Childhood Mental Health Effects of Early-Life Exposure to Paternal Job Loss[*]

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Abstract

We study the mental health effects of early life exposure to paternal job loss. Using nationwide individual-level administrative registry records, we focus on firm-closure-induced job losses for fathers with children below age five in the Netherlands. These children are more likely to take mental health-related medicines in their later childhood, and this increase is mainly driven by psychostimulant drugs. The increased uptake of psychostimulants ranges from 15 percent of mean uptake in the control group at age five to around 9 percent at age twelve. The effects are significantly larger for families with mothers being the main breadwinner. We further find that the father is more likely to take mental health medication around the time of job loss, and that the children exposed to paternal job loss are more likely to live in dissolved families. We find no evidence of exposed children living in neighborhoods with different rates of psychostimulants consumption compared to control children, while parents of exposed children do report more impulsive and inattentive behavior. These findings indicate that family environment changes such as family dissolution and paternal mental distress are the most likely pathways leading to higher mental health medication usage among children exposed to early-life paternal job loss.

[*]This project has used data provided by Statistics Netherlands via a remote access facility. As stipulated in the data agreement, Statistics Netherlands previewed the findings of this project prior to publication to ensure that privacy sensitive, individual-specific information was not revealed. The data from this study can only be applied for through a government data sharing portal of Statistics Netherlands. Part of the work was undertaken while Tom Van Ourti was a visiting researcher at the Milken Institute School of Public Health of the George Washington University. The authors would like to thank Janet Currie, Max van Lent, Julia Schmieder, Kelli Marquardt, Alexandra Roulet, Uta Schönberg; and participants of the ASHEcon conference, Essen Economics of Mental Health Workshop, Barcelona GSE Summer Forum, Essen Health Conference, AES-APES Virtual Early Career Researchers Seminar Series (VECR) for useful comments and suggestions. We have no conflicts of interest to disclose, and all errors are our own.

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1 Introduction

Job loss has adverse consequences on the displaced individuals, including short- and long-term income reductions, physical and mental health problems and higher mortality rates. Partners of the displaced employees are also affected: couples are more likely to dissolve, and partners face mental and physical health problems.[1] The combination of these adverse consequences on the dismissed employees and their partners with the importance of early-life shocks for long-term individual outcomes (Currie and Almond, 2011; Almond et al., 2018), raises the important question whether and why children of dismissed parents face adverse consequences. In this paper, we study the effects and underlying mechanisms of early-life exposure to paternal job loss on later childhood mental health.[2]

Childhood mental health problems are common. Half of the individuals with mental disorders, first develop symptoms when they are below age 14 (Kessler et al., 2007). Childhood mental health also matters for future outcomes. It is more predictive than physical health in explaining long-term outcomes such as educational attainment or welfare programs dependency (Currie and Stabile (2006, 2007); Currie et al. (2010)). It is also correlated with later adverse behaviors such as crime commission, drug dependency, and teenage pregnancy (Layard, 2013).

In this study, we use rich Dutch administrative data on firm-closure-induced job losses between 2002 and 2012. This comprehensive dataset allows detecting all plant closures and their induced job losses. Comparing children exposed to an exogenous paternal job loss before age five with children whose fathers work in stable firms when they are below age five, controlling for a series of child and parent characteristics, contract and plant characteristics as well as socioeconomic variables allows us to detect the causal effect of early-life paternal

[1] Couch and Placzek (2010) and Couch et al. (2011) provide evidence that job loss leads to an income reduction for the household. There is evidence that job loss triggers divorce (e.g. Eliason (2012); Huttunen and Kellokumpu (2016)), mental health problems for both the dismissed employees and their partners (e.g. Bubonya et al. (2017); Kuhn et al. (2009)), physical health issues, alcohol and tobacco abuse, and mortality among the employees and their partners (e.g. Bloemen et al. (2018); Falba et al. (2005); Deb et al. (2011); Gathmann et al. (2020)).

[2] The effects of early-life exposure to maternal job loss are presented in Appendix D. Statistical power is strongly reduced because maternal job loss is much less common in the Netherlands, i.e. the sample for maternal job loss is half the size of the paternal job loss sample. Additionally, more than half of working women in the Netherlands work part-time, and this number is even larger for mothers with young children (Booth and van Ours, 2013) Our analyses indicate no conclusive and significant effects of job loss on childhood mental health among children of working mothers. Among full-time employed mothers, there is more evidence in line with increased childhood mental health medication consumption after early-life exposure to maternal job loss, but this group of children is too small (around 14% of the paternal job loss sample) to replicate all analyses implemented for the paternal job loss sample with sufficient statistical precision.

job loss on later childhood mental health (age five to thirteen). As Currie and Almond (2011) note, it is unlikely that the sensitivity of humans to events changes sharply at any age threshold after birth. However, surveying the literature, there is evidence that postnatal events before age five have “fairly definitively” long-term consequences for health and human capital. We follow Currie and Almond (2011) and focus the first five years after birth when we define early-life paternal job loss exposure[3].

Looking at the characteristics of the exposed and non-exposed households before the job loss and conducting a series robustness checks, including a doubly-robust estimator, suggest that the two groups are comparable and the findings are robust against using alternative analysis and sample selection methods. Moreover, placebo analyses confirm that the results are not driven by preexisting differences between the exposed and non-exposed children.

We find that children exposed to paternal job loss are more likely to consume mental health medication during their childhood and early adolescence. The medication uptake rate increases by 6% at age five to 9% at age twelve compared to the average uptake rate among the control children. These increases are entirely driven by take-up of Psychostimulants which are used to treat Attention Deficit/Hyperactivity Disorder (ADHD) and Conduct Disorder (CD) and coincide with increased parental reporting more impulsivity and inattention symptoms among their children. Our results thus indicate that children exposed to early-life paternal job loss are more likely to be medicated for ADHD or CD. This is in line with CD being a mental disorder for which family and social environment are influential and explanatory for the onset and severity of the symptoms (Fairchild et al., 2019). While such a causal link unlikely holds between paternal job loss and ADHD due to ADHD being highly heritable, the change in family interaction patterns following the paternal job loss may influence the aetiology of ADHD or contribute to secondary development of conduct problems (Faraone et al., 2015; American Psychiatric Association, 2013). One can argue that early-life exposure to paternal job loss may lead to misdiagnosis and overmedication of ADHD or CD. Unfortunately, we cannot formally test if the medication type accurately reflects the underlying conditions due to lack of measurement-error-free information on ADHD or CD symptoms. Nevertheless, our finding of similar child psychostimulant uptake rates in the neighborhoods where exposed and non-exposed children reside indicates that differential practices in diagnosis of mental health problems by school or region are unlikely drivers of our estimates. All in all, our estimates

[3]There are too few firm-closure induced job losses in the Netherlands to study exposure in utero. Also, heterogeneity analyses by age of exposure (age 0 to 4) are imprecise and therefore uninformative on very early exposure leading to different medication uptake compared to slightly less early exposure, see Appendix B.

therefore allow concluding that individuals exposed to early-life paternal job loss are more likely to show behavioral/conduct problems during childhood and early adolescence[4].

We find no evidence in line with income loss being the main mechanism behind the estimated effects. Thanks to the generous Dutch welfare system, the drop in household income is small and on average less than three percent. Moreover, we find smaller effects on medication uptake among children in those households where fathers are the main earner compared to those households where mothers are the main earner, even though the household income drop after a job loss is larger in the former case. Job loss is also known to potentially affect the likelihood that families move to another neighborhood (Huttunen et al., 2018) and thus give access to different schools and medical providers. We find that the exposed children are more likely to reside at their old addresses several years after paternal job loss. The non-exposed children instead move more and to slightly less deprived areas. The neighborhood difference in terms of deprivation and average child psychostimulant take-up rate is however small (less than 5% of standard deviation) for job-loss induced residential sorting to be a likely and important mechanism leading to higher pscyhostimulant use among the exposed children. We however do find that family environment, and in particular children living in dissolved households, becomes more likely after paternal job loss. Additionally, mental health medication uptake of the dismissed fathers themselves increases around the time of job loss. The higher rates of separation and the worse mental health of the parents in a sensitive period of life are, in the Dutch setting, the most likely channels via which job loss leads to higher psychostimulant uptake of children.

Our findings contribute to the existing evidence on the adverse effects of job loss on the children of displaced workers. Research has documented that these children have worse school performance including lower grades, higher probability of retention and lower college enrollment (Stevens and Schaller, 2011; Hilger, 2016; Ruiz-Valenzuela, 2015; Rege et al., 2011; Coelli, 2011). Some studies also suggest negative effects of parental job loss on long-term income or unemployment probability of the children (Oreopoulos et al., 2008; Hilger, 2016; Schmidpeter, 2020), while others do not find any impact on employment outcomes (Gregg et al., 2012). There are also studies pointing to negative health impacts of parental job loss on physical health of the children (e.g., see Schaller and Zerpa (2019); Briody (2021)).

A small and recent body of literature studies effects of parental job loss on mental health and behavior of children. Most evidence points to negative effects on mental health and behavioral outcomes (Schaller and Zerpa, 2019; Bubonya et al., 2017; Page et al., 2019;

[4]In Section 5, we discuss the interpretation of the findings in more details.

Mari and Keizer, 2021).[5] However, most of the previous literature on the mental-health and behavioral effects of parental job loss on children focuses on contemporary or short-run effects. There is not much evidence on persistence of these contemporaneous effects or existence of any effects in the long-term. Mörk et al. (2020) are, to the extent of our knowledge, the only ones studying long-term effects of parental job loss on, among other outcomes, probability of mental-health related hospitalization of the children. They do not find any effects of parental job loss on the mental-health related hospitalization rates of the children. However, mental-health related hospitalizations are an extreme health outcome, as most mental health problems are treated outpatient.

In this paper, we estimate the impact of early-life exposure to paternal job loss on mental health conditions of children and young adolescents. In addition, we take advantage of the richness of our data to explore - using the same identification strategy - the potential role of several mechanisms suggested by previous economic or medical literature. First, we provide evidence that the effects go beyond the household income drop channel, Second, we rule out that these effects are driven by moving decisions that could influence the quality of the neighbourhood, the school choice or GP preferences. Instead, we show that these effects are most likely driven by changes in family environment, such as paternal mental health or family dissolution.

Our results also have implications for the literature of intergenerational mobility of socioeconomic outcomes. We find that paternal job loss increases mental health problems during childhood and early adolescence, while Currie et al. (2010) and Layard (2013) show the importance of mental health in explaining educational and labor market outcomes. Therefore, the mental health effects of exposure to parental job loss are a likely channel via which parental job loss events translate into worse adulthood outcomes; and more broadly one of the mechanisms explaining the intergenerational mobility of socioeconomic outcomes.

The rest of this document is organized as follows. In section 2, we provide background information on the context of our study. In section 3, we discuss the data and methods used. Section 4 presents the baseline results and several tests that confirm the robustness of our approach. In Section 5, we discuss the interpretation of our findings and the potential role of overdiagnosis and overmedication. Section 6 discusses the potential mechanisms such as income drop, change in the household environment, and neighborhood mobilization. Section

[5] The evidence on the effects of maternal job loss is mixed. Some papers find negative effects of maternal job loss on mental health and behavior (e.g., see Peter (2016); Marsh et al. (2020)), while others suggest positive effects (e.g. see Page et al. (2019)).

7 discusses policy implications and concludes the paper.

2 Background Information

In this study, we focus on firm-closure-induced job losses to evaluate the effect of early-life exposure to paternal job loss on later-life mental health problems in the Netherlands. This section reviews labor market regulations such as the business close-down procedure and the unemployment insurance system. These institutions aim to protect the dismissed employees and their families from the negative (income) effects of job losses. We also review the Dutch health care system with focus on the diagnosis and treatment procedures for mental health problems among children.

2.1 Labor market regulations

2.1.1 Business Close-Down Procedure

In the Netherlands, the process of business closure includes several steps. The most relevant one for this research is the dismissal of the staff.[6]. Under Dutch law, an employment agreement in case of business close down or a mass layoff is terminated by requesting the Employee Insurance Agency (UWV) to issue a permit for contract termination[7]

Dismissing a worker requires a payment by the employer to the employee. During the period of our study, there was no binding severance payment scheme in the Netherlands.[8] Nevertheless, the law requires the employer to make a severance payment if it decides to terminate a contract. In the absence of a severance payment scheme, in the case of a collective dismissal, the firm needs to negotiate the severance payment conditions with the UVW. Out of the negotiations, based on the number of years of service of the employee, the salary, relationship of the employer and the employee, the job market position of the employee, and the financial position of the employer a redundancy payment amount is set. In this study, we do not observe the severance payments. However, we observe the relevant characteristics of

[6]Other main steps are deregistration from the Dutch Commercial Register, deregistration from the Dutch Tax and Customs Administration and keeping the records of the business for at least seven years. For more information, check the checklist for closing down a business provided by the Netherlands Chamber of Commerce, the Netherlands Enterprise Agency and Statistics Netherlands (CBS).

[7]There are three common ways for the employers to terminate their employment agreement with their employees; (1) Termination of the contract by mutual consent, (2) termination of the contract by request of the employer resulting to a court order, and (3) issue of permission by the Employee Insurance Agency (UWV) after a request made by the employer. The first two ways of terminating an employment agreement, namely a court order or mutual consent, mostly happen in individual contract termination cases.

[8]After 2015 a binding scheme was put in place.

employees that could influence their severance payment. Moreover, for part of the period of the study, we have data on the total disposable household income of individuals which include all the disposable income from work or from the welfare system, including the severance payments (See Appendix A).

2.1.2 Unemployment Insurance System

After a job-loss, the employee can apply for unemployment benefits when she has been working for at least 26 weeks out of the last 36 weeks before the dismissal. Each year of tenure entitles the employee to one month of unemployment benefits with a minimum of three months. The primary condition for receiving this benefit is that the person should be available for a new job. The amount of the benefit is 75% of the gross salary of the terminated job in the first two months of unemployment and 70% for the following months with a cap of €168 per day (€44,000 per year; Euro values for 2004)(Bloemen et al., 2018).

Given the severance payment and the unemployment benefits in place, the income drop after a job-loss in the short-term is limited, compared to a situation in which the employees would not have been dismissed.[9] In Appendix A and Section **??**, we discuss the monetary consequences of a job loss in more details.

2.2 Health Care System

The Netherlands has a universal and comprehensive health care system. Everybody working or living in the country must have basic health insurance offered by a Dutch health insurer. Every health insurer has to offer the same basic insurance package covering a wide range of conditions, including general practitioner care, medical consultations and treatments including mental health care, hospital admission and care, psychological treatments, treatments by specialists, medication and dental care for children. Basic insurance is free for children under 18 years old, while the rest of the population faces a deductible.[10]

To receive non-emergency health care, each individual needs to register with a general practitioner (GP). The GP plays an important role as it is the entry point to receive most of the health care provided by the Dutch system. Parents and schools are actively involved in the diagnosis of mental health disorders among the children. In the early stages, the parents

[9] The income drop in the long-term in case of job loss can be sizeable due to the effect on the career path which matters in the context of tenure-based protection laws (Eliason and Storrie (2006)).

[10] There was one important reform of the Dutch mental health care system during our study period (2006-2017). In 2014 the organization of child mental health care was transformed from the central to the municipality level, but the gatekeeping role of the general practitioner did not change.

and the schools observe symptoms that need further analysis. Then the children are visited by their general practitioners. In case the child needs medical treatment, the practitioner may prescribe medications or refer the child to a psychologist or a pediatrician in case of more severe problems (Zwaanswijk et al. (2011)). The practitioners use the recommendations by "Diagnostic and Statistical Manual of Mental Disorders" (DSM) for diagnosing mental health problems. The diagnosis requires the parents and the schools to be actively involved in the process. For most common mental health problems among children such as ADHD or CD, DSM guidelines only rely on symptoms for diagnosis.

