with 149,565 individuals for a total of 1,164,296 observations. We kept only those individuals with at least one parent interviewed by the SOEP when the individual was between 0 and 15 years old. Hence, these parents could have been either married, cohabiting or singles when the individual was a child. We restricted on individuals born from 1984 to 2000 and aged between 18 and 31 years old when interviewed. In addition, we required individuals to have lived with their parents until they turned 15. Then, we dropped individuals who had missing observations in the outcome variables.⁵ Finally, we removed those individuals with at least one parent who experienced unemployment not due to plant closure. Moreover, for the sake of having similar control and treated units, we also required that the parents of both groups had the same initial labor market condition: at the time when an individual was born, her/his father had to be a private employee, whilst her/his mother had to be a either private employee or not employed.⁶ We ended up with 1,859 individuals for a total of 4,822 observations. Table 1 reports how the sample size shrank through our selection process.

We applied these sample selection criteria for different reasons. First, by requiring parents to be in the sample, we are able to collect information on parental unemployment directly from their files, with their children providing information about themselves when adult. By doing so, we reduced the risk of reporting bias, i.e. the measurement error due to an individual misreporting information, in this case, about someone else. Second, by focusing on children born between 1984 and 2000, we can observe the full history of each individual and his/her family and we avoided losing potentially relevant information. Third, by requiring individuals to have spent their whole childhood living with their parents, we are sure that the kid was fully exposed to parental unemployment when it occurred. Finally, with the last sample selection criterion, we leave in our sample only individuals who either did not experience parental unemployment during their childhood (the control units) or experienced parental unemployment due to plant closure during their childhood (the treated units). The latter sample selection criterion is the pillar of our identification strategy, which is discussed in Subsection 3.4.

5 The health information of the participants is collected by means of the SOEP version of the Short Form Health Survey (SF-12v2) (Ware, Kosinski, and Keller 1996). The SOEP introduced this questionnaire for the first time in 2002 and administered it every two years ever since.

6 We defined non-working mothers using the SOEP item for the occupational status. We used the category “*Not employed (NE): without further information*”. The condition on the mothers was meant to avoid additional possible sample selectivity (Heckman 1979; Mroz 1987).

Table 1: Sample size across the selection process.

	Individuals in the sample	Individual-per-year observations (<i>n</i>)	Dropped observations
Initial gross merged sample ^a	149,565	1,164,296	
After identifying kids with at least one parent identifier	21,508	774,288	390,008
After removing kids born prior 1984	12,649	455,364	318,924
After restricting on kids aged 18 to 31	11,920	98,705	356,659
After restricting on kids who lived with parents during their childhood	10,089	79,498	19,207
After removing missing values in the outcomes ^b	5,479	13,103	66,395
After removing individuals with at least one parent having experienced Unemployment not due to plant closure or with father not a private	1,859	4,822	8,281
Final restricted sample	1,859	4,822	

Source: German Socio-Economic Panel version 36 (SOEP-Core v36, EU edition). ^aThe term ‘gross merged sample’ refers to the output of a merging process involving several SOEP datasets. The main building block is the tracking data file ‘ppath!’. This dataset describes the development of the sample over years and contains information on all individuals who have ever lived in a SOEP household when a survey was conducted. ^bThe SOEP module recording health information of the participants is available in the following survey waves: 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, and 2018. For each wave, we retained information only for those individuals that completed the health module.

We defined the treatment using information from two SOEP questions. The first question is about the reason for the job termination, which is part of the survey since 1985 and since 1991 it includes “due to shutdown” among the possible answers. The second question is on the (un-)employment status. We defined as treated those individuals who, when they were between 0 and 15 years old, had at least one parent that was fired once or more times due to a plant shut-down and registered the unemployment event at the Federal Employment Agency. Individuals whose parents became unemployed for reasons different from a plant closure were excluded from the sample.⁷ We also excluded individuals whose

⁷ Only three individuals in our sample experienced multiple parental unemployment events due to plant closure.

parents were in other labor market status, like workers for the public sector, retired or self-employed.⁸

Given our sample selection criteria as summarized by Table 1 and our treatment definition, we identify the effect of interest by comparing health outcomes of individuals who were born between 1984 and 2000, whose fathers worked as private employees and for whom at least one parent experienced at least an unemployment event due to plant closure when they were 0–15 years old to health outcomes of similar individuals whose parents never experienced any type of unemployment. Therefore, one may wonder if our findings may have enough external validity. Some of the adopted sample selection criteria are not likely to have an impact on the external validity, like the exclusion of persons with fathers who were in the public sector, self-employed or retired. This is justified by the fact that we are interested in a population that is homogeneous in terms of previous labor market history, health insurance status, or probability of job dismissal. Similarly, the selection of individuals who lived either in single-parent or two-parent households until they were 15 years old should very likely represent the vast majority of the German population born between 1984 and 2000. However, individuals born in single-parent households may fare differently against stressful events such as unemployment compared to peers born in two-parent households. Typically, two-parent households can benefit from the insurance of the ‘added worker effect’, that is the labor supply response of spouses to the loss of job of the partner (see e.g. Halla, Schmieder, and Weber 2020; Lundberg 1985; Stephens 2002). As such, individuals born in two-parent households may be more resilient toward parental unemployment, as one parent may have compensated the income loss of the other. In Subsection 4.3, we tested this hypothesis considering only individuals born in two-parent households. Finally, the most important restriction to the external validity of our analysis is probably the choice of limiting the focus on job displacements due to plant shutdowns (Suppa 2021). This was done to reduce endogeneity concerns about selection into treatment. It comes nonetheless with a loss of external validity, because the effect of a parental unemployment due to other causes may differ from the one due to a plant shutdown. As a sensitivity check, in Subsection 4.3, we provide estimates when the treatment is enlarged to those who experienced at least one parental unemployment event, independently on the reason for the job displacement.

⁸ The definition of the treatment is based on the idea that a person may lose his/her own job due to plant closure. Neither the self-employed nor the retired can experience this event. For public employees, the occurrence of the event is very unlikely, as they enjoy higher job protection than private employees.

3.2 Health Outcome Variables

Our health outcome variables are built on the items available in the SOEP version of the Short Form Health Survey (SF-12v2) (Ware, Kosinski, and Keller 1996). The SOEP introduced this questionnaire for the first time in 2002 and ever since every two years. This survey covers several health dimensions like bodily pain, emotional draining, and social functioning, with each item referring to the last 4 weeks period of the life of the individual.⁹

By a factor analysis and as suggested by Andersen et al. (2007),¹⁰ we calculated two indicators of general health, the Mental Component Summary (MCS) and the Physical Component Summary (PCS) scales (Ware, Kosinski, and Dewey 2000). They take values from 0 to 100, with mean 50 and standard deviation 10 in the 2004 SOEP sample. Higher scores indicate better health. The two variables were proved to be valid and reliable measures of the current general health status compared to other scales (Gill et al. 2007) and are widely used in the economic and psychological literature (Marcus 2013; Neubert et al. 2019; Schmitz 2011; Stauder 2019).¹¹

Table 2 reports their summary statistics and Figure A.1 in the Online Appendix plots the density distributions of the outcome variables distinguishing between treated and control units. On average, the treated individuals reported worse mental and physical health conditions. Whereas the difference in mental health is very tiny, it is substantial in terms of physical health, with the treated having a lower physical health of almost one third of the standard deviation.

9 Table D.1 in the Online Appendix presents a facsimile of the questionnaire. From the psychological side, respondents were asked how often in the last four weeks felt rushed, in low spirits, melancholy, calm, balanced and full of energy and if, due to psychological problems, work, everyday activities and social contacts were restricted. About their physical health, respondents were questioned about suffering physical pain, difficulties in climbing stairs and performing strenuous activities and their impact on work and everyday activities.

10 See also Nübling, Andersen, and Mühlbacher (2006) for the open access SPSS code.

11 There are advantages and disadvantages in compressing the information contained in a number of variables in a single mental or physical health score. A clear disadvantage is that we lose detail. Summarizing multiple variables into a single score can hide distinct aspects of mental and physical health that may be worth investigating. However, especially if one is interested in evaluating the impact on general health, rather than specific health conditions or symptoms, using summary scores generally makes interpretation easier and more intuitive. Moreover, without the need to interpret numerous individual health measures, it is of help in comparing different groups or populations, facilitating policy discussions.

Table 2: Summary statistics of the MCS and PCS indicators standardized to have mean 0 and standard deviation of 1.

Variables	Treated					Controls				
	Obs.	Mean	σ	Min.	Max.	Obs.	Mean	σ	Min.	Max.
MCS	208	-0.080	0.846	-2.258	1.729	4,614	-0.041	1.003	-4.867	2.357
PCS	208	-0.322	1.039	-3.303	1.877	4,614	0.013	0.965	-5.017	2.606

Source: German Socio-Economic Panel version 36 (SOEP-Core v36, EU edition).

Our health variables and the life satisfaction used by Nikolova and Nikolaev (2021) are positively correlated.¹² This and the figures in Table 2 suggest that previous findings by Nikolova and Nikolaev (2021) on life satisfaction may be the consequence of both a physical and a psychological scar.¹³ On top of the speculation in Nikolova and Nikolaev (2021) for their findings, which was based on parental unemployment generating a psychological trauma, it may be that the treated individuals engaged in risky behaviors later in life, like smoking or drinking, which in turn impaired their physical health, leading to a decreased level of life satisfaction. One of the contributions of our analysis is that it sheds light into the mediating channels possibly explaining the findings about life satisfaction in Nikolova and Nikolaev (2021).

3.3 Control Variables

Following previous studies on parental unemployment effects on individuals' outcomes (see e.g. Bratberg, Nilsen, and Vaage 2008; Ekhaugen 2009; Oreopoulos, Page, and Stevens 2008; Siedler 2011), we included a large set of individual and family socio-economic characteristics. The individual characteristics were gender, age, migration background and whether the individual was the first-born child in his/her household. We also included number of siblings when the individual was born and three sets of dummy variables for the survey in which the individual was interviewed, the year of birth and the region of Germany where the individual was born. This set of variables allowed to control for time and spatial heterogeneity. The family characteristics were the age that the parent had when the child was born, the parental migration background, the highest educational level achieved

¹² The correlation between MCS (PCS) and life satisfaction is 0.431 (0.179).

¹³ The correlation levels are in line with other previous studies. For instance, using SOEP data, Marcus (2013) found that the ρ between mental health and life satisfaction was equal to 0.4.

by parents, the cumulative unemployment experience of parents and the income quintile in which the household found itself (Bratberg, Nilsen, and Vaage 2008), measured when the individual was born. We included the household income variable in order to separate the potential poverty component from the parental unemployment effect (Siedler 2011). Furthermore, we controlled for local labor market conditions at the time of the eventual treatment by using the average unemployment rate at länder level.¹⁴ Finally, we included missing indicators for each of the aforementioned variables in order to save observations and avoid losing statistical power. Tables containing summary statistics of the control variables are in Online Appendix A.

We did not control for contemporaneous characteristics because their realization may be the consequence of the treatment and be therefore themselves outcome variables, i.e. “bad controls” (Angrist and Pischke 2009, p. 64). For example, the educational level that an individual achieves may be causally impacted by past parental unemployment. Education is linked with earnings and income which, in turn, are used to buy health goods and improve the health condition (Grossman 1972, 2000; Mincer 1974).