In the Netherlands, mental health problems among children and adolescence have been increasing in the recent years. Dutch Government (2014) reports that the use of youth mental health services (GGZ) among people up to age 17 has increased around 10% per year from 2001 to 2011. Moreover, the number of students using aids for intellectual problems, sensory or physical disabilities, and behavioral issues has been doubled from 2004 to 2012 (Dutch Government, 2014).

In this study, we focus on the probability of consuming mental health-related medicines during childhood as the main outcome. In 2012 one in every twenty individual below age 21 consumes mental-health-related medications (Dutch Government, 2014). The medications mostly include psychostimulants, antipsychotics, antidepressants, and sleep and sedative drugs. Methylphenidate (available under various brand names including Ritalin) which is a drug common in ADHD treatment, is by far the most widely used mental-health-related pharmaceutical among children and adolescence in the Netherlands as it accounts for more than 75% of the total medication uptake among this population.Using medication uptake as a proxy for mental health problems among the children might lead to underestimation of the effects because the main outcome neglects mild cases and disorders which do not require pharmaceutical treatments. So, we expect that the results to be mostly driven by more severe cases that require pharmaceutical treatments, or diagnosis that are primarily treated using medications. In Section 5, discuss the possibility that mis/overdiagnosis drive our results.

3 Data and Empirical Method

We use administrative data from Statistics Netherlands (CBS) containing detailed information on firms, employees, and their household characteristics. In this section, we first describe how we select our sample of analysis and the variables of interest, and then, we describe our empirical method and show the descriptive statistics.

3.1 Sample selection

First, we use the information available for all firms in the Netherlands for the period 2002 to 2012. It includes the date at which a firm starts its operation, categorical indicators for its size and the operating sector of the firm, and whether any events happen to the firm including merger, restructure, and closure. We select private firms with at least five years of age and with at least five full-time equivalent employees in each year that the firm appears in the data. We choose the five full-time employee cut-off following Bloemen et al. (2018) and Browning and Heinesen (2012) to avoid inclusion of small and unstable firms or self-employed and their employees in the study. Then, we focus on private sector firms as firm-closure events are less common (e.g. see Bloemen et al. (2018)), and the consequences for the employees can be different from those experienced by private-sector employees. For example, public sector employees can be more easily reallocated to another public firm, and this can lead to mis-identification of job losses in the public sector after a firm closure.

Firm closures are directly recorded in the administrative registry. This improves upon the common practice of using sudden changes in firm size or disappearance of the firm identifier in the data to detect firm closures (for example see Bloemen et al. (2018); Sullivan and von Wachter (2009)), and thus avoids mistaking other events such as mergers or restructuring of the firms for firm closures. We construct a sample of "closing firms" and a sample of "stable firms", consisting of firms that did not face major firm-level events during the years of observations.

Figure 2 illustrates the construction of the estimation sample. The subsample with *closing firms* restricts to employees with at least one year of tenure who lose their jobs at most one year before the firm closure event. The tenure restriction excludes employees hired during the process of closure. Moreover, employees with low tenure are expected to be less affected by the shock due to low job attachment (Bloemen et al. (2018)). The exclusion of employees losing their jobs more than one year before the closure event is meant to exclude job losses due to reasons other than the closure event. Figure 1 shows the distribution of contract end dates before firm closures. We see that most of the job losses happen during the last year of the activity of the firm.

Among these employees with more than one year of tenure who lose their jobs within the year leading to the closure event, we focus on the employees (parents) who have at least a child below age five at the time of job loss. The children of these employees who are below age five at the time of job loss are defined as the treated group.

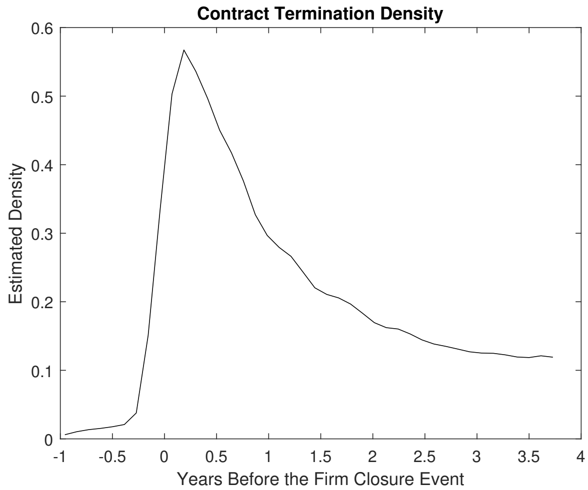

Figure 1: Distribution of Contract Ending Dates Relative to the Firm Closure Date

*Note: the Epanechnikov kernel is estimated using all the employees losing their jobs at most four years before the firm closure event.

As Currie and Almond (2011) note, it is unlikely that the sensitivity of humans to events changes sharply at any age threshold after birth. However, surveying the literature, they document that some postnatal events before age five have "fairly definitively" long-term consequences for health and human capital. We follow Currie and Almond (2011) to define early childhood parental job losses those after birth and before the fifth birthday of the children in our sample. In Appendix B, we present the baseline estimates separately for different ages of exposure.

To construct the control group, we focus on the *stable firms*, as we want to avoid any other firm-level shocks that could contaminate the estimates by (exogenously) affecting the control children. For each year that we observe a *stable firms*, we assume that the firm could close down at the end of that year (pseudo close-down date). For the employees of the *stable firms*, we assign a pseudo job-loss date in the middle of the year of pseudo close-down date. As almost all of the variables of interests are measured on yearly basis, the exact choice of pseudo job-loss date is irrelevant for most of the variables of interest. The pseudo job-loss date is mainly relevant for sample selection.[11] To define the control group, we use the same criteria that we used to form the treatment children, namely having one year of tenure and having a child below age five on the pseudo-job loss date. The children of these employees are defined as the control group. In case of observing a child more than once in the control group, we only keep the first time the child appears in the sample. We also guarantee no overlap between the treatment and the control group by removing the children which appear

[11]The exact pseudo job-loss date is also used in calculating the tenure and age of the employees. However within a calendar year, the impact of the exact date of pseudo job loss is small.

in both groups, from the control group.

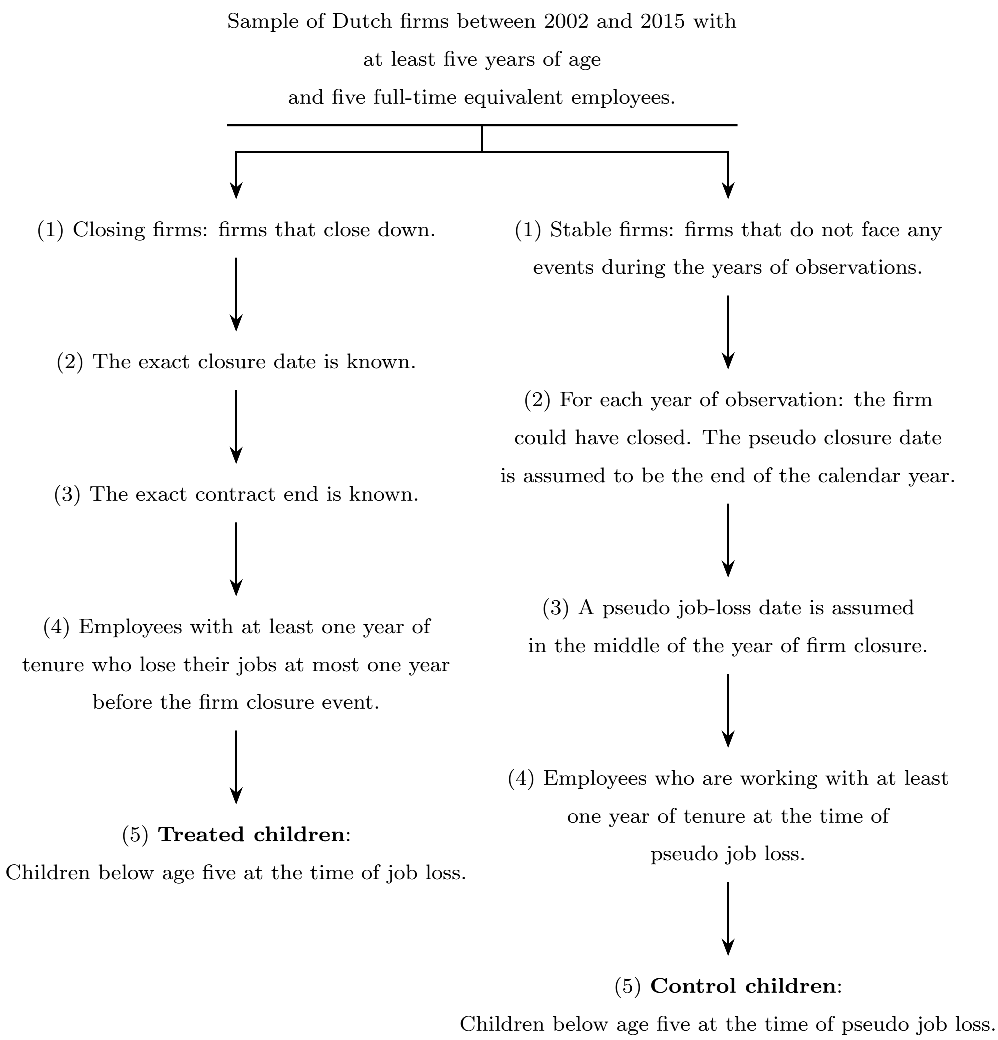

Figure 2: Sample Construction Method

3.2 Variables of interest

For each child in the treatment and the control group, we observe their date of birth, gender, birth order, the date of birth of their parents, their place of residence, their immigration background, the socioeconomic status of the parents such as their salary, if they are working, or if they are receiving unemployment benefits. For the dismissed parent, we observe their sector of employment as well as the firm size. We also have the information on medication consumption of the children.[12] In particular, the data includes information about prescribed medicines dispensed at a pharmacy from 2006 to 2017. As Discussed before, basic insurance

[12]The Dutch administrative data does not have a high quality record of the education level of the parents in our sample of analysis.

is compulsory in the Netherlands, and it covers mental health treatments for the children. So, the data includes all the prescribed mental-health related medicines that an individual uses in the period of observation.

The medicine consumption is stored as a dummy variable for each person-year that shows if a person takes up a certain type of medication in a year. The data uses the the Anatomical Therapeutic Chemical code (ATC code) system up to four digits for classification of the medicines. ATC coding is a system maintained by the World Health Organization (WHO) assigning the medicines a unique code according to the organ or system they work on. We indicate medication groups starting with "N05"(psycholeptics) and "N06"(psychoanaleptics) codes as mental-health-related medicines.

3.3 Methodology

We use the following model to estimate the effect of early-life exposure to parental job loss on mental-health related medication uptake. We run this model separately for outcomes measured at ages from five to thirteen.[13]

$$y_i = \alpha + \beta t_i + \gamma^T X_i + \theta^T E_i + \lambda^T S_i + \varepsilon_i \tag{1}$$

where y_i is the desired outcome of the child, namely, a dummy showing if the child consumes mental health related medication at a certain age. t_i is a dummy variable showing if the child is in the treatment group, and β is the coefficient of interest showing the effect of treatment on the desired outcome. X_i is a vector of basic characteristics of the child including cohort of birth dummies, gender of the child, age of the parents, if the parents are living together three years before the job loss, and dummies for parents being immigrants. We include month of birth dummies and birth order control as it has been shown that children with different months of birth and with different birth orders have different propensity of diagnosis with mental health issues (e.g. see Schwandt and Wuppermann (2016); Carballo et al. (2013))

E_i is a vector containing the information about the job of the dismissed parent. It includes dummies for the year of job loss, tenure of the dismissed parent, dummies for the size of the firm, dummies for sector of the firm, and dummies showing if the dismissed parent contract includes disability insurance (DI) and unemployment insurance (UI). S_i includes the socioeconomic status information of the parents including the salary of the parents before the job loss, average household income in the neighborhood that the mother is living before

[13]One needs to keep in mind that sample used in different regressions might be different depending the availability of outcome and control variables in each regression.

the job loss[14,15], and dummies for working status of the parents as well as if the parents are receiving unemployment benefits. ε_i is the error term. We use Huber-White robust standard errors to calculate the uncertainty in our estimations[16].

3.4 Descriptive statistics

The main assumption in the identification of the effect in this study is that job loss, conditional on the characteristics of the children, their parents, and the firms, is exogenous. In Section 4.2, we test this assumption by running a placebo analysis, and we do not find evidence of endogeneity of the job loss as the older children of employees working in the *closing firms* are similar to their counter-parts in the *stable firms* in terms of mental health medication consumption. We also provide evidence that conditional on the observables, consuming mental health medication cannot predict future exposure to paternal job loss. Moreover, using Equation 1, we look at the salary, working status of the parents, and household resources around the time of the job loss in Appendix A. We find that two groups are similar in socioeconomic characteristics before the job loss event.

In Table 1, we show the summary statistics for the observations in the treatment and the control groups. To look at the before job loss characteristics, we focus on the characteristics of the households three years before the job loss event. The reason for looking at the SES and family characteristics three years before the job loss event is to make sure that the job loss does not affect these variables. However, the patterns are similar if we look at other lags of pre-shock characteristics, and our main results are robust against using different lags of control variables.

In the sample of analysis (Table 1), we see that tenure of the fathers in the treatment group is around five months higher than the control group. The parents in the control group have higher income, live in slightly richer neighborhoods and are more likely to live together three years before the job loss. The children in the treatment group have higher rate of using mental-health-related medicines. The firms in the control and the treatment groups are from similar sectors, however, the firms in the treatment group are considerably smaller, because generally larger firms have lower probability of closure (Bloemen et al. (2018)).

By using job losses due to plant closures, we focus on involuntary job lob losses. However, our analysis requires that the treated and the control group to be similar to be comparable.

[14] In section 4.3, we run a robustness check using postal code fixed effects instead of controlling for the average neighborhood household income.

[15] We use the postal code information of the mother aiming to control for prenatal or early-life conditions of the child.

[16] We do not use clustered standard errors following Abadie et al. (2017).

As shown in Table 1, the characteristics of the children and the households, even-though different, do not differ to the extent that we need to use a non-linear method e.g. matching, to account for the differences. The standardized differences for the children and parents mostly stay below 10%. However, the treated fathers work in smaller firms because plant closures happen more regularly in smaller size plants. To address the potential differences between the two groups, in section 4.3, we show that the results are robust against using a nonlinear (doubly-robust) method. Moreover, we also show that our results are robust against focusing on smaller firms. To address any potential unobserved differences between the two groups that might affect our analysis, using a placebo regression, we provide evidence supporting that job loss event is exogenous after controlling for the observable characteristics of the children and their parents.

Table 1: Paternal Job Loss, Summary Statistics

	Control Group		Treatment Group		Standardized Bias[17]
	N	Mean (SD)	N	Mean (SD)	%
Child Gender (1:=Female)	767135	0.49 (0.50)	55874	0.49 (0.50)	0.0
At the Time of Job Loss					
Age of the Child	767135	2.72 (1.46)	55874	2.69 (1.43)	-2.1
Age of the Father	767135	34.86 (5.29)	55874	34.54 (5.35)	-6.0
Age of the Mother	767135	32.2 (4.76)	55874	31.77 (4.78)	-9.0
Immigrants Parent	767135	0.18 (0.39)	55874	0.20 (0.40)	5.1
Birth Order	767135	1.77 (0.90)	55874	1.78 (0.93)	1.1
Tenure of the Father	767135	6.69 (5.22)	55874	7.09 (4.95)	7.7
Dissolved Contract					
Includes UI[18]	767135	0.98 (0.14)	55874	0.99 (0.11)	7.2
Includes DI[19]	767135	0.98 (0.14)	55874	0.99 (0.12)	7.2
Full-Time Equivalence Factor	767135	0.95 (0.14)	55874	0.95 (0.15)	0.0
Three Years Before the Job Loss					
Father's Salary (€)	767135	36019 (32361)	55874	33405 (24993)	-8.2
Mother's Salary (€)	767135	15918 (14562)	55874	15045 (13992)	-6.0
Father is Working	767135	0.96 (0.17)	55874	0.96 (0.16)	0.0
Mother is Working	767135	0.76 (0.40)	55874	0.75 (0.41)	-2.5
Neighborhood Mean Income	767135	30882 (5493)	55874	30255 (5294)	-11.4
Parents Living Together	767135	0.9 (0.31)	55874	0.88 (0.32)	-6.4
	N	%	N	%	%

[17]Standardized bias (or standardized difference in means) is measured by differences between the means of the groups over the standard deviation of the population.