3.4 Identification Strategy

Identifying the causal effect of parental unemployment on children’s health later in life may be tricky due to omitted variables (Brand 2015; Farré, Fasani, and Mueller 2018; Kassenboehmer and Haisken-DeNew 2009). In our framework, omitted variables are those unobservables which are jointly correlated with the likelihood of parental unemployment and children’s health later in life, for example family and social background, predetermined and innate offspring’s health conditions and household wealth. We tackled this endogeneity concern by using plant closures as the reason for unemployment entry. Plant closures may be regarded as a quasi-experimental variation of the individual labor market condition (Brand 2015). However, this assumption has been questioned (see e.g. Hilger 2016). A plant closure rarely happens overnight. Typically, a public announcement is made in advance. The time interval between the announcement and the shutdown may represent a ‘breeding ground’ for a selectivity bias to arise (Suppa 2021). Those workers who are more likely to find a new job elsewhere may anticipate the plant closure, look for a new job before the plant closure and avoid the transition into unemployment. Those who do not anticipate the plant closure and/or are not able to find a new job before the layoff experience transit to unemployment. Therefore, they may not be

¹⁴ Data come from Federal Employment Agency statistics. We took the average for the whole treatment period.

a random sample from the workforce and they may be endowed with labor market characteristics that are systematically different from those of individuals at work. We tried to limit these concerns about the exogeneity of plant closures by including in our empirical model a rich set of control variables predetermined with respect to the treatment (e.g. parental migration background, parental education, parental cumulative unemployment and lagged parental job loss expectations)¹⁵ As the question was asked biennially, missing indicators were used when this information was unavailable to mitigate potential non-random attrition bias due to non-response (Nikolova and Ayhan 2019). And by checking whether the estimated parental unemployment effect changed across the various model specifications (Marcus 2013; Nikolova and Ayhan 2019; Nikolova and Nikolaev 2021).

We observed the treatment and the outcomes in two different moments. The outcome variables were observed multiple times when the individuals were adults, between 18 and 31 years of age, while the treatment was observed when they were children, between 0 and 15 years old.¹⁶ For individual i at time t , the health outcome variable y_{it} is specified as follows:

$$y_{it} = \delta U_i + \beta \mathbf{X}_{it} + \alpha_i + \varepsilon_{it}, \quad (1)$$

where U_i is the binary indicator for parental unemployment, \mathbf{X}_{it} is a vector of individual and family controls and α_i and ε_{it} are the error term components.¹⁷ Because parental unemployment is time invariant with respect to the outcome, we could not include fixed-effects; α_i is therefore assumed to be a random effect, uncorrelated with the covariates and with the treatment.¹⁸

15 The job loss expectation variable measures parents' expectations regarding job loss over the next two years. It is derived from a survey question that asks respondents to estimate the likelihood of losing their job within this time frame. Before 1994, respondents could choose from four options: (1) 'absolutely', (2) 'probably', (3) 'rather unlikely', and (4) 'absolutely not'. Since 1995, respondents have been able to choose from ten options, each representing a ten-percent probability of job loss (e.g., 0 for 0 %, 10 for 10 %, 20 for 20 %, and so on). We constructed our job loss indicator as a categorical variable, maintaining the range of 1–4 used before 1995. To ensure comparability between responses before and after 1994, we assigned a value of 1 to respondents who reported a '100 % probability' of losing their job, 2 (or 3) for those expecting a 10–50 % (or 60 %–90 %) probability of job loss, and 4 for those expecting no chance of job dismissal. We took the lagged value of the job loss indicator in order to measure the parental expectations in the year before the child's birth.

16 In a sensitivity analysis, which we present in the Online Appendix in Table C.3, we used only one observation per individual after taking the within-individual average over time of the outcome variables.

17 Although \mathbf{X}_{it} is indexed by t , all the covariates are either predetermined with respect to the treatment, and therefore constant over t , or they change over t following an exogenous path, like age.

18 As a sensitivity check, we also estimated the model by pooled ordinary least squares (OLS), which does not impose a particular error structure in Equation (1) and is therefore more robust,

Equation (1) imposes a particular parametric structure to the conditional mean of the dependent variable. The estimates of the treatment effect using Equation (1), for instance by Generalized Least Squares (GLS), may be biased if the functional relationship with the control variables is misspecified or if there are areas outside of common support which require extrapolation (Ho et al. 2007; Peter 2016). In order to reduce biases due to model dependence, we followed Ho et al. (2007); Hainmueller (2012); Gambaro, Marcus, and Peter (2019) and combined matching methods and standard outcome regression. More in detail, it consists in preprocessing the data over a set of observed confounders using matching methods so that the relationship between U_i and \mathbf{X}_{it} is eliminated or reduced. Thereafter, standard outcome regression techniques for modeling the conditional mean of the dependent variable are applied on the preprocessed sample. The matching part, by covariate balancing, is meant to reduce the risk of model dependence in the subsequent parametric estimation step, while the outcome regression to model the conditional mean of the dependent variable is meant to address the potentially leftover sample imbalance (Gambaro, Marcus, and Peter 2019; Ho et al. 2007).

In the matching step, we used entropy balancing (EB) (Hainmueller 2012). EB increases the balancing properties of the sample by reweighting the control units in a such way that the joint distribution satisfies some pre-specified moments conditions. The selected weights minimize an entropy distance metric on a r -dimensional set of constraints. We followed Marcus (2013) and imposed the conditions on the first and second moments of the full set of pre-treatment variables.¹⁹ Table 3 reports the gains in balance for the mean of each covariate. Table B.1 in the Online Appendix instead shows the gains in balance for the variance. The balancing properties improved remarkably. Before matching, significant differences were observed between treated and control individuals in terms of the means of family socio-economic characteristics at the time of birth. Treated individuals were more likely than their control counterparts to be born into households with younger, less educated parents and limited financial resources. These differences were statistically significant at the 1% level. However, after matching, the socio-economic profiles of the treated and control groups became very comparable. The biases, i.e. the standardized differences of the mean and the variance between treated and controls, were importantly reduced for every covariate. Further, each difference in the

although less efficient. We found very similar point estimates and standard errors that were twice as large as those obtained with random effects. POLS estimates are not reported. They are available from the authors upon request.

¹⁹ As a sensitivity analysis, we replaced EB with inverse probability weighting, finding very similar point estimates, but larger standard errors. Table C.1 in the Online Appendix reports inverse probability weighting estimates.

Table 3: Pre- and post-matching bias on the mean.

Variables	Pre-matching			Post-matching				
	Mean treated	Mean controls	Difference	Bias	Mean treated	Mean controls	Difference	Bias
<i>Individual characteristics</i>								
Age	21.207	21.334	0.127	0.599 %	21.207	21.173	0.034	0.160 %
Sex (1 if female)	0.663	0.485	0.178***	26.848 %	0.663	0.662	0.001	0.151 %
Migration background	0.255	0.218	0.037	14.510 %	0.255	0.255	0.000	0.000 %
Firstborn:								
Missing	0.096	0.100	0.004	4.167 %	0.096	0.096	0.000	0.000 %
Yes	0.336	0.381	0.045	13.393 %	0.336	0.336	0.000	0.000 %
Number of siblings	0.293	0.170	0.123***	41.979 %	0.293	0.296	0.003	1.024 %
Region of Germany where child was born/grew:								
East Germany	0.519	0.180	0.339***	65.318 %	0.519	0.516	0.003	0.578 %
West Germany	0.481	0.819	0.338***	70.270 %	0.481	0.483	0.002	0.416 %
<i>Maternal characteristics</i>								
Age when child was born:								
Missing	0.000	0.000	0.000		0.000	0.000	0.000	
20 years old or less	0.120	0.052	0.068***	56.667 %	0.120	0.120	0.000	0.000 %
21–25 years old	0.418	0.273	0.145***	34.689 %	0.418	0.415	0.003	0.718 %
26–30 years old	0.327	0.382	0.055	16.820 %	0.327	0.327	0.000	0.000 %
31–35 years old	0.072	0.225	0.153***	212.500 %	0.072	0.073	0.001	1.389 %
36–40 years old	0.062	0.058	0.004	6.452 %	0.062	0.064	0.002	3.226 %

Table 3: (continued).

Variables	Pre-matching			Post-matching			
	Mean treated	Mean controls	Difference	Mean treated	Mean controls	Difference	Bias
41 years old or more	0.000	0.009	0.000	0.000	0.000	0.000	
Migration background	0.250	0.185	0.065**	0.250	0.250	0.000	0.000 %
Educational level achieved:							
Missing	0.000	0.003	0.003	0.000	0.000	0.000	
Less than HS	0.139	0.111	0.028	0.139	0.141	0.002	1.439 %
High school diploma	0.687	0.642	0.045	0.687	0.683	0.004	0.582 %
More than HS	0.173	0.243	0.070**	0.173	0.176	0.003	1.734 %
Cumulative unemployment experience when child was born:							
Missing	0.678	0.641	0.037	0.678	0.675	0.003	0.442 %
Unemployment experience	0.076	0.094	0.018	0.076	0.076	0.000	0.000 %
<i>Paternal characteristics</i>							
Age when child was born:							
20 years old or less	0.034	0.017	0.017*	0.034	0.034	0.000	0.000 %
21–25 years old	0.370	0.144	0.226***	0.370	0.367	0.003	0.811 %
26–30 years old	0.317	0.360	0.043	0.317	0.317	0.000	0.000 %
31–35 years old	0.139	0.314	0.175***	0.139	0.140	0.001	0.719 %
36–40 years old	0.086	0.114	0.028	0.086	0.087	0.001	1.163 %
41 years old or more	0.053	0.051	0.002	0.053	0.055	0.002	3.774 %
Migration background	0.250	0.176	0.074***	0.250	0.250	0.000	0.000 %

Table 3: (continued).

Variables	Pre-matching			Post-matching				
	Mean treated	Mean controls	Difference	Bias	Mean treated	Mean controls	Difference	Bias
Educational level achieved:								
Missing	0.000	0.001	0.001		0.000	0.000	0.000	
Less than HS	0.115	0.049	0.066***	57.391 %	0.115	0.116	0.001	0.870 %
High school diploma	0.880	0.676	0.204***	23.182 %	0.880	0.871	0.009	1.023 %
More than HS	0.005	0.273	0.268***	5,360.000 %	0.005	0.013	0.008	160.000 %
Cumulative unemployment experience when child was born:								
Missing	0.678	0.646	0.032	4.720 %	0.678	0.675	0.003	0.442 %
Unemployment experience	0.093	0.103	0.010	10.753 %	0.093	0.094	0.001	1.075 %
<i>Household characteristics</i>								
HH income quintile when child was born:								
Missing	0.726	0.640	0.086**	11.846 %	0.726	0.722	0.004	0.551 %
1st quintile	0.111	0.079	0.032*	28.829 %	0.111	0.111	0.000	0.000 %
2nd quintile	0.144	0.109	0.035	24.306 %	0.144	0.143	0.001	0.694 %
3rd quintile	0.005	0.104	0.099***	1,980.000 %	0.005	0.007	0.002	40.000 %
4th quintile	0.014	0.049	0.035**	250.000 %	0.014	0.015	0.001	7.143 %
5th quintile	0.000	0.018	0.018		0.000	0.001	0.001	

Source: German Socio-Economic Panel version 36 (SOEP-Core v36, EU edition). Notes: *Significant at 10 %, **significant at 5 % and ***significant at 1 %. The various länders are grouped in two macro-areas. 'East Germany' includes Brandenburg, Mecklenburg-Vorpommern, Sachsen, Sachsen-Anhalt and Thüringen. 'West Germany' includes Schleswig-Holstein, Hamburg, Niedersachsen, Bremen, Nordrhein-Westfalen, Hessen, Rheinland-Pfalz, Bayern, Baden-Wuerttemberg, Saarland and Berlin.

means of family socio-economic characteristics became statistically insignificant after matching.

Finally, we computed the Average Treatment Effect on the Treated (ATT) by estimating Equation (1) using the EB weights. To account for within-individual correlation, we estimated standard errors using Liang and Zeger's (1986) cluster-robust variance estimator.

4 Results

4.1 Main Findings

The main findings are reported in Table 4. Its column (1) reports the results for the baseline specification. It includes the set of pre-treatment characteristics used in the EB matching plus the controls for the local unemployment rates and the sets of dummy variables for the year when the individual was interviewed and born. Local unemployment rates are meant to control for the precariousness in the labor market at the period of when the treatment occurred. The survey year and the year of birth are meant to control for potential unobserved heterogeneity at time level, at both the childhood and the adulthood periods. Column (2) extends the baseline specification by adding other predetermined family characteristics, measured when the child was born, in order to reduce the risk of possible omitted variables bias: household size and house size in squared meters. Finally, column (3) includes the lagged parental job loss expectation. Being the richest specification in terms of predetermined covariates, column (3) is our preferred specification.