[18]Unemployment Insurance in case of unemployment of the employee

[19]Disability Insurance in case of disability of the employee

Closing Firm Sector					
Agriculture and Forestry	15921	2.1	1409	2.5	2.7
Industries	172155	22.5	12274	22	-1.2
Construction	83906	10.9	8081	14.5	10.8
Retail	161865	21.1	11388	20.4	-1.7
Transport and Storage	72590	9.5	4006	7.2	-8.3
Financial Institute	23988	3.1	1551	2.8	-1.8
Real state	177456	23.2	13070	23.4	0.5
Education and Health	6015	0.8	639	1.1	3.1
Others	52559	6.9	3410	6.1	-3.2
Closing Firm Size (fte[20])					
5 to 50	302170	39.4	31038	55.5	32.7
50 to 500	172496	22.5	13789	24.7	5.2
More than 500	292469	38.1	11047	19.8	-41.2
	N	Mean (SD)	N	Mean (SD)	
Child Consumes Mental-Health Medicine					
Age 5	727381	0.0092	53103	0.0101	
		(0.0953)		(0.1000)	
Age 6	685181	0.0169	51520	0.0181	
		(0.1290)		(0.1331)	
Age 7	632343	0.0303	48418	0.0324	
		(0.1714)		(0.1770)	
Age 8	565242	0.0446	44093	0.0474	
		(0.2065)		(0.2124)	
Age 9	498370	0.0560	39321	0.0591	
		(0.2299)		(0.2358)	
Age 10	432445	0.0640	34391	0.0679	
		(0.2448)		(0.2515)	
Age 11	370096	0.0697	29291	0.0731	
		(0.2546)		(0.2603)	
Age 12	308638	0.0719	24033	0.0764	
		(0.2583)		(0.2656)	
Age 13	246084	0.0734	18949	0.0761	
		(0.2608)		(0.2652)	
	N	%	N	%	
Fathers Working Full-Time (FTE>0.8)	706410	92.1	51116	91.5	

4 Baseline Results

In this section, we review the estimates of the effects of early-life exposure to paternal job loss on later mental health medication uptake probability. After reviewing the results, we discuss a series of robustness checks to assess the internal validity of the estimates; i.e. to check if the results are driven by either pre-existing differences between the groups or by the sample, the method or the specification we use in our analyses.

4.1 Baseline Results

In Figure 3, the estimates of the effect of exposure to an early-life parental job loss (β) using Equation 1 are presented. The effects are shown separately from age five to thirteen. We see in Figure 3 that among the children exposed to an early-life paternal job loss, the probability of using mental health medications is significantly higher at ages eight to twelve. Moreover, during the age window that we are considering, an increasing pattern of the point estimates

[20] Full Time Equivalent Employees

from age 5 to age 12 is visible. The relative effects (Figure 24) account for a stable increase equivalent to 6-9% of the average uptake among the children of the control group.

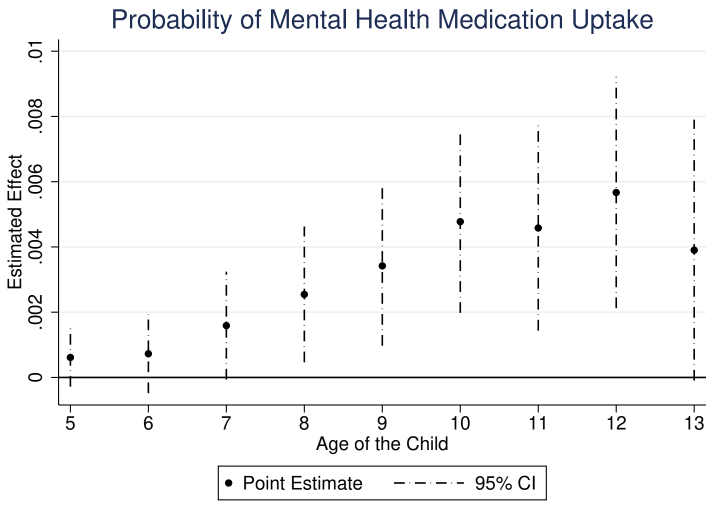

Figure 3: Paternal Job Loss, Estimated Effects on Mental Health Medicines

4.2 Preexisting Differences

One might be concerned that the treatment children and the control ones are different from each other even without the job loss event happening, and this difference is the driver of the higher mental health medication rate among the treatment children in the paternal job loss analysis. The reason behind this preexisting differences can be explained by assortative matching of better employers with better employees (Hilger (2016)). Moreover, one might be concerned that the employees displaced close to the firm closure date, compared to the ones displaced earlier, are a selected sample of employees. In Appendix A, we show that in terms of the observable socioeconomic characteristics, the two groups are similar before the job loss event. However, the concern might still remain that the two groups differ in terms of unobserved characteristics.

To evaluate the possibility that different preexisting characteristics are the driver of our estimates, we establish a placebo test. Using exactly the same procedure in the main analysis, we focus on the children whose fathers are dismissed at least three years and at most eight years after the observation of their mental-health-related medication consumption. We choose three years before the job loss, to be consistent with the main identification as we control for SES variables at three years before the job loss. The choice of eight years is because we want to keep the length of exposure window the same as in the main analysis; i.e. five years. To give an example, when we run the placebo regression for the outcome being mental-health-related medication consumption at age five, in the treatment group, we have children whose fathers lose their job when the children are between eight and twelve, and we compare them with a control group of children constructed in exactly the same way as in the baseline analysis but with the new age criteria.

In Figure 4, we see that the placebo point estimates are close to zero and insignificant. These placebo estimates do not show any evidence that the children of the parents working in the closing firms are different from the children of parents working in the stable firms in terms of mental health prescriptions before the job loss event happens[21]. Additionally, we see that the estimated effects in the main analysis are statistically different from the placebo estimates for ages eight to twelve. In all the ages, the placebo estimates are smaller in size compared to the baseline estimates.

To address the concern of preexisting differences, as an additional check, we focus on all children whose fathers are displaced because of a plant closure when they are between six and fourteen. We construct the control group, using this new age criteria, the same way as the baseline control group. Controlling for the variables as the baseline, In Table 2 Column 1, we check if mental health medication consumption during the year before can predict the exposure to parental job loss event. For children age five to thirteen, we see that mental health medication consumption is not correlated to firm-closure job loss event in the next year (estimates are small and insignificant)[22]. This provides an additional piece of evidence that it is unlikely that there exists preexisting differences between the children of fathers working in *closing firms* and the children of fathers working in *stable firms.*

4.3 Alternative Specifications

We study the robustness of the estimates in Figure 10 against using different specifications or methods. First, using Equation 1, we drop some of the controls variables in the regression. In Figure 5, we show that estimating the effects with a basic set of controls including the children cohort dummies, month of birth dummies, gender, age of the parents, dummies for immigrant parents, and dummies for year of displacement yields very similar results compare

[21]We believe it is unlikely that the propensity to having mental health problems changes differently by age of the child at the time of job loss for the children of the employees working in closing firms and the children of the employees working in stable firms. The concern for this different propensities generally stem from the fact that the sample of baseline analysis and the placebo sample could be from different cohorts (Hilger (2016)). However, as we are focusing on a wide exposure window (a five-year age window) and including job losses in different calendar years, this issue is not relevant in the context of our study.

[22]In the sample, 6% of the children are in the treatment group. So, the point estimate is around 1.5% of the rate and insignificant.

to the specifications with more characteristics on the household level and on the employee-employer level.

As another robustness check, we include postal code fixed effect for the place that the mother lives three years before the job loss. The postal code fixed effects controls for the potential disparities and difference on the neighborhood level before the job loss happens, and the disparities earlier in life of the child. The reason for focusing on the place of residence of the mother is that children stay almost always with their mothers in their early-life in our sample, and also we can control for prenatal disparities in this way. We see that the estimations are very much similar to the baseline estimates (Figure 5). The robustness of the results to different specifications suggests that the treatment assignment is orthogonal to the children and parents characteristics[23].

As we discussed in Section 3.4, the standardized differences between the variables are mostly below 10%. However for some of the characteristics such as firm size, the differences are considerable. This might raise the concern that using a linear regression cannot control for the differences in the distribution of the characteristics of the individuals. To address this concern, we show that our results are robust against using a doubly robust estimator. We use the same estimator proposed by Robins et al. (1995). The doubly robust combines linear regressions with inverse probability weighting, and it improves upon simple matching methods by giving the model robustness against either (but not both) of the models for estimating the propensities or the linear regression being misspecified (Imbens and Rubin (2015); Bang and Robins (2005)).

In the doubly robust estimating procedure, we use the same pool of children with the same variables in the baseline analysis. We use bootstrapping to evaluate the standard errors of the estimate. We see in Figure 6 that the estimates using the doubly robust estimator are similar to the main results. These results suggest that using a linear model suffices to control for the different distributions of covariates in our context. Additionally, it suggests that the common practice of using matching methods (e.g. see Browning and Heinesen (2012)) in studying the effects of job loss does not necessarily improve the estimates in the contexts where the characteristics of the individuals do not differ to a large extent. Specially, when naive matching estimates, such as (unadjusted) nearest neighborhood matching, comes with the cost of inefficiency and bias in the estimator (Abadie and Imbens, 2011, 2006).

[23]The estimates are also robust against using postal code times year of displacement job loss fixed effects. The results are available upon request.

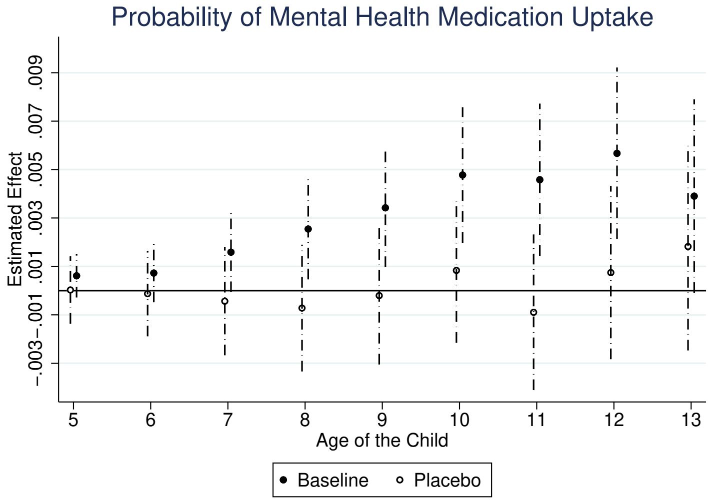

Figure 4: Paternal Job Loss, Baseline Effects vs. Placebo Effects

Variables	(1) Full Sample	(2) Sample of Full-Time Fathers (FTE>0.8)
Mental-health Medication Last Year	0.000900	0.00108
	(0.00104)	(0.00107)
Observations	1,286,069	1,197,368
R-squared	0.056	0.055

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- note: The sample includes all the children who face a job loss (real or pseudo) between age six to age fourteen. We see if mental health medication between age five to thirteen is correlated to being in the treatment or control group in a linear regression controlling for similar controls as the baseline. We check if prior mental health medication consumption can predict future job loss.

Table 2: Estimated Association between Mental-Health Medication Consumption of the Child and Future Paternal Job Loss

4.4 Robustness to the Sample of Analysis

In this part, we check if our main estimates are sensitive to the inclusion criteria for the sample of analysis. As the first check, we focus on the firm size criteria we impose on our sample. As we discussed in Section 3, we include firms with at least five full-time equivalent employees in our sample. In Table 1, we can see that dismissed fathers are more likely to work in smaller firms than the control group. In Figure 6, we show that using a nonlinear matching method does not change our estimations. As another robustness check here, in Figure 7, we show that there are no systematic and significant differences in the estimated effects if we only focus on smaller firms . This finding also suggests that the baseline results are not sensitive to the firm-size criteria for inclusion in the sample.

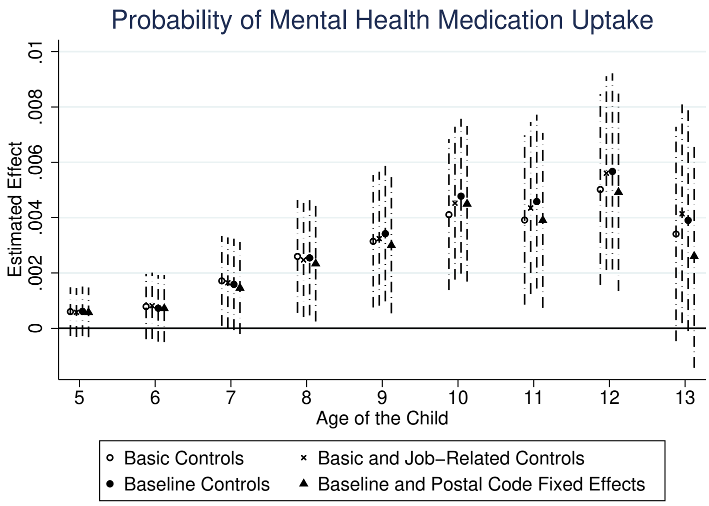

Figure 5: Paternal Job Loss, Estimated Effects on Mental Health Medicines
*note: Basic Controls includes cohort fixed effects, month of birth fixed effects, age of the parents, dummy for immigrant parents, birth order. Job-Related Controls include tenure, dummies for sector and size of the firm, and dummies for UI and DI in the contract.