We found very similar results across the three different specifications, with parental unemployment affecting differently mental and physical health. On the one hand, mental health is positively but not significantly affected by parental unemployment. On the other hand, physical health is negatively and significantly reduced by treatment: those individuals who experienced parental unemployment in their childhood have a lower physical health of approximately 26 % of their standard deviation.

Our findings may be the result of different mechanisms that occurred during individuals' lives. The small and insignificant effect on mental health may be the consequence of a 'normalization' process that the laid-off parent operated over his/her unemployment condition (Georgellis et al. 2008; Thill, Houssemand, and Pignault 2019). Individuals often use coping strategies to overcome stressful situations (Ashforth and Kreiner 2002). A laid-off parent might have justified his/her condition by pointing to the impossibility of preventing an event that was out of his/her control, like a plant closure (Pignault and Houssemand 2017, 2018). Moreover, when generalized precarious conditions occur, people suffer less from their own misery

Table 4: Parental unemployment effects: main estimation results.

Outcome	Sample size	Baseline specification (1)		With further family characteristics, not including parental job loss expectations (2)		With further family characteristics, also including parental job loss expectation (3)	
		ATT	R ²	ATT	R ²	ATT	R ²
MCS	4,822	0.018 (0.038)	0.155	0.023 (0.038)	0.159	0.052 (0.039)	0.162
PCS	4,822	-0.252*** (0.036)	0.162	-0.246*** (0.036)	0.167	-0.267*** (0.037)	0.168

Source: German Socio-Economic Panel version 36 (SOEP-Core v36, EU edition). Notes: * Significant at 10 %, ** significant at 5 % and *** significant at 1 %. Clustered standard errors at the individual level are reported in parentheses. Dependent variables are expressed as standardized scores. The baseline specification (column (1)) includes the following controls: individual age, gender, individual migration background, whether the individual is the first born child, average number of siblings, länder in which the individual was born, year of birth, survey year, paternal age when the child was born, paternal migration background, achieved paternal educational level achieved, achieved paternal cumulative unemployment, maternal age when the child was born, maternal migration background, maternal educational level achieved, maternal cumulative unemployment, average household income quintile and local unemployment rates during the treatment period. Column (2) adds to the previous specification household size and house size in squared meters at individual's birth. In column (3) also the parental job loss expectation when the child was born is included.

because it is becoming the prevailing social norm (Clark 2003, 2006; Clark, Knabe, and Rätzel 2009; Stavrova, Schlösser, and Fetchenhauer 2011). Normalizing his/her own unemployment might prevent displaced parents from developing anxiety or depression disorders, which are likely to affect offspring's well-being. The negative effect on physical health may be instead explained by a longer exposure of the child to parental risky behaviors. Laid-off workers are more likely to engage in unhealthy behaviors, like smoking or drinking (Mörk, Sjögren, and Svaleryd 2020; Reine, Novo, and Hammarström 2013; Schunck and Rogge 2010). Children with parents who smoke or consume alcohol are at increased risk of developing health problems while growing (Kuppens et al. 2020; Richter and Richter 2001). If displaced workers are more likely to develop unhealthy habits, then a far-reaching effect of parental unemployment may be the capability of triggering unhealthy behaviors on children, impairing offspring's physical health.

We empirically tested whether parental unemployment may have consequences on children's physical health later in life by increasing their probability of engaging in risky behaviors or incurring in unhealthy physical behaviors or diet. More in detail, we examined the impact of parental unemployment on child alcohol and tobacco consumption, as proxies of risky behaviors, and obesity when adult, as potentially correlated to physical activity and diet. We coded alcohol consumption as a dummy indicator equal to 1 if the individual had a moderate/severe level of alcohol intakes.²⁰ Tobacco consumption was defined by using a binary indicator which took value 1 if the individual reported to be a smoker at the time of the interview and 0 otherwise. Finally, obesity was defined using a binary indicator which took the value 1 if the individual reported a BMI score equal to or greater than 30, and 0 otherwise. We estimated three linear probability random-effect models for these three binary variables. Table 5 reports the results.

We found that parental unemployment increases the probability of engaging in risky behaviors later in life. Treated individuals are more likely to consume alcohol and tobacco. Individuals who experienced parental unemployment due to plant closure are, compared to their control peers, 6.6 and 12.3 percentage points more likely to frequently consume alcohol and to smoke, respectively. These findings are in line with those in Ermisch, Francesconi, and Pevalin (2004), who found that parental joblessness increases the likelihood of both smoking and experiencing greater distress later in life. Furthermore, the treated are also more prone to obesity (+5 percentage

²⁰ SOEP has four questions, each of which refers to a different type of drink (i.e. beer, wine, spirits and cocktails). The questions ask how often the interviewee consumes that specific alcoholic beverage. Four options are available: never, rarely, once in a while and often. We assigned value 1 to 'never' and 4 to 'often'. We defined an individual as having a moderate/severe level of alcohol intake if the sum of the four scales was equal to or greater than 10.

Table 5: Mediating channels estimation results.

Dependent variables:	Moderate/severe alcohol consumption (1)			Being a smoker (2)			Obesity (BMI \geq 30) (3)		
	<i>n</i>	ATT	<i>R</i> ²	<i>n</i>	ATT	<i>R</i> ²	<i>n</i>	ATT	<i>R</i> ²
Parental unemployment	1,732	0.066*** (0.026)	0.174	4,819	0.123*** (0.018)	0.255	4,740	0.050*** (0.010)	0.183

Source: German Socio-Economic Panel version 36 (SOEP-Core v36, EU edition). *Notes:* *Significant at 10 %, **significant at 5 % and ***significant at 1 %. Clustered standard errors at the individual level are reported in parentheses. Model specification for each outcome variable and each treatment interval is the same as in column (3) of Table 4. Observations are lower in model (1) because SOEP interviewees were asked about their alcohol consumption only in the 2006, 2008 and 2010 waves. The number of treated observations is 110 in model (1) and 208 in models (2) and (3). The outcome average of the treated observations is 0.254 in model (1), 0.413 in model (2) and 0.067 in model (3).

points). These estimates are substantial when compared to the baseline prevalence of alcohol consumption, smoking, and obesity among the treated group, which are 25.4 %, 41.3 %, and 6.7 %, respectively.²¹ However, these estimates should be interpreted with caution, as they may be subject to omitted variable bias due to our limited ability to control for parental risk factors.

4.2 Heterogeneity Analysis

Cunha and Heckman (2007) argued that parental investments are not equally effective at any point in childhood for the human capital formation process. Childhood is a complex and heterogeneous moment in the lives of individuals. It is made up of many different stages, with different impacts in human development. Because parental inputs are transformed in human capital and since human capital tends to both accumulate over time and increase in efficiency, investments made in the early periods of childhood may generate higher returns compared to those made later. In the same spirit, setbacks suffered in the early periods of the childhood may generate greater losses in the future. Following these ideas, we checked whether parental unemployment exerts different effects on the human capital of individuals depending on the timing of its occurrence. We interacted the treatment indicator with the indicator which divides the sample into those who experienced parental

²¹ For the treated, parental unemployment is associated with a 26 % increase in the likelihood of alcohol consumption, a 30 % increase in the likelihood of smoking, and a 75 % increase in the likelihood of obesity.

Table 6: Parental unemployment effects with treatment at different ages.

Dependent variables:	MCS (1)			PCS (2)		
	<i>n</i>	ATT	<i>R</i> ²	<i>n</i>	ATT	<i>R</i> ²
Parental unemployment at 0–8 years of age	4,822	0.107** (0.053)	0.163	4,822	−0.111** (0.049)	0.167
Parental unemployment at 9–15 years of age		0.029 (0.047)			−0.301*** (0.045)	
Test for equality of coefficients, <i>p</i> -value	0.235			0.002		

Source: German Socio-Economic Panel version 36 (SOEP-Core v36, EU edition). *Notes:* * Significant at 10 %, ** significant at 5 % and *** significant at 1 %. Clustered standard errors at the individual level are reported in parentheses. Dependent variables are expressed as standardized scores. Model specification includes both jointly. Model specification is the same as in column (3) of Table 4. The number of treated observations is 100 at 0–8 years of age and 112 at 9–15 years of age.

unemployment during the pre-pubescent period (0–8 years of age) and those who suffered it subsequently and we re-estimated the model. Table 6 reports the results. On the one hand, we found that there is a positive effect on mental health if parental unemployment occurred in earlier years. The positive effect may originate from the positive elements of the unemployed condition, such as the increase in leisure time that parents can use in a more intensive parenting activity with their own children (Doepke, Sorrenti, and Zilibotti 2019; Knabe et al. 2010). On the other hand, we found that parental unemployment due to plant closure remains negatively and significantly related to physical health regardless of the childhood period when it occurred. However, the effect is not evenly distributed across periods. It is significantly stronger if parental unemployment occurred in the later years (9–15 years old) compared to the earlier years (0–8 years old). This piece of evidence is in contrast to the idea proposed by Cunha and Heckman (2007), for which setbacks in early childhood periods may generate greater losses later in life. Nonetheless, this may be attributable to the fact that parental unemployment experienced between the ages of 9 and 15 occurred closer in time to the observation of health outcomes, allowing less time for its effects to fade away.

Parental unemployment may exert different effects according to the gender of the parent or the child. We followed the previous empirical literature and tested this hypothesis in our sample (Briody 2021; Haisken-DeNew and Kind 2012; Nikolova and Nikolaev 2021; Pieters and Rawlings 2020; Powdthavee and Verhoit 2013). First, we decomposed the treatment distinguishing between maternal and paternal unemployment. Second, we did it according to the gender of the child. Tables 7 and 8

Table 7: Maternal and paternal unemployment effects at comparison.

Dependent variables:	MCS (1)			PCS (2)		
	<i>n</i>	ATT	<i>R</i> ²	<i>n</i>	ATT	<i>R</i> ²
Maternal unemployment	4,822	0.000 (0.048)	0.163	4,822	-0.225*** (0.045)	0.167
Paternal unemployment		0.059 (0.051)			-0.257*** (0.049)	
Test for equality of coefficients, <i>p</i> -value	0.385			0.621		

Source: German Socio-Economic Panel version 36 (SOEP-Core v36, EU edition). *Notes:* *Significant at 10 %, **significant at 5 % and ***significant at 1 %. Clustered standard errors at the individual level are reported in parentheses. Dependent variables are expressed as standardized scores we split plant closure treatment into two: maternal and paternal. Model specification includes both jointly. Model specification is the same as in column (3) of Table 4. The number of maternal (paternal) unemployment observations is 129 (88). The number of observations that jointly reports maternal and paternal unemployment is 9.

Table 8: Parental unemployment effects on daughters and sons.

Dependent variables:	MCS (1)			PCS (2)		
	<i>n</i>	ATT	<i>R</i> ²	<i>n</i>	ATT	<i>R</i> ²
Parental unemployment on daughters	4,822	0.061 (0.049)	0.162	4,822	-0.376*** (0.046)	0.172
Parental unemployment on sons		0.035 (0.068)			-0.059 (0.064)	
Test for equality of coefficients, <i>p</i> -value	0.765			0.000		

Source: German Socio-Economic Panel version 36 (SOEP-Core v36, EU edition). *Notes:* *Significant at 10 %, **significant at 5 % and ***significant at 1 %. Clustered standard errors at the individual level are reported in parentheses. Dependent variables are expressed as standardized scores. We split the plant closure treatment in two: maternal and paternal. Model specification includes both jointly. Model specification is the same as in column (3) of Table 4. The number of treated observations is 138 for daughters and 70 for sons.

report the findings. The estimates for both mental health in model (1) and physical health in model (2) of Table 7 suggest that the effect does not dependent on whether it is the mother or the father to experience the dismissal due to plant closure. By splitting the sample according to the gender of child, we found that daughters suffered from parental unemployment in terms of physical health, whereas sons remain generally unaffected. This piece of evidence is in contrast to previous empirical literature, which instead found that sons suffered the most from the

negative dynamics of the parents' labor market (Haisken-DeNew and Kind 2012; Nikolova and Nikolaev 2021). However, this literature focused on life satisfaction, while our article focuses on mental and physical health. In addition, we speculate that the differential effect of parental job loss on daughters may be due to sons and daughters having different mechanisms to cope with family stressors. In fact, women can internalize and ruminate more (Johnson and Whisman 2013) and can take on more care-giving roles, leading to larger physical strain, fatigue and somatic complaints.