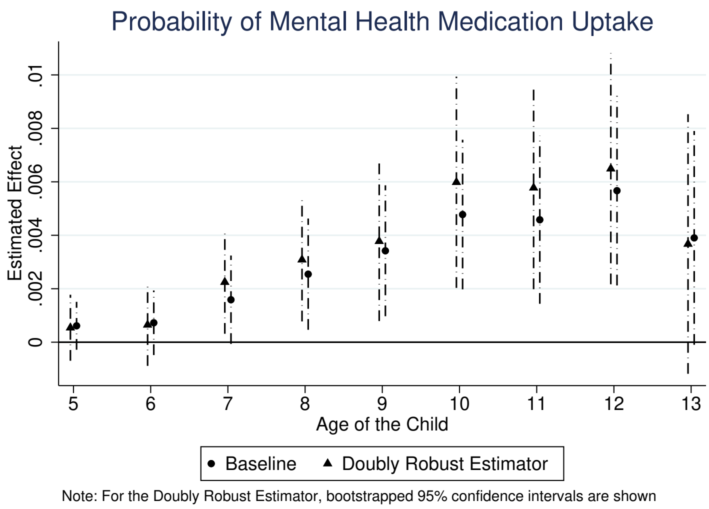

Figure 6: Paternal Job Loss, Estimated Effects on Mental Health Medicines using Doubly Robust Estimator

We also check if our results are sensitive to excluding lower tenure employees. For this purpose, we focus on the fathers with tenure of five years or more. The five-year threshold is a common choice in the literature (e.g. see Bloemen et al. (2018)) to define a stable employment. Compared to our choice of one year of tenure, the employees with at least five years of tenure might be more attached to their jobs. In Figure 8, we see that the effects on the high tenure parents are slightly higher, but not significantly different from the main results. This shows that our results are robust against using alternative tenure levels.This result is also consistent with the claim that higher tenured individuals are hit harder by a

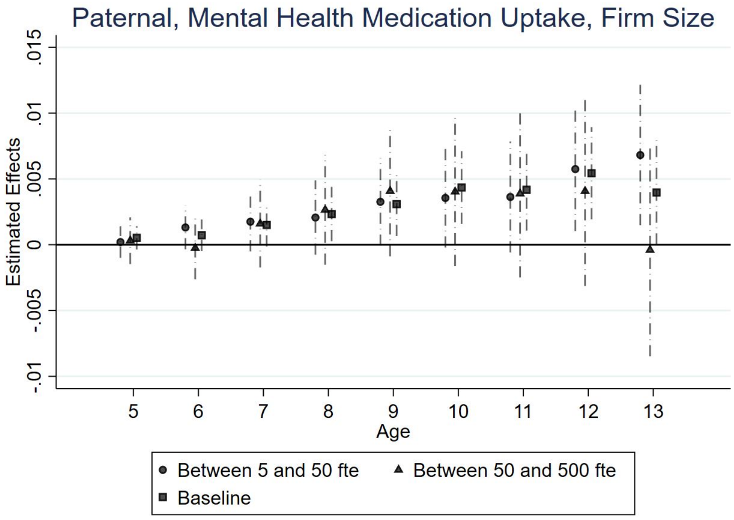

Figure 7: Paternal Job Loss, Estimated Effects on Mental Health Medicines by Firm Size

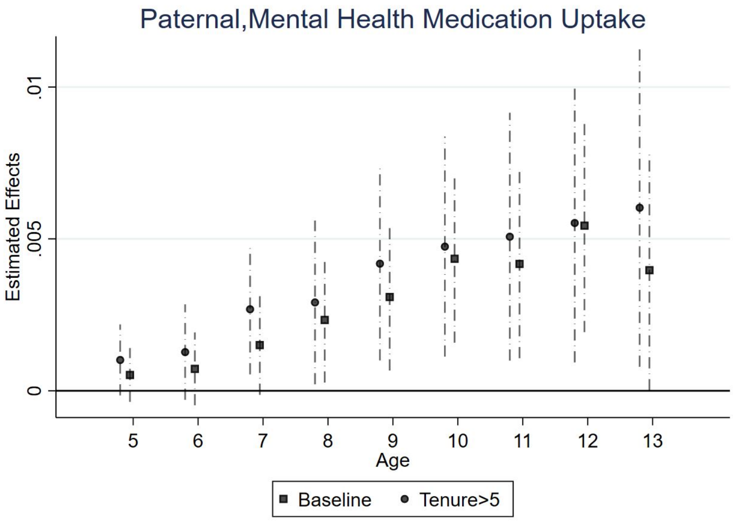

Figure 8: Paternal Job Loss, Estimated Effects on Mental Health Medicines for Higher Tenure Fathers

job loss event. In Figure 9, we can see that if we focus of the sample of full-time employees[24] instead of all employees, we see that children of these fathers are slightly more (but not significantly) more affected by the shock.

5 The Interpretation of Increased Mental-Health Medication Uptake

Exposure to an early-life event such as a parental job loss have different consequences for individuals. These consequences might influence the individuals through *biological pathways*

[24]We define a full-time employee to be an employee with full-time equivalence factor of at least 0.8.

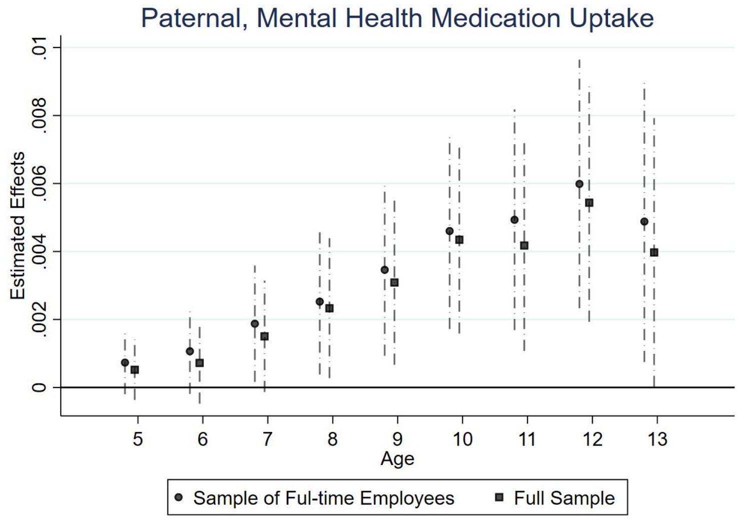

Figure 9: Paternal Job Loss, Estimated Effects on Mental Health Medicines for Full-Time Fathers

or *environmental changes.* The environmental changes can also be thought of an investment response to the health changes of the children (as discussed in Currie and Almond (2011)), or long-term changes in the family and environment circumstances due to the shock that can affect both the health of the child as well as the detection of health problems among children.

The (direct) biological effects, the parental investment responses and the long-term environmental consequences of the shock lead to *actual changes in the health* of the children, while the changes in the detection procedure is *a change in diagnosis propensity* of a health problem due to the change in the environment. Conceptually, the latter mechanism can lead to higher diagnosis and medication rate without any change in the health of the individuals. Additionally, the interaction of the latter and the former mechanisms after an early-life shock can lead to misdiagnosis of health problems among children. As Currie and Almond (2011) discuss, looking at the causal relationship between an early-life event and later-life outcome tells little about the biological pathways. The reason for this is that in addition to biological pathways, the behavioral responses and the environmental changes are part of the process that translate the early-life shock into changes in the later-life outcomes. In this section, we try to shed light on how one can interpret the baseline findings of the paper, given this framework.

5.1 Medication Type

As the first step, in Figure 10 and Figure 11, we look at the effects of paternal job loss on two different broad categories of mental health medications. We divide the mental health medications into (1) Psychostimulants and (2) other mental health drugs. The reason for this division is the high prevalence of psychostimulant medications among children who consume mental health-related drugs in the Netherlands (and around the world) compared to other types of medications. In 2012, among 4 million young individuals below 21 years old, about 200,000 took a form of mental-health-related medication. Among this population, more than 130,000 of them were using psychostimulants (Dutch Government (2014))[25]. The reason for this high prevalence is that Psychostimulants are the main medication category used in the treatment of ADHD or Conduct Disorder[26], and ADHD and conduct disorder are the most common mental health disorders among the children and adolescence worldwide (Faraone et al. (2015); Fairchild et al. (2019)). In the sample of our study, the ratio of children using psychostimulants to the sample of children who take any form of mental health medications[27] is 0.54 at age five increasing to more than 0.87 at age thirteen.

[25] Almost all reported the use of Methylphenidate. However, as we discussed in Section 3.4, we have access to ATC codes of the medications at 4 digit level, and we cannot identify the exact medications. Therefore, we split the medication categories into Psychostimulants (which includes Methylphenidate and other medicines that are widely used in treating ADHD or Conduct Disorder) and other mental-health-related drugs.

[26] Some of the psychostimulants are used for the treatment of narcolepsy. However, given that narcolepsy is very rare, it cannot be the driver of the baseline results.

[27] Share of children using medicines with ATC code starting with *N06B* of all the children using any medicines with ATC codes starting with either *N05* or *N06*.

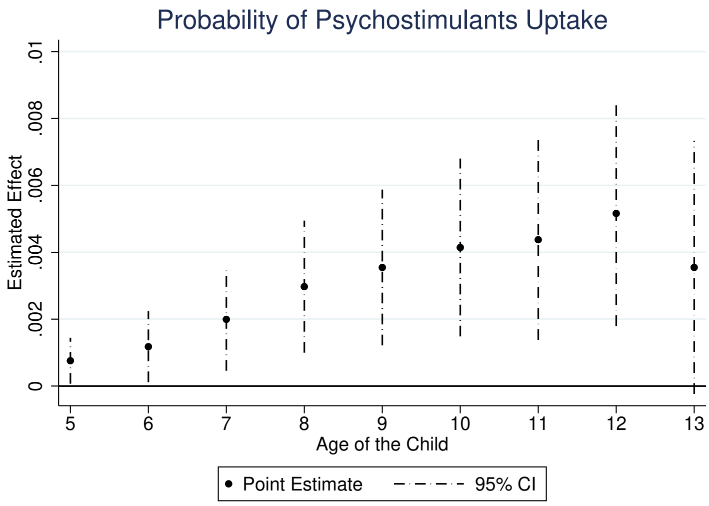

Figure 10: Paternal Job Loss, Estimated Effects on Psychostimulants

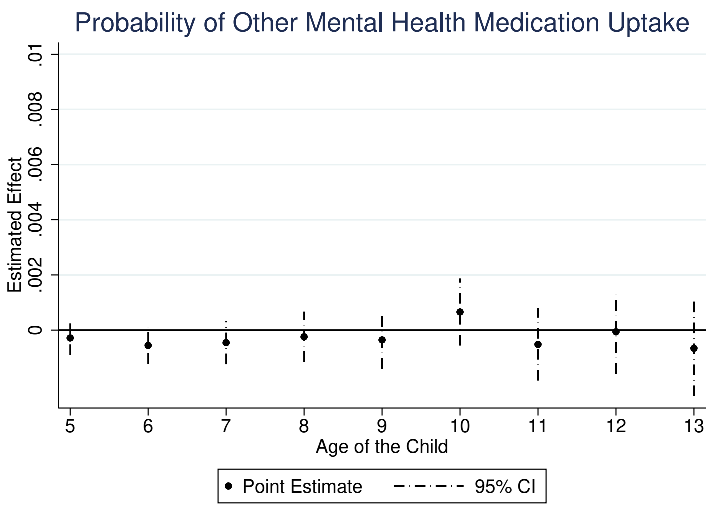

Figure 11: Paternal Job Loss, Estimated Effects on Mental Health Medicines other than Psychostimulants

In Figure 10, we observe that if we focus on the effects of being exposed to a paternal job-loss on psychostimulants, we find that these effects are significantly different from zero at ages five to twelve. The fact that the effects of job loss on psychostimulants are significant from age five to twelve suggests that in the reported estimates in Figure 3, the reason for having insignificant estimates at age five to seven is the noise induced by medications other than psychostimulants.

Our findings suggest that the children facing a paternal job loss in early ages are more likely to be diagnosed or receive medication for ADHD or conduct disorder. On the contrary, looking at Figure 11, we see that the estimated effects on other types of mental health medications are close to zero and insignificant[28]. This suggests that paternal job loss does not significantly increase the uptake of other types of mental health medications[29].

5.2 Increased Diagnosis Propensity

The increasing rate of Psychostimulants takeup among children after exposure to a paternal job loss can be due to *a change in diagnosis propensity* of a health problem. These different propensities can be induced by the different practices of schools and physicians in diagnosis and referrals for children as well as different reaction of parents regarding (deviant) behaviors of the children.

It is noteworthy that mental health disorders, and especially CD and ADHD, are diagnosed based on the behavioral symptoms of the child, and biomarkers are hardly available. Research have relied (directly or indirectly) on the reported behaviors of the children by the parents and schools to measure mental health problems (e.g., see Furzer et al. (2020)).

Given the limitations in objectively measuring mental health of children, in this part, we address the issue of *differential diagnosis propensity of diagnosis* by first focusing on the factors outside the household environment and look at the psychostimulants consumption rate in the neighborhoods that the children live. Living in a different neighborhood changes the type of schools that the treated children go, and if the school has a different attitude towards deviant behaviors, the children without an actual mental health status change might end up with higher probabilities of mental health medication uptake. Moreover, the same issue arises if the households of the dismissed employees have different access to different types of health care practices. This could be both on the access to care margin[30], and on

[28]The main medications in this group are Antidepressants and Antipsychotics. We can rule out higher rates of medication consumption for depression, anxiety disorder and autism.

[29]We can rule out effects larger than 3% of uptake in the control group in most of the ages.

[30]As we discussed in Section2.2, the health care system in the Netherlands provides a free and universal health access

the margin of referral to specialists and medication prescription approaches. In the context of our study, individuals register in the (primary) schools in/close to their neighborhood and also have access to general practitioners working close to their place of residence.

To check for the differences in diagnosis and prescription procedures in different neighborhoods, for all the neighborhoods in our sample we calculate the rate of Psychostimulants consumption for children between age five and fifteen living in those neighborhoods[31]. Using the baseline model (Equation 1), we estimate the differences between the neighborhoods of the children at different ages in terms of Psychostimulants consumption rates. In Figure 42, we see that the differences are insignificant and close to zero[32]. This finding, while we know that the treatment children live in slightly more deprived neighborhoods (see Section 6.3, and children from lower socioeconomic status backgrounds are more likely to suffer from ADHD or CD (Banerjee et al., 2007; Russell et al., 2015; Faraone et al., 2015; Fairchild et al., 2019), suggests that the diagnosis and referral patterns at school and neighborhood effects are unlikely to drive our results.

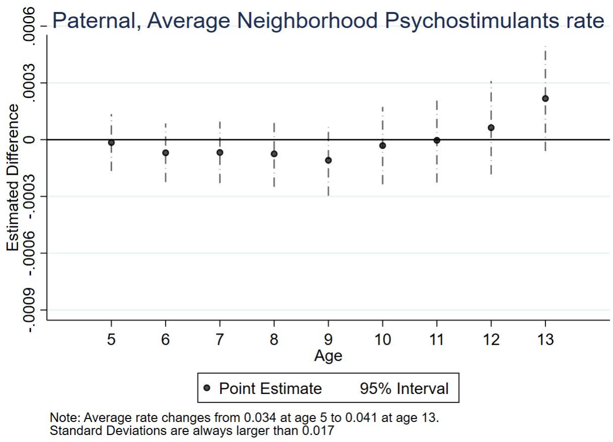

Figure 12: Paternal Job Loss, Neighborhood Psycostimulants Consumption Rate

As another piece of evidence, we focus on a health survey[33] on the Dutch population. This survey includes three questions about ADHD symptoms on children between age three and eleven, between year 2010 and 2019. The first question asks if the child "only focuses briefly on a particular focus activity"[34], the second question asks if the child is "constantly

for all the children below 18. So, we believe access to care on the extensive margin is not an issue in our context.

[31]We exclude the children in our sample from the calculation of average neighborhood psychostimulant uptake.

[32]We can rule out effects as large as 2% of a standard deviation in all the ages.

[33]The survey (*Gezondheidsenquete* in Dutch) is done by Netherlands Statistics. We use the survey waves from 2010 to 2019.

[34]In Dutch: "zich slechts kort op een bepaalde bezigheid richten"

fidgeting and twisting"[35], and the third question asks if the child "exhibits restless behavior, almost never silent and cannot sit"[36]. The parents report the frequency of this symptoms in the past four weeks. The parents indicate if the child always/sometimes/never had the symptoms. These questions are closely related to the symptoms used in diagnosis of ADHD recommended by DSM-V guidelines. The first question refers to inattention, and the latter two refer to impulsively/hyperactivity dimension of the disorder. Even though the number of the questions are limited, these questions can compliment the analysis in the baseline.

In total we have 3754 children in our survey analysis. For these children we only observe them once in the survey when they are between five and eleven. To gain more statistical power, we define a child having concentration problems if the child is being reported to always have concentration problems in the past four weeks in the survey (it could be any age between five to eleven). We define fidgeting and restlessness outcomes in a similar way.

In using the baseline model (Equation 1), we need to drop some observations because of missing control variables[37]. As we have shown in Figure 5, the estimates are not sensitive to controlling for a minimal set of variables compared to the baseline controls. For this reason, here we focus on the full sample that we observe their cohort of birth, month of birth, age of the parents, immigrant background, birth order, the year of job loss. We use Probit model in our analysis which is more efficient compared to linear probability models. We also focus on the overlapping sample (2889 children) for which we can run the baseline model (Equation 1). For the overlapping sample, we use a Probit model with exactly similar control variables as the baseline. Motivated by the results reported in Figure 9, we also present results separately for the children with full-time working fathers which can be more severely affected by the job loss event.

In Table 3, we see that all the estimated odds ratios are larger than one, however the confidence intervals are relatively large. In the full sample we find suggestive evidence that the children exposed to early-life paternal job loss are reported to have more concentration and restlessness problems. Looking at the overlapping sample, we see that the treated children are significantly (at 5% level) more likely to be reported to have all the three surveyed symptoms of ADHD. The evidence presented in Table 3 and Figure 42 suggests that parents of treated children report ADHD-like symptoms among their children, and it is unlikely that environmental differences outside the households are driving our findings.

The within household environmental factors can also play a role in changing the med-

[35]In Dutch: "voortdurend zitten friemelen en draaien"

[36]In Dutch: "rusteloos gedrag vertonen, bijna nooit stil kunnen zitten"

[37]In most of the cases, the lag variables are not available for those fathers losing their jobs between 1999 to 2001.

ication and diagnosis propensities. This could happen if parents have different reporting probabilities for different symptoms after exposure to a job loss compared to the control parents. However, the DSM guidelines for diagnosis rely on reports from more than just one environments. For example, for ADHD diagnosis, the symptoms need to be present in two separate environments. For CD, the diagnosis requires persistent antisocial behavior towards others and animals[38] which requires symptoms to be present in a social environment. Additionally, the schools are often involved in the process of diagnosis of mental illnesses among children. We believe it is unlikely that the change in the reporting of the parents after the job loss, without any actual change in child mental health conditions, to be the main driver of the results[39], however, we cannot completely rule-out this possibility.

		Estimated Odds Ratio [95% Confidence Interval]			
	N	Concentration problems	Fidgeting	Restlessness	All of the Three
Full Sample	3754	1.228*	1.111	1.181	1.245
		[0.989,1.526]	[0.891,1.385]	[0.952,1.466]	[0.942,1.645]
Full Sample, Full-Time	3460	1.297**	1.170	1.256**	1.287*
		[1.038,1.620]	[0.934,1.466]	[1.007,1.568]	[0.968,1.711]
Overlapping Sample	2889	1.100	1.065	1.134	1.377**
		[0.850,1.424]	[0.829,1.369]	[0.888,1.499]	[1.026,1.847]
Overlapping Sample, Full-Time	2559	1.111	1.089	1.149	1.390**
		[0.851,1.451]	[0.837,1.417]	[0.889,1.485]	[1.026,1.883]

- Note: full sample refers to all the children who face a job loss between 1999 to 2012, and we are able to run a Probit model with the Basic Controls. They include cohort fixed effects, month of birth fixed effects, age of the parents, dummy for immigrantparents, birth order, and dummies for year of job loss.
- Note: overlapping sample refers to all the observations we also observe them in our baseline regressions (Figure 3), and we are able to run a Probit model with the same controls as the baseline.
- Note: full-time refers to the subsample with their fathers being working full-time at the time of job loss (FTE factor > 0.8)
- Note: the outcome of the models measures if the parents report their children, between age five to eleven, show concentration problems, fidgeting, restlessness, or all the three. The estimated odds ratio using Probit models are reported (Treatment over Control). *: p-value<0.1 , **: p-value<0.05, ***: p-value<0.01

Table 3: Probit Model Estimates, Parents Reporting ADHD-like Symptoms

5.3 The Interpretation of the Increased Take-up

We find that the increased mental health medication take-up is driven by higher psychostimulant use after the exposure to the paternal job loss. We also document higher parental-

[38] Also, note that CD frequently co-occurs with ADHD (Fairchild et al., 2019).

[39] We also document worse school performance among the children which is another indicator of actual change in children's characteristics. Results are available upon request.

reported inattention and hyperacitivity symptoms among the children. These findings suggest that the children are more diagnosed with or medicated for ADHD or CD.

As discussed in Appendix C, the studies on the ADHD point out to genetics and prenatal conditions as the main causes of ADHD[40]. As American Psychiatric Association (2013) notes the "*family interaction patterns in early childhood are unlikely to cause ADHD but may influence its course or contribute to secondary development of conduct problems.*" Although, there is no (causal) evidence that after-birth events can cause ADHD, after-birth events are considered among factors that change aetiology of the disorder.(Banerjee et al., 2007; Faraone et al., 2015). For CD, there is evidence that after-birth events such as family environment and parenting style can influence the aetiology of the disorder (Fairchild et al., 2019).

All in all, our findings suggest that exposure to early-life paternal job loss can lead to more ADHD-like symptoms or conduct problems among children. However, the question remains if the diagnosis accurately matches the underlying conditions, and if the children are benefiting from the increased consumption of psychostimulants. Answering to these questions is outside the scope of this paper.

6 Mechanisms

In this section, we discuss different mechanisms that can explain the increased rate of mental-health-medication uptake by the children of the dismissed fathers. In all the regressions in this section, we use a model exactly similar to the baseline model (Equation 1) with the same control variables. We only focus on different sub-samples or different outcomes of interest.

6.1 Income Drop

One of the most immediate consequences of a job loss is the income drop for the household. There is evidence that the income drop after a job loss is higher in the short-run, and eventhough mitigated, persists for long-term periods (Couch et al. (2011); Couch and Placzek (2010)). Looking at the salaries of the parents in Figure 21 and Figure 30, we observe a drop in the earnings of the dismissed employees both in the short-term and in the long-term. The short-term income drop is higher, but after a few years of recovering, the wage of the dismissed employee persists to be lower in the long-term as well. However, considering the Dutch institutions, one can expect that the income effect of the job loss for the households to be milder than the salary drop for the individuals (Bloemen et al. (2018)). The reason for

[40]Causal studies on the effect of early-childhood environment are scarce.

this difference is that the state provides generous financial compensations (in the short-term) to support the households against the income shock of the job loss.

The income drop channel is potentially an important channel that affects the households in different manners. However, looking at the household income drop after the job loss (Figure 23 and Figure 32)[41], we see that the effect of job displacement on household income is much lower than the effects on the salaries of the dismissed employees (21).

To study the role of the income drop channel in more details, we first look at families where the dismissed parent is the main bread-winner of the household compared to the families where the spouse is the main bread-winner.

As we see in Figure 13, the household income drop is larger for the families where the father is the main earner[42] before job loss. However, when we look at the effects of the job loss on mental-health-related medicine consumption of the children, we observe that the effects are significantly higher, in later ages, for the children in households with the mother being the main earner (Figure 14). This suggests that, for a paternal job loss, the income drop is not the main channel for the higher rate of mental health medication uptake among the children.

We also separate the household into two groups based on the household income[43] three years before the job loss. Then, we look the size of the effects by socioeconomic status of the household. In Figure 15, we see that the effects do not systematically differ by household income[44]. We do not find any indications that the children of different SES groups get affected differently by the job loss, suggesting that even though the poorer households might face more income difficulties, the children of this group do not show worse mental health problems later.

We find larger effects on mental health of the children facing a paternal job loss with mothers being the main earner of the household. Moreover, we do not observe indications of different effects by SES groups. These findings suggest that for the children exposed to a paternal job loss, the income drop channel is not the main driver of the baseline effects on the mental health of the children.

[41] The figures with household income is generated by summing up the personal income (including benefits) of the parents. We only observe personal income of the parents from year 2003 to 2015. So, these graphs show the effect of job loss on a subsample of the parents.

[42] We use salaries of the parents three years before the job loss to detect the main earner.

[43] The data is only available from 2003, so the estimates here only include a subsample of children. These children face paternal job losses after 2006. Also there are missing observations for household income.

[44] The average of uptake rate for different household income groups is similar.

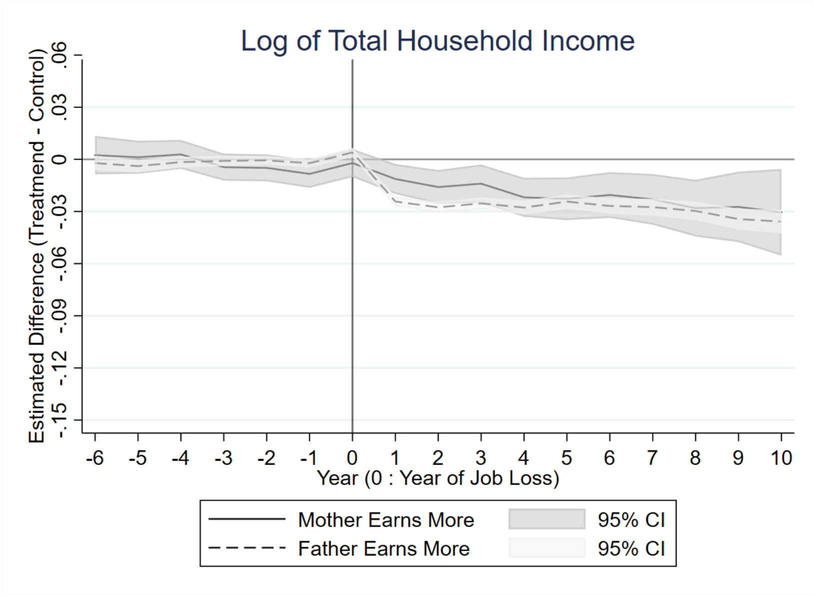

Figure 13: The Effects of Job Loss on Sum of Personal Income of the Parents by the Main Earner, Paternal Job Loss

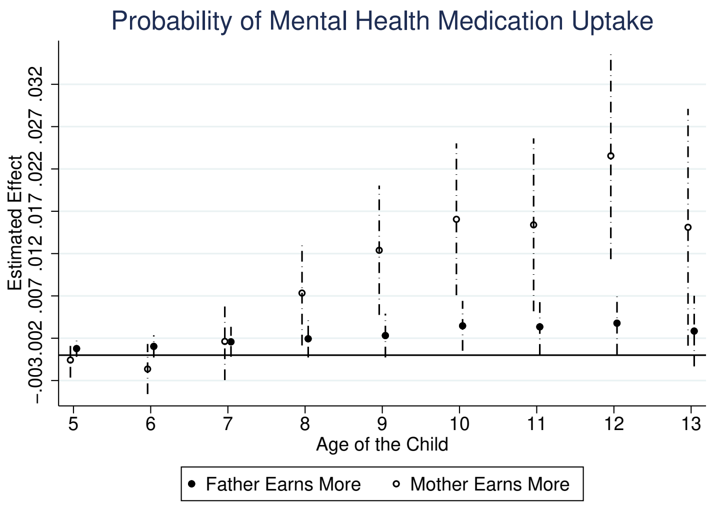

Figure 14: Paternal Job Loss, Estimated Effects on Mental Health Medicines by Main Earner

6.2 Household Environment

Changes in the household environment is another likely consequence of a job loss. Kuhn et al. (2009) reports that the unemployed male workers consume more mental health related drugs and have more mental health costs. Eliason (2012) reports a 13% higher divorce rates in a 12 year time span among the couples with one of them facing a job loss. Moreover, Lindo et al. (2018) show that higher unemployment rates for men are associated with higher maltreatment of the children. Browning and Heinesen (2012) document higher hospitalizations due to to traffic accidents, alcohol-related disease, and mental illness. Bloemen et al. (2018) look at male displaced workers with high job attachments in the Netherlands and report the stress

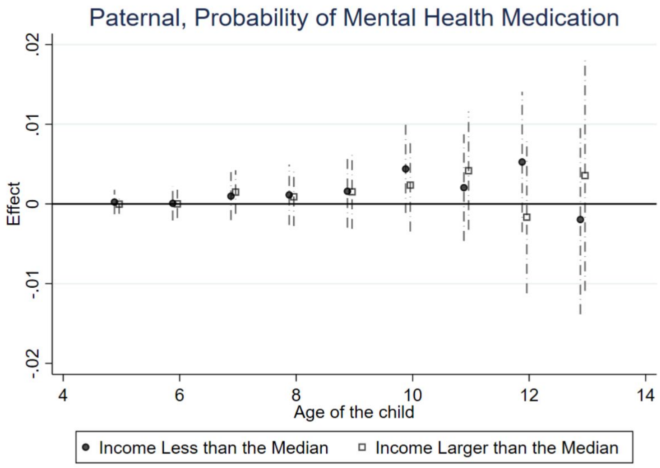

Figure 15: Paternal Job Loss, Estimated Effects on Mental Health Medicines by Household Income

and the change in their life style induce higher mortality rates among them. Bubonya et al. (2017) and Marcus (2013) report mental health deterioration of other family members of dismissed male employees. Gathmann et al. (2020) finds more physical (alcohol-related) and mental problems among the male displaced workers and their spouses.

In Appendix C, we discuss that after-birth family environment can change the aetiology of ADHD and CD. Other mental health and behavioral problems can be triggered by family environment (e.g. see Marsh et al. (2020); Valiente et al. (2007); Coley et al. (2015); Fiese and Winter (2010); Coldwell et al. (2006)). The worse mental health status of the parents in a critical stage of life and the potential tension at home or absence of one of the parents might directly and indirectly affect the care giving style and mental health of the child.

To check the environment of the household after a job loss, we look at the probability that the parents of the children live separately after the job loss. We see that the children facing a paternal job loss, across the same age window as we consider in the main estimates, have higher likelihood of having their parents living separately (see Figure 16). The higher probability of separation after a paternal job loss is a sign of more tension and chaos at home, and this higher tension can explain the higher mental issues among the children in this group[45]. In Figure 27, we provide evidence that this higher rates of separations start to increase after the shock.

The fact that facing a paternal job loss impacts the children with their mothers being the main breadwinner of the household also suggest that the household environment is an

[45]Looking at Figure 25, we show the effect of paternal job loss on separation probability by the main earner. We see that in later ages the point estimates are larger for those with mothers being the main earner. However, these differences are not significant.

important factor for the mental health of the children (check Figure 14). Bertrand et al. (2015) find that in mixed-gender relationships, divorce rate increases with the income gap between the partners (income of female - income of male). Moreover, relationship quality and satisfaction measures also drop with the income gap.

We also look at the mental health medication take-up by the parents[46]. In Figure 17 to Figure 29, we see that mental health medication uptake by the dismissed fathers around the time of job loss increases, but the effects are not persistent. However, we do not see any effects on the mothers. This worse mental health of the dismissed father around the time of job loss in a sensitive period of life for the kids can also contribute to the worse childhood mental health of the children.

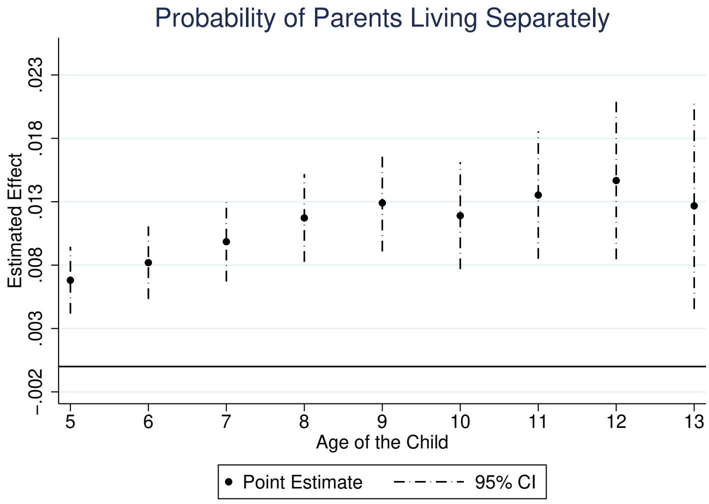

Figure 16: Paternal Job Loss, Parents Living Separately

6.3 Neighborhood Mobilization

Job loss can lead to change in regional mobility patterns (Huttunen et al. (2018)). This different mobility patterns have different monetary and non-monetary reasons. The income drop, a separation, or finding a new job in a different area are among the probable reasons for a child to live in a different neighborhood. The new neighborhood exposes the child to a different environment, school and peers. The neighborhood environment can expose the child to adverse factors such as community violence or deviant peers. These factors are considered among the environmental risk factors of CD and ADHD (Fairchild et al., 2019; Banerjee et al., 2007).