Next, we assessed if the effects of parental unemployment depended on the status of the labor market in the year of job loss. More in detail, we estimated the treatment effect by distinguishing those who were affected by parental unemployment before and after 2003. The choice of the 2003 cutoff is related to important changes in the German labor market occurring between 2003 and 2005, when employment services were restructured, temporary employment was made more attractive, the duration of unemployment benefit for the elderly was lowered and activation schemes were planned for all welfare recipients considered able to work (Rinne and Schneider 2017). After these reforms, the unemployment rate steadily decreased. Given the institutional changes in the labor market and its improved shape after these reforms, also the consequences of an unemployment event may have mutated, becoming less important after the reforms because the labor market has become more flexible, with shorter unemployment duration and higher tightness. Table 9 shows the results: the negative effect of parental unemployment on the physical health of their offspring is due to those parental unemployment events experienced in a difficult time for the German labor market. However, given that we

Table 9: Parental unemployment effects on individuals before (after) the German labor market reform.

	MCS (1)			PCS (2)		
	<i>n</i>	ATT	<i>R</i> ²	<i>n</i>	ATT	<i>R</i> ²
Parental unemployment in pre-reform period	4,822	0.083* (0.045)	0.162	4,822	-0.331*** (0.042)	0.171
Parental unemployment in post-reform period		-0.033 (0.074)			-0.082 (0.071)	
Test for equality of coefficients, <i>p</i> -value	0.180			0.003		

Source: German Socio-Economic Panel version 36 (SOEP-Core v36, EU edition). *Notes:* * Significant at 10 %, ** significant at 5 % and *** significant at 1 %. Clustered standard errors at the individual level are reported in parentheses. Dependent variables are expressed as standardized scores. Model specification is the same as in column (3) of Table 4. The number of treated observations in pre-reform period is 169 and 39 in post-reform period.

observe only 39 individuals who experienced a parental unemployment event after 2003, the heterogeneity results in Table 9 must be taken with caution as affected by low statistical power.

Finally, we checked if parental unemployment differently affected individuals depending on whether they were from East or West Germany. Regional differences between East and West Germany due to different historical, economic, institutional and labor market backgrounds may translate into different reactions to and consequences of a job displacement, with differential impacts on children. For example, women in East Germany might be more hurt by unemployment than women in West Germany because historically they were more attached to employment (Kassenboehmer and Haisken-DeNew 2009). We distinguished the treatment indicator between parents who were living in West Germany and those who were residing in East Germany at the time in which the individual was born²² and we redid the main analysis. Table 10 shows the estimated parental unemployment for East and West Germany. Although the negative effect of parental unemployment on physical health does not depend on the region of origin, the impact on mental health was nil in East Germany and significantly positive in West Germany. The positive effect on mental health in West Germany may be due to positive factors of parental unemployment, such as the increase in the amount of leisure time to be spent with children (Knabe et al. 2010) and the development of soft skills, like resilience (Masten and Narayan 2012; Masten and Palmer 2019), dominating negative ones, such as the higher chances of incurring economic and emotional deprivation (Jahoda 1982; Janlert and Hammarström 2009) and emotional distress leading to family breaks (Di Nallo et al. 2022; Eliason 2012; Jensen and Smith 1990; Marcus 2013; Mörk, Sjögren, and Svaleryd 2020). This dominance is more likely in West Germany than in East Germany, because in West Germany the attachment to employment was historically lower and the wealth of the household was higher than in East Germany.

4.3 Sensitivity Analysis

We performed a series of sensitivity checks to verify the robustness of our baseline findings. The corresponding results are reported in Online Appendix C.

First, we tested the robustness of the EB weighting scheme by re-estimating the model by inverse probability weighting (IPW). IPW assigns to each control

²² If the area of residence of parents at the time the individual was born was missing because parents were not interviewed in that year, we used the next available information about area of residence.

Table 10: Parental unemployment effects in East and West Germany.

Dependent variables:	MCS (1)			PCS (2)		
	<i>n</i>	ATT	<i>R</i> ²	<i>n</i>	ATT	<i>R</i> ²
Parental unemployment in East Germany	4,822	−0.009 (0.057)	0.162	4,822	−0.317*** (0.053)	0.169
Parental unemployment in West Germany		0.107** (0.054)			−0.220*** (0.052)	
Test for equality of coefficients, <i>p</i> -value	0.144			0.198		

Source: German Socio-Economic Panel version 36 (SOEP-Core v36, EU edition). *Notes:* *Significant at 10 %, **significant at 5 % and ***significant at 1 %. Clustered standard errors at the individual level are reported in parentheses. The model specification is the same as in column (3) of Table 4. The number of treated observations is 108 in East Germany and 100 in West Germany.

unit a normalized weight equal to $\frac{P(X_i)}{1-P(X_i)} / \bar{\pi}_0$, where $P(X_i)$ is the predicted probability of being treated and $\bar{\pi}_0$ is the average of $\frac{P(X_i)}{1-P(X_i)}$ for the controls. Treated units are instead assigned weights equal to 1. Then, the outcome equation is estimated by weighted least squares using the square root of the normalized weights. Table C.1 reports regression adjusted estimated effects for IPW. Using IPW instead of EB weighting did not lead to relevant changes. The estimated effects are indeed very similar to the benchmark ones. The only difference is in the precision, which is reduced when using IPW.

Second, we tested whether our results were sensitive in magnitude and significance to the sample size of the treated group. Table 2 showed that the number of treated units is not very large. We replicated the analysis nine times by removing each time one of the survey waves from the sample. In a particular wave, answers given by respondents about their health may be affected by something exceptional that took place in that year. By excluding one wave from the dataset at a time and re-estimating the model with the remaining data and by doing so for each wave, we can evaluate how much the estimated effects change when each wave is excluded. We can therefore verify that our findings are not driven by specific peculiarities in some waves and that they are not too sensitive to observations of any single wave. Table C.2 reports the results, which are in line with the baseline findings.