[46]The data on medications are only available after 2006. Because of this, we can only do this analysis for a subsample of the baseline analysis.

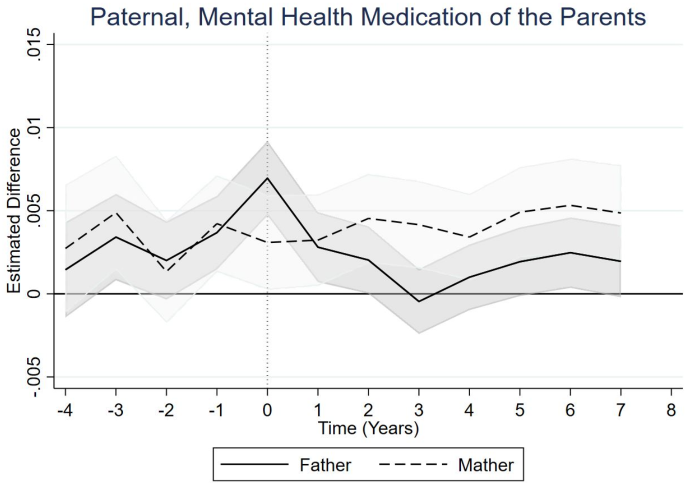

Figure 17: Paternal Job Loss, Parents Using Mental Health Medication

To look at the mobility changes for the children aftr the job loss, we first look at the moving pattern differences between the treated and control children. We see in Figure 18 that the the affected households tend to move less than the control households. The findings here are similar to the findings of Meekes and Hassink (2019) that in the Dutch context, the displaced employees face a reduction in their moving probabilities[47]. This gap start to close when the child becomes older. Looking at Figure 19, we see that the treated children live in slightly poorer neighborhood[48]. The neighborhood income gaps increases when the children are older. This suggest that eventually, the affected households move to poorer neighborhoods. In Figure 20, we find some suggestive evidence that the treated children live in neighborhoods with slightly higher violence rate. However, overall the neighborhood characteristic differences are small (less than 5% of standard deviation).

We cannot completely rule out the role of neighborhood differences in the estimated baseline results. However, given the small estimated effect sizes for differences in neighborhood characteristics between the two groups, we believe it is unlikely that this differences are driving the main results.

[47]The results are not similar to the results reported in Huttunen et al. (2018). In addition to the tight housing market in the Netherlands that can explain this finding, another explanation is that we focus on a subsample of job losses happening around age 30. This age group is in their earlier and growing stages of their careers and potentially different from other employees.

[48]We use the statistics reported by the Netherlands Statistics to look at neighborhood characteristics.

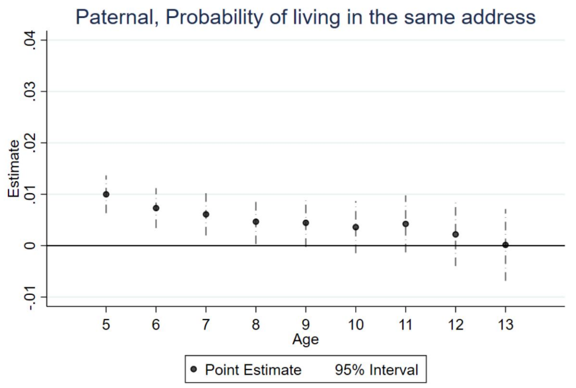

Figure 18: Paternal Job Loss, Probability of Living in the Same Address as Three Years Before the Job Loss Event

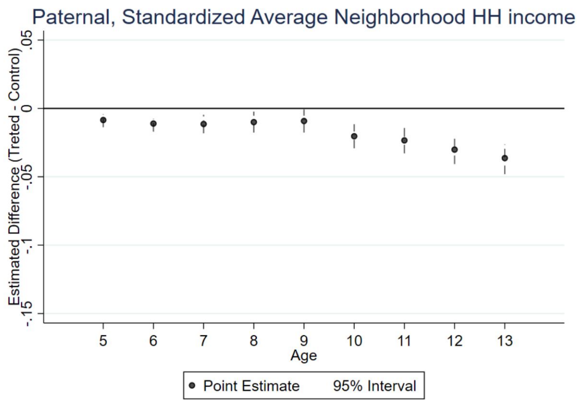

Figure 19: Paternal Job Loss, Standardized Average Neighborhood Income

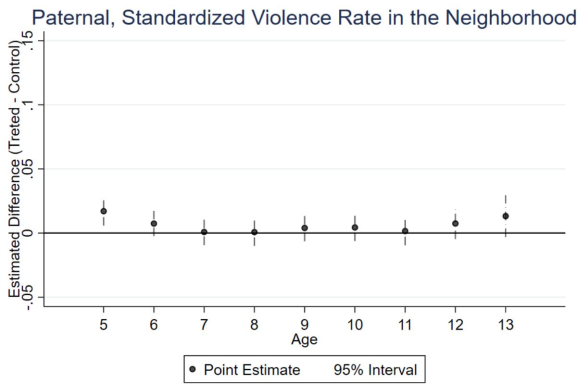

Figure 20: Paternal Job Loss, Standardized Average Neighborhood Violence Rate

7 Conclusion

In this paper, we find that early-life exposure to paternal job loss leads to childhood increased mental-health medication uptake. Our results suggest that the income drop following the job loss is unlikely to drive the results, and the change in the within-family environment is the likely pathway that early-life exposure to paternal job loss translates into the increased mental health medication uptake. Our analysis show that the children exposed to early-life paternal job loss are more likely to be diagnosed with or medicated for ADHD or CD. Additionally, our analyses suggest this increase in mental health medication take-up is driven by an actual change in mental health status of the children.

Our findings suggest that the adverse economic conditions can transfer to the next generations. Exposure to common economic shocks such as parental job loss increase mental and conduct problems in later childhood. Mental health problems among children are frequent, and around half of individuals with mental health disorders develop the symptoms before age fourteen. Our results suggest that higher employment stability and better economic conditions can improve mental health and wellbeing of children through better early-life household environment.

Childhood mental health is important in explaining adulthood outcomes of individuals. The worse childhood mental health induced by the parental job loss could be part of the mechanism that household economic conditions result worse adulthood outcomes among the next generations. Lower socioeconomic status individuals have less stable employment profiles, and hence, their children might suffer more in terms of mental health as a consequence of this less stable employment profile. Our findings suggest that the mental health consequences of (common) household economic shocks can play a role in the intergenerational mobility of socioeconomic status.

These findings suggest that policies facilitating higher job stability or better support for the dismissed employees with young children and their families have positive returns in terms of improved mental health of the children. This improved mental health and wellbeing can translate in better adulthood outcomes for these individuals and also reduce the burden on the child and adolescence mental health services. Additionally, these policies can provide a more equal ground for individuals who would be vulnerable otherwise and eventually reduce intergenerational mobility of socioeconomic status.

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A Pre-trends

Using Equation 1, we look at the salary and working status of the parents around the time of job loss. We consider SES outcomes in each year separately, controlling the characteristics of the children and lagged SES variables, we identify the differences between the control and the treatment groups. When we look at SES outcomes observed more that three years before the job loss event, we control for lag one of SES variables to be consistent with the main specification(Equation 1) and avoid using concurrent or future information. When we look at SES outcomes realised after three years before the job loss, we always control for SES variables realised three years before the job loss event. This means that in estimation in Figure 21 to Figure 23, we use the same specifications as the main estimates in section 4.

In Figure 21, we see that the differences in salaries between the control and treatment groups are small and insignificant before the job loss event. For the probability of working of the parents (Figure 22), we see that the two groups look similar before the job loss event.

After the job loss event however, the control and treatment group diverge in their socioeconomic characteristics. The dismissed parents, face a drop in their salary and probability of working in a year after the job loss. However, they are able to partially recover from the shock with time. For their partners, we see that in the case of a paternal job loss (Figure 22), mothers start to work more after the job loss and earn higher salaries (Figure 21). This finding is in line with the findings of Halla et al. (2020) that female partners react to an income shock to the family by working more.

To illustrate the role of the welfare state in ameliorating the income effects of the unemployment shock, we focus on a subgroup of the parents for which we have personal income information[49]. Personal income includes earned and unearned income net of social security premium and tax. The personal income also includes data on severance payments to the employees at the time of job loss. This broad definition of income is more relevant compared to the salary of the parents, because the summation of the personal income of the parents shows the disposable resources available to the family. In Figure 23, we see that the drop in sum of personal income of the parents right after the job loss is much less than the drop in their salary (Figure 21). This indicates that the social security benefits supports the affected families, and as a result the income drop for the household is lower in the short-term compared to the salary drop. However, in the long-run the summation of personal income of the households with dismissed members stays always lower than the control parents. In

[49]The data on personal income information starts at 2003 and ends in 2015. There are also some individuals that their personal income is missing during this period.

Figure 23, we also observe a spike in income at period 0 which indicates that the employees are being compensated for their involuntary contract ends (for more explanation see Section 2).

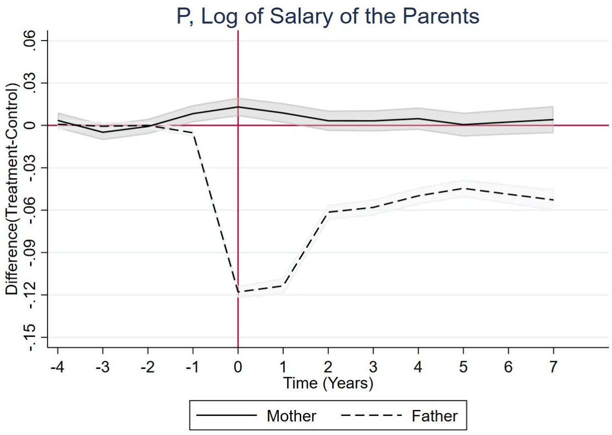

Figure 21: The Effects of Job Loss on Salaries, Paternal Job Loss

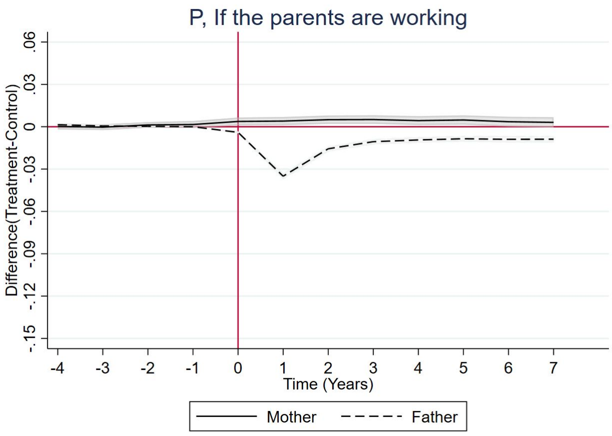

Figure 22: The Effects of Job Loss on Probability of Working, Paternal Job Loss

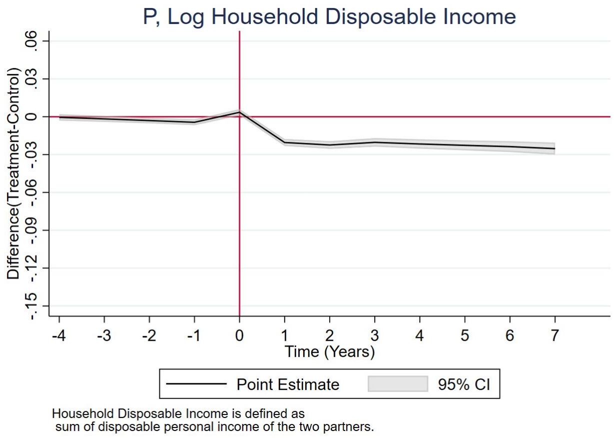

Figure 23: The Effects of Job Loss on Sum of Personal Income of the Parents, Paternal Job Loss

B Complementary Figures and Tables

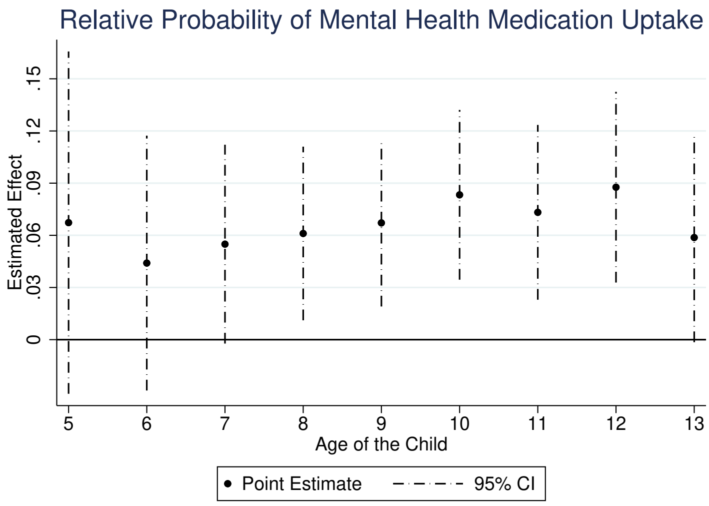

Figure 24: Paternal Job Loss, Estimated Effects on Mental Health Medicines Relative to the Mean of Control Group (to see the means, check Table 1)

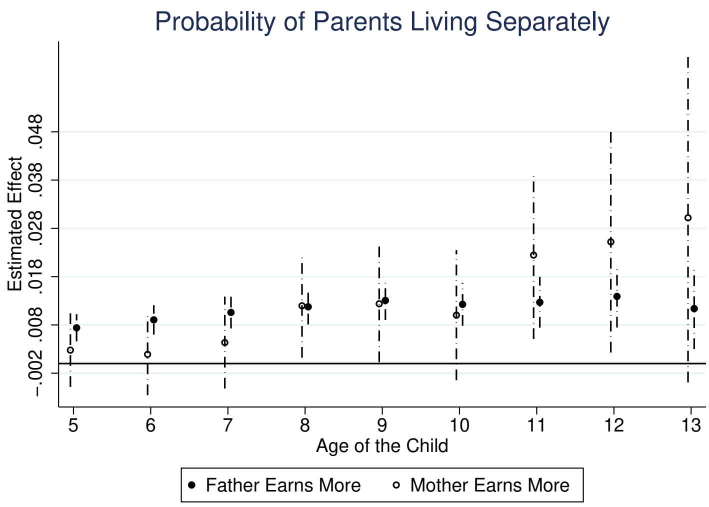

Figure 25: Paternal Job Loss, Estimated Effects on Probability of Parents Living Separately by the Main Earner

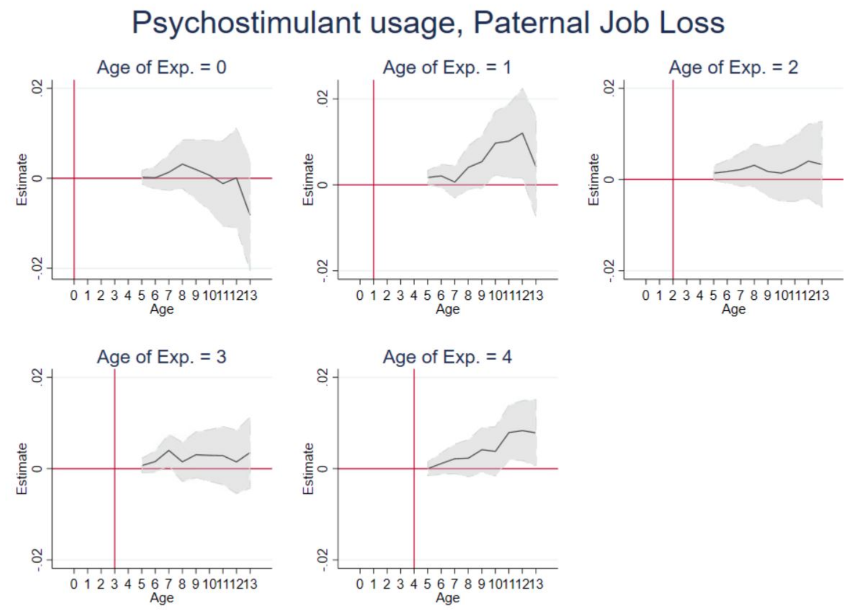

Figure 26: Paternal Job Loss, Psychostimulant Usage Probability by Age of Exposure to the Shock