Third, in our sample, the health outcomes are observed multiple times for each individual and each individual enters the dataset as many times as the times we observe her/his health between 18 and 31 years of age. We reestimated the parental unemployment effect using as outcome variable the within-individual average of

the health outcome. We therefore collapsed the sample to one observation per individual. Table C.3 reports the results and shows that they are very similar to the benchmark estimates.

Fourth, we assessed whether the effects of parental unemployment depend on the cohorts of birth. If these effects are heterogeneous across cohorts or over years and in each subsample we have a different composition of other observables, we may get biased estimates of the ATT. In fact, this imbalance may affect both the outcomes and the impact that the treatment generates on them. Hence, we estimated the treatment effect by distinguishing it between those born before and after 1991. The choice of the 1991 threshold is suggested by two reasons: first, the German reunification after the fall of the Berlin wall in November 1989; second, the fact that plant closure as a reason for unemployment was collected in the SOEP starting from 1991, which results in an under-representation in our sample of individuals born before 1991 and treated in the first years since childbirth. Table C.4 in the Online Appendix reports these results, which are very similar to the benchmark ones: there is no effect on mental health and there is a negative effect on physical health, independently on being born before or after 1991. The negative effect on physical health is larger in magnitude for those born after 1991. However, the test for equality of coefficients rejected the null hypothesis, suggesting that there may be possible imbalances across cohorts or over years.

Fifth, we tested whether our results may be driven by the presence of individuals born in single-parent households. Typically, single-parent and two-parent households possess different earning capacities. In particular, in case of unemployment, two-parent households may rely on the insurance of the ‘added worker effect’, that is the increase in the labor supply response of one partner to the joblessness condition of the other (Lundberg 1985). This compensation mechanism may make individuals born and grew in two-parent households more resilient to episodes of parental unemployment compared to their single-parent household peers. If the effect of parental unemployment is heterogeneous across the household type, this unbalancedness may have generated bias in our previous results. We re-estimated the parental unemployment effect considering only individuals born in two-parent households.²³ Table C.5 reports the estimated coefficients showing that they are in line with the benchmark estimates.

Finally, we assessed the parental unemployment effect by changing the definition of the treatment and enlarging it to include unemployment events

²³ In our study, single-parent household observations account for less than 9 % of the total sample. In order to provide asymptotically meaningful results, we focused only on observations belonging to the two-parent household group.

due to other reasons for job displacement. By doing so, we increase the external validity in terms of the population to which our results can speak, but we are likely to generate biases because the chances that the treatment indicator is endogenous due to omitted variables are larger. The results are presented in the Online Appendix in Table C.6. On the one hand, the negative effect on physical health is confirmed and it is in line with the one generated by dismissals due to plant shutdown. On the other hand, the relation between parental unemployment and mental health becomes significantly negative.

5 Conclusions

In this paper, we estimated the impact of parental unemployment on children's mental and physical health later in life. We assessed the causal effect of parental unemployment by using plant closures as an exogenous variation of the individual labor market condition (Brand 2015). We combined it with bias-adjusted methods robust to model misspecification to strengthen the causal interpretation of the estimates (Hainmueller 2012; Ho et al. 2007). Information on parental unemployment referred to the period when individuals were children (i.e. 0–15 years old). Information on health outcomes referred to the period when individuals were adults (i.e. 18–31 years old). We used health data from the German Socio-Economic Panel from 2002 until 2018.

We found that parental unemployment exerted mixed effects on individuals' health later in life. On the one hand, mental health was positively but not significantly affected. On the other hand, we found that parental unemployment exerted a negative and significant effect on physical health. The impact was larger if parental unemployment occurred during the late childhood (i.e. between 9 and 15 years of age). This is in contrast to the idea proposed by Cunha and Heckman (2007), for which setbacks in early childhood periods may generate greater losses later in life in terms of human capital accumulation. However, this may be due to the fact that parental unemployment experienced between the ages of 9 and 15 occurred closer in time to the observation of health outcomes, allowing less time for its effects to fade away. We found that the effect was heterogeneous by gender of the child experiencing parental unemployment, with daughters driving our findings. Maternal and paternal unemployment similarly affected mental and physical health. We also found that parental unemployment determined a higher probability of smoking and drinking later in life, which may be some of the mediating channels through which the negative impact on physical health was triggered.

Our findings raise important policy considerations. First, we provided evidence of long-term scarring effects of parental unemployment on children's health. Most

of the previous empirical research discussed only short-term effects, while neglecting possible consequences in the long-run. Policy makers should be aware that parental unemployment generates long-lasting negative effects on physical health and that intervention is needed to alleviate them. Second, because we detected that the effect is driven by daughters, the intervention should be gender-specific. Third, we found that parental unemployment generates higher chances of smoking and drinking later in life. Hence, policy-makers may consider tax increases on alcohol beverages and tobacco in order to discourage people, especially the unemployed, to initiate the consumption since the very beginning (Chaloupka, Grossman, and Saffer 2002; Chaloupka, Straif, and Leon 2011; Elder et al. 2010).

Finally, our results have some limitations and should be qualified for some reasons. First, we studied an intergenerational phenomenon by relying on survey data and self-reported measures of health. In this kind of analysis, administrative records should be preferred, because they are less likely to be plagued by measurement errors and may provide more objective measures of health. Second, even though we exploited an exogenous variation in the individual labor market condition and we used entropy balancing to create balanced weights based on covariates combined with outcome regression to identify the causal effect of the parental unemployment, it could still be possible that there were other confounding unobserved components, which may undermine the reliability of our results. Third, studying the long-term consequences of parental unemployment experienced during childhood on health outcomes during adulthood is demanding in terms of number of observations for a survey data, because an individual should be observed both during her/his childhood and during her/his adulthood. This resulted in a large loss of observations, in a reduction in the representativeness of the final sample and in a loss of statistical power of the empirical analysis.

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