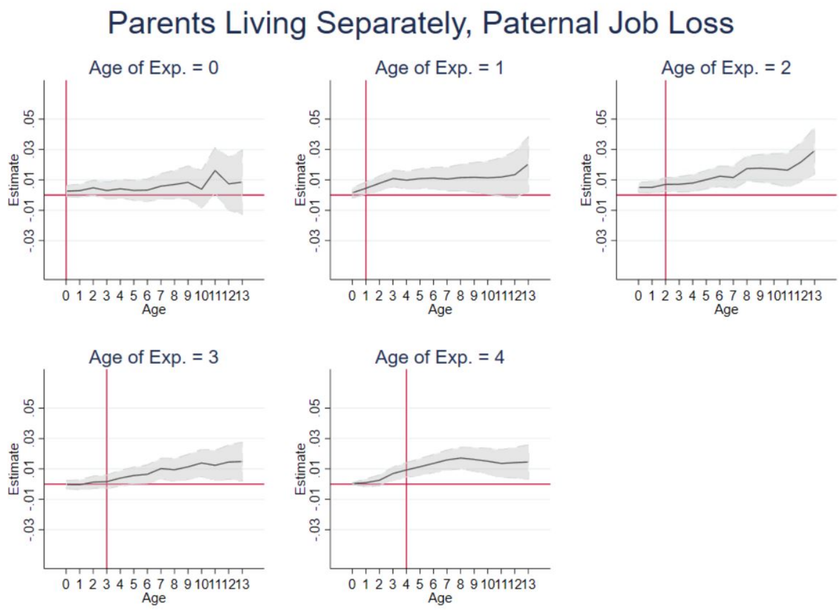

Figure 27: Paternal Job Loss, Separation Patterns by Age of Exposure to the Shock

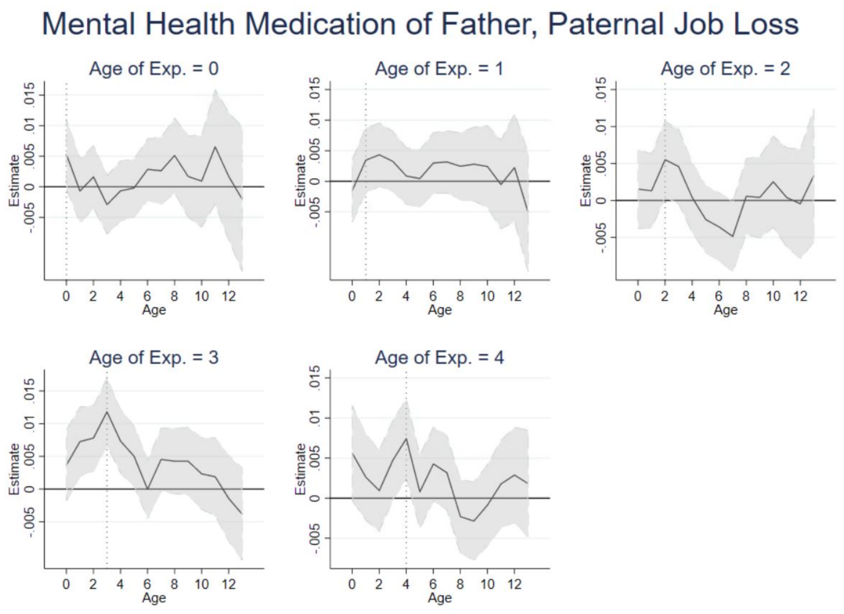

Figure 28: Paternal Job Loss, Father Using Mental Health Medication by Age of Exposure

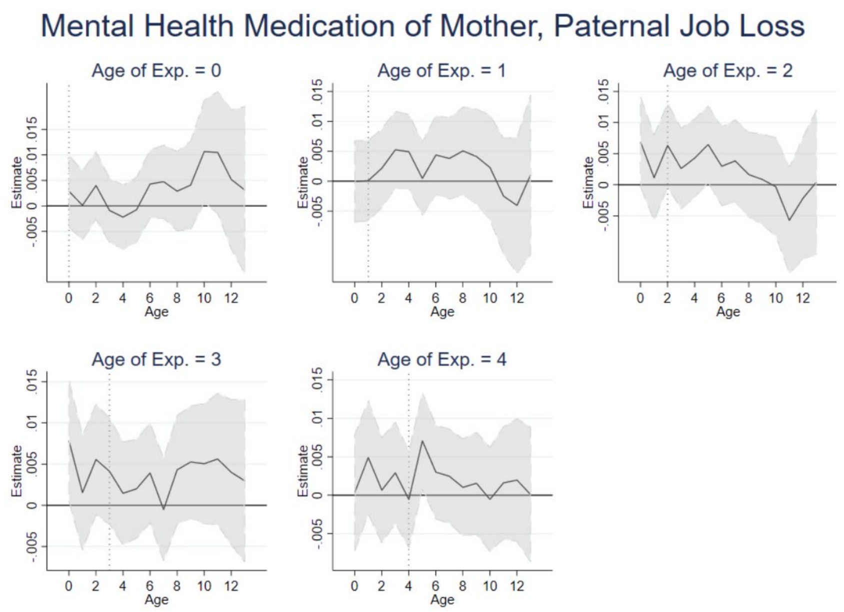

Figure 29: Paternal Job Loss, Mother Using Mental Health Medication by Age of Exposure

C Attention Deficit/Hyperactivity Disorder (ADHD) and Conduct Disorder (CD)

Here, we review some information on Attention Deficit/Hyperactivity Disorder (ADHD) and Conduct Disorder (CD).

ADHD

ADHD is a common neurodevelopmental disorder characterised with attention deficit symptoms and/or hyperactivity-impulsivity. ADHD affects around 5% of children and adolescence around the world. ADHD is more frequent among males with 2.5-4 higher rates compared to females (Faraone et al., 2015).

Overdiagnosis and underdiagnosis of ADHD coexists among different sub-populations. Younger individuals (and specifically males) in school cohorts tend to be overdiagnosed, while older females in school tend to be underassessed for ADHD symptoms (Furzer et al., 2020).

ADHD is a highly heritable disorder. Twin studies show around 70-80% heritability among both children and adults. The environmental factors can influence the disorder through the gene-environment interaction or potentially through non-shared familial environment, however the high heritability of ADHD suggests that the gene-environment interaction is the main mechanism that the environment can influence the course of ADHD among individuals (Faraone et al., 2015).

The main group of ADHD environmental risk factors are prenatal and perinatal factors. Some of these risk factors include maternal smoking and alcohol consumption, premature birth, exposure to environmental toxins such as lead, or maternal stress (Faraone et al., 2015; Persson and Rossin-Slater, 2018; Banerjee et al., 2007). Although there is scare evidence of causal link between after-birth environment factors and ADHD development, these factors are also considered to contribute to the aetiology of the disorder. Psychosocial adversity in the home environment, chaotic family environments, peer influences, and environment mismatches are considered among the factors that could influence the aetiology of ADHD (Faraone et al., 2015; Banerjee et al., 2007). **?** notes that "family interaction patterns in early childhood are unlikely to cause ADHD but may influence its course or contribute to secondary development of conduct problems."

The diagnosis of ADHD is done according to DSM-V by checking the inattentive and hyperactivity/impulsivity symptoms with onset before age 12[50] that cause functional impairment for the individuals. For the children, the diagnosis relies heavily on detailed clinical interviews as the gold-standard (similar to many other psychiatric disorders). In the interview, the presence, the intensity, and the onset of several symptoms are assessed. Although the interviews rely on the information presented by the parents, the information from the schools and other informants play a significant role in the diagnosis process. DSM criteria for diagnosis of ADHD requires that the symptoms to be present at least in two different settings (e.g., home and school environment.)

Treatments of ADHD mainly focus on controlling the symptoms and improving the functionality of the individuals. Pharmacological treatments are the main treatments for ADHD. (Psycho)stimulants (amphetamine and methylphenidate) are the first-line psychopharmacological treatment of ADHD, however, nonstumulants such as atomoxetine, guanfacine and clonidine are also used to improve the ADHD symptoms. Non-pharmacological treatments might also be used in cases where the individual is too young, or if patients do not respond positively to medication. Moreover, medication alone might not effective in improving all the dimensions of ADHD symptoms. In these cases, non-pharmacological treatments can be used in combination with pharmacological interventions (Faraone et al., 2015).

Conduct Disorder (CD)

Conduct disorder (CD) is a common psychiatric disorder among children and adolescence. Around 3% of school-age children suffer from CD (with the lifetime accurance of around 10%), with the disorder being twice prevalent among males than females. Antisocial behaviors such as theft, property damage and violation of rules and aggressive behavior against people or animals are the main characterizing factors of CD (Fairchild et al., 2019). CD very frequently co-occurs with ADHD. Individuals with CD are 10 times more likely to be diagnosed with ADHD[51].

CD is reported to be between 5% to 74% heritable in twin studies (Fairchild et al., 2019). Additionally, several environmental risk factors are reported for CD. Some of the perinatal risk factors are maternal substance abuse, maternal stress and anxiety, perinatal exposure to heavy metals, and malnutrition.

CD is one of few psychiatric disorders that the family and social environment environ-

[50] In 2013, the age for the onset was increased from seven to twelve. However, the change had insubstantial effects for the diagnosis rate among children Faraone et al. (2015).

[51] A similar increased risk of diagnosis with Oppositional Defiant Disorder (ODD) is reported (Fairchild et al., 2019).

ments are found to be substantially influential and explanatory for the onset and severity of the symptoms (Fairchild et al., 2019). The after-birth risk factors of CD include parental maltreatment, child-parents conflict, stressful life events, harsh and inconsistent parental behavior, deviant peers and violent community (Fairchild et al., 2019). Some of the perinatal and after-birth risk factors of CD are shared with the risk factors reported for ADHD.

Similar to ADHD, CD is diagnosed through interviews. The interviews try to detect antisocial, age-norm violation and aggression among children. The interview relies on the information from the parents, but also uses reported information from the school/teacher (Fairchild et al., 2019).

Like ADHD, the treatment of CD aims to control symptoms. However, unlike ADHD, non-pharmacological treatment is the first-line treatment used in CD patients. Interventions during childhood mostly focus on quality of parenting and behavioral parent training. In cases that non-pharmacological treatments are not effective such as severe cases of CD, or patients with other disorders such as ADHD, pharmacological treatments are used. Psychostimulants and neuroleptics are the main medications used in treatment of CD in children with ADHD.

D Maternal Job Loss

In this appendix, we discuss our findings for early life exposure to maternal job loss. The reason why we look at maternal job loss separately is that the effects of job loss on the household could be different. Specifically in our context where females are less likely to work, and also among the working females most of them work part-time. Looking at the summary statistics for maternal job loss analysis (Table 4), we observe that the overall sample of analysis is less than half of the sample in the paternal job loss analysis (Table 1). Moreover, the full-time equivalence factor of the mothers on average is 0.65 which is considerably smaller that the number for the paternal job loss 0.95. To have a comparable sample with the paternal job loss sample, we can focus on mothers working full-time. However, this will reduce the sample size to 134,000 children which is less than 16 percent of the sample size in the paternal job loss analysis.

The smaller sample of analysis and lower job attachment among mothers reduce the statistical power in this analysis. However, here we show some of the results for the maternal job loss sample.

Looking at Table 4, compared to the paternal job loss group, mothers have higher salaries. Moreover, the dismissed mothers are less likely to work in agriculture, industry, or construction sectors.

Table 4: Maternal Job Loss, Summary Statistics

	Control Group		Treatment Group		Standardized Bias
	N	Mean (SD)	N	Mean (SD)	%
Child Gender (1:=Female)	368490	0.49 (0.50)	29047	0.49 (0.50)	0.0
At the Time of Job Loss					
Age of the Child	368490	2.64 (1.48)	29047	2.62 (1.45)	-1.4
Age of the Father	368490	35.11 (5.37)	29047	34.64 (5.17)	-8.9
Age of the Mother	368490	32.47 (4.62)	29047	32.11 (4.50)	-7.9
Immigrants Parent	368490	0.17 (0.38)	29047	0.14 (0.35)	-7.9
Birth Order	368490	1.65 (0.76)	29047	1.62 (0.73)	-4.0
Tenure of the Mother	368490	6.28 (4.63)	29047	6.98 (4.37)	15.5
Dissolved Contract					
Includes UI	368490	0.99 (0.11)	29047	0.99 (0.07)	0.0
Includes DI	368490	0.99 (0.11)	29047	0.99 (0.09)	0.0
Full-Time Equivalence Factor	368490	0.65 (0.25)	29047	0.65 (0.24)	0.0
Three Years Before the Job Loss					
Father's Salary (€)	368490	32021 (25918)	29047	31063 (22371)	-3.9
Mother's Salary (€)	368490	20888 (16791)	29047	19615 (12955)	-8.5

Father is Working	368490	0.94	29047	0.95	4.6
		(0.22)		(0.20)	
Mother is Working	368490	0.90	29047	0.93	11.3
		(0.27)		(0.22)	
Neighborhood Mean Income	368490	31090	29047	30801	-5.2
		(5669)		(5315)	
Parents Living Together	368490	0.88	29047	0.88	0.0
		(0.32)		(0.33)	
	N	%	N	%	%
Closing Firm Sector					
Agriculture and Forestry	4166	1.1	461	1.6	4.3
Industries	41964	11.4	3079	10.6	-2.5
Construction	8256	2.2	689	2.4	1.3
Retail	107479	29.2	8238	28.4	-1.7
Transport and Storage	22991	6.2	1179	4.1	-9.5
Financial Institute	19442	5.3	1125	3.9	-6.7
Real state	99455	27	7707	26.5	-1.1
Education and Health	15568	4.2	2602	9.0	19.4
Others	48784	13.3	3954	13.6	0.8
Closing Firm Size (fte)					
5 to 50	150000	40.7	18689	64.3	48.6
50 to 500	63558	17.2	5719	19.7	6.4
More than 500	154932	42	4639	16	-59.8
	N	Mean (SD)	N	Mean (SD)	
Child Consumes Mental-Health Medicine					
Age 5	352396	0.0072	28055	0.0081	
		(0.0844)		(0.0894)	
Age 6	330372	0.0140	26861	0.0147	
		(0.1174)		(0.1204)	
Age 7	302856	0.0260	24982	0.0285	
		(0.1590)		(0.1665)	
Age 8	269134	0.0396	22643	0.0401	
		(0.1950)		(0.1962)	
Age 9	235720	0.0509	20004	0.0508	
		(0.2198)		(0.2197)	
Age 10	203060	0.0586	17203	0.0618	
		(0.2348)		(0.2408)	
Age 11	171874	0.0643	14382	0.0675	
		(0.2453)		(0.2509)	
Age 12	141441	0.0669	11509	0.0698	
		(0.2499)		(0.2548)	
Age 13	110747	0.0697	8717	0.0774	
		(0.2547)		(0.267)	
	N	%	N	%	
Mothers Working Full-Time (FTE>0.8)	109990	29.8	8395	28.9	

Looking at the pretends, we see similar patterns as the paternal job loss sample (Figure 30 to Figure 32). Overall, the two groups seem similar before the job loss event. After the job loss event, there are drops in salary and household income, however, the drops are smaller in size.

Looking at the main results in Figure 33, contrary to our findings on paternal job loss, if we look at the children whose mothers lose their jobs when the children are younger than five, we do not see the same increasing pattern in the uptake rates of mental health-related medicines. In most of the years, the point estimates are insignificant. However, the confidence intervals are too large to exclude effects of similar size as the effects in case of paternal job loss.

As one can see in Table 1 and Table 4, in our context, the full-time equivalence factor for the dismissed mothers are lower compared to the fathers. In Figure 34, we split the sample of maternal job loss into two groups based on their full-time equivalence (FTE) factor. Those who have FTE factor more than 0.8 at the time of job loss are defined as full-time workers and the rest as part-time workers. We see that the children of mothers who were full-time workers are adversely affected from the job loss event, while the children of mothers who work part-time seem to be less affected[52]. This comparison shows that the adverse effects of early-life exposure to maternal job-loss can be significant in cases where the mother has high level of labor market attachment.

When we look at the effects on mental health medications in Figure 35 and Figure 36, it is hard to comment on which medications are being affected by the shock. In Figure 37 to Figure 41, we conduct similar robustness checks as the paternal job loss analysis. The overall picture looks similar to the findings in the paternal analysis. There are some indications of pre-existing differences between the two groups in Table 5, but this difference vanishes if we focus on larger firms or bigger firms. These findings suggest that mothers working in smaller firms or working part-time might differ in some aspects before the job loss. Looking at different firm sizes, we also see that mothers working in smaller firms are not very much affected by the shock (Figure 40). Due to low number of observations, we cannot look at the survey results.

For completeness, we replicate the additional analyses done for the Paternal sample in Figures 42 to 51 and find that the overall picture does not strongly deviate from the paternal analysis.

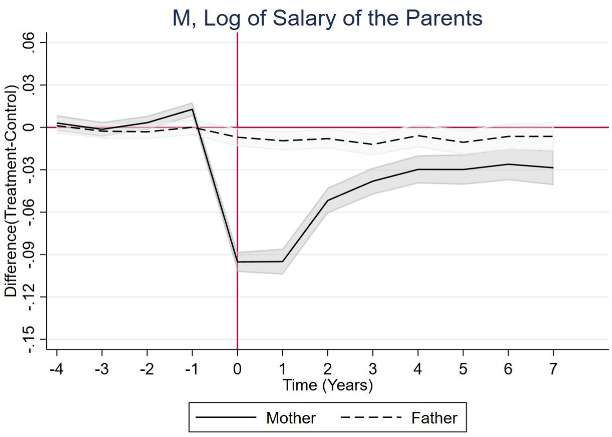

Figure 30: The Effects of Job Loss on Salaries, Maternal Job Loss

[52]Given the low power and wide confidence interval, the significant findings might be overstating the magnitude of the true effect size (Black et al., 2019)

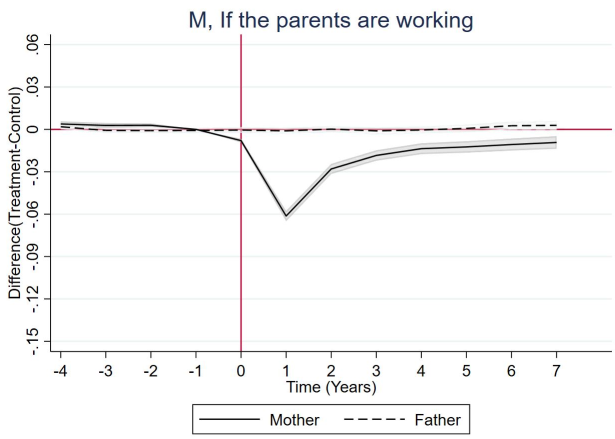

Figure 31: The Effects of Job Loss on Probability of Working, Maternal Job Loss

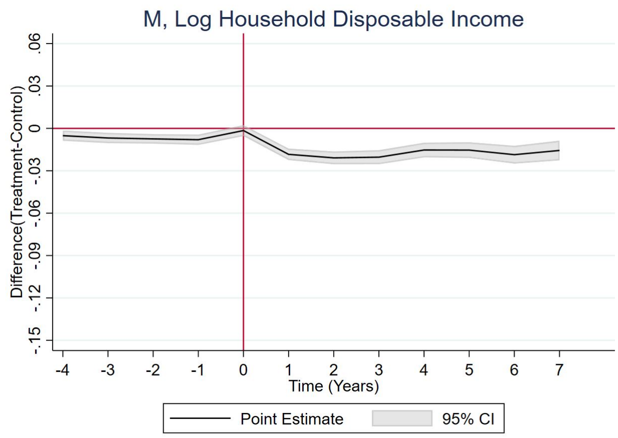

Figure 32: The Effects of Job Loss on Sum of Personal Income of the Parents, Maternal Job Loss

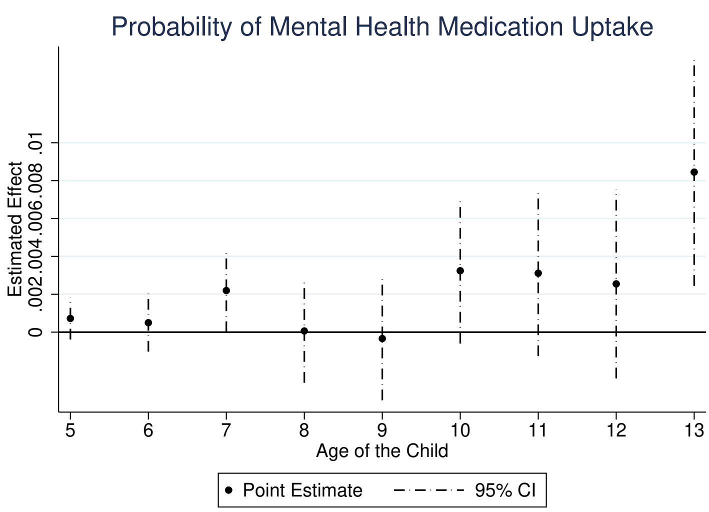

Figure 33: Maternal Job Loss, Estimated Effects on Mental Health Medicines

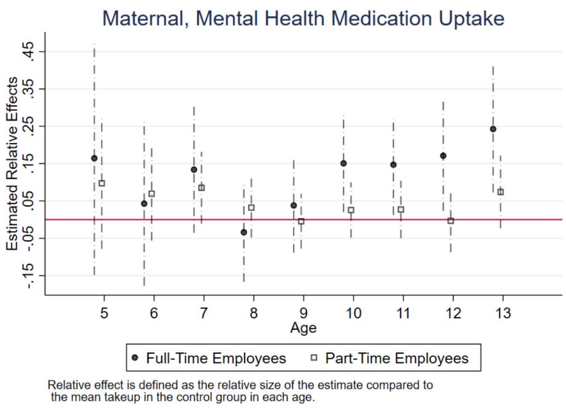

Figure 34: Maternal Job Loss, Relative Effects on Mental Health Medicines, Full-time vs Part-time

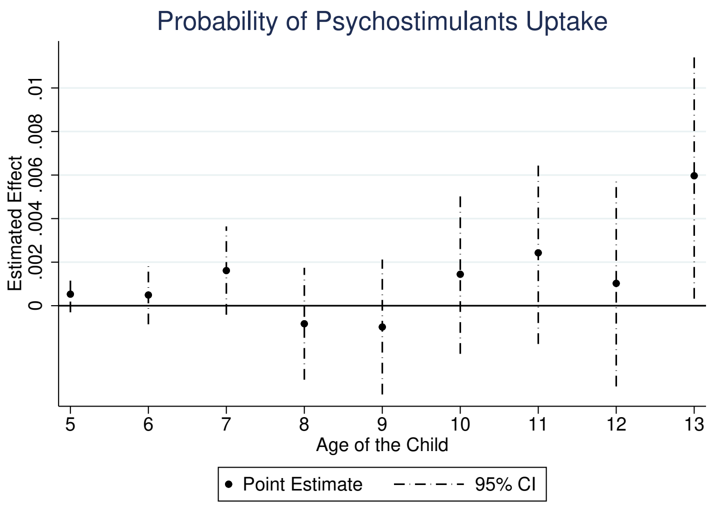

Figure 35: Maternal Job Loss, Estimated Effects on Psychostimulants

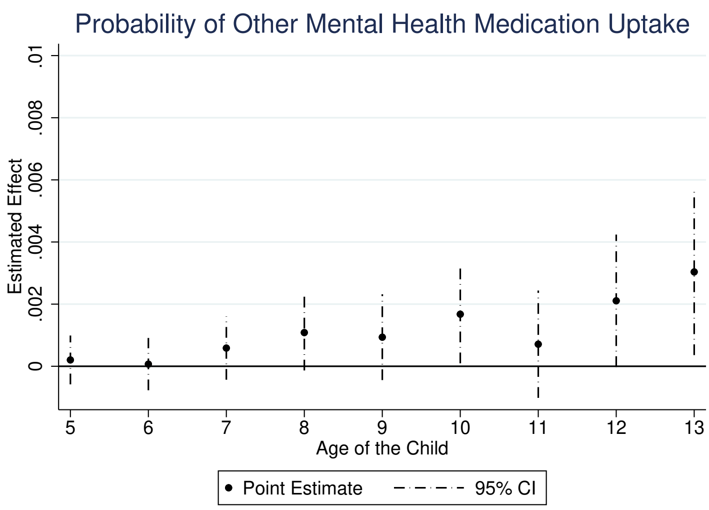

Figure 36: Maternal Job Loss, Estimated Effects on Mental Health Medicines other than Psychostimulants

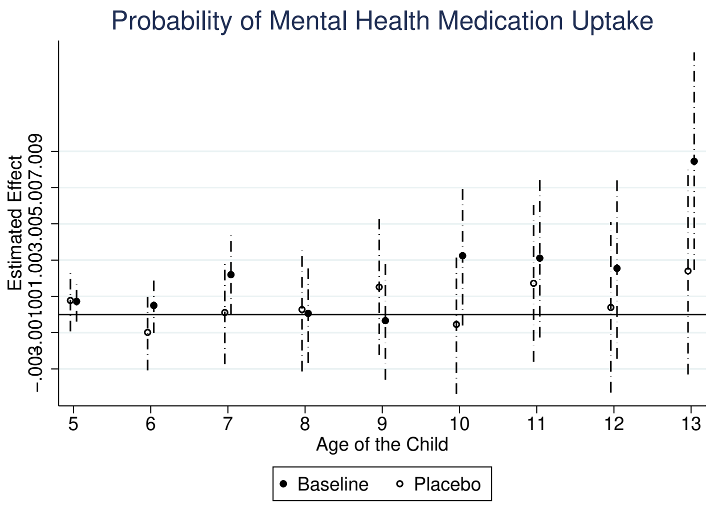

Figure 37: Maternal Job Loss, Baseline Effects vs. Placebo Effects

Variables	(1) Full Sample	(2) Full-Time Mothers (FTE>0.8)	(3) Larger Firms (>50fte equivalence)
Mental-health Medication Last Year	0.00374**	0.000553	-0.000148
	(0.00155)	(0.00317)	(0.00165)
Observations	659,742	149,214	310,064
R-squared	0.081	0.081	0.060

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- note: the sample includes all the children who face a maternal job loss (real or pseudo) between age six to age fourteen. We see if mental health medication between age five to thirteen is correlated to being in the treatment or control group in a linear regression controlling for similar controls as the baseline. We check if prior mental health medication consumption can predict future job loss.
- note: in column 2, we focus on the subsample of children with their mothers working full-time.
- note: in column 3, we focus on the subsample of children with their mothers working in larger firms (excluding <50FTE firms)

Table 5: Estimated Association between Mental-Health Medication Consumption of the Child and Future Maternal Job Loss

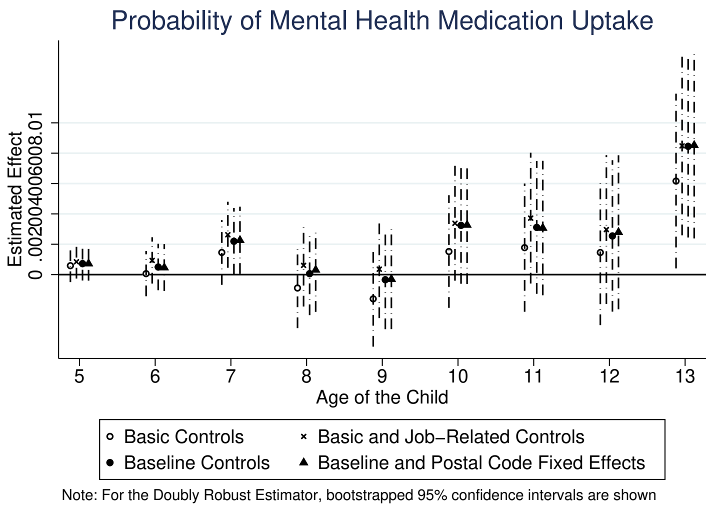

Figure 38: Maternal Job Loss, Estimated Effects on Mental Health Medicines
*note: Basic controls include cohort fixed effects, month of birth fixed effects, age of the parents, dummy for immigrant parents, birth order. Job related controls include tenure, dummies for sector and size of the firm, and dummies for UI and DI in the contract.

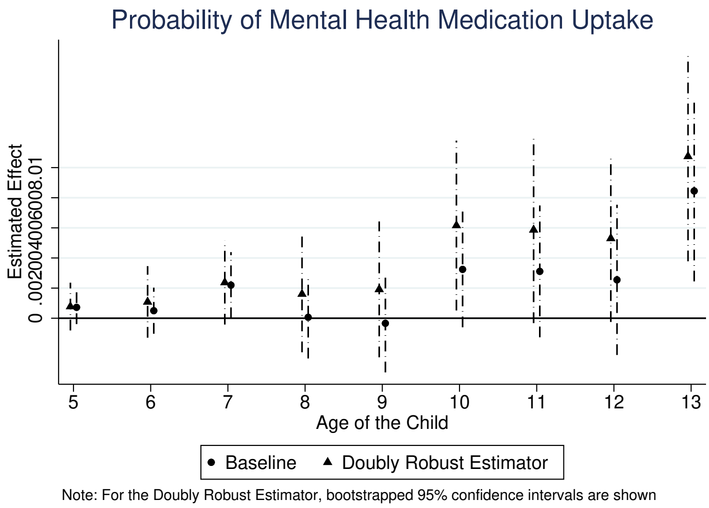

Figure 39: Maternal Job Loss, Estimated Effects on Mental Health Medicines using Doubly Robust Estimator

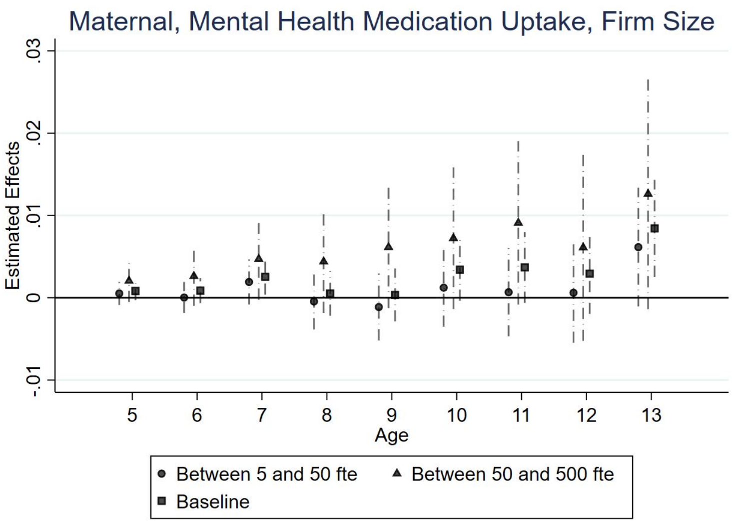

Figure 40: Maternal Job Loss, Estimated Effects on Mental Health Medicines by Firm Size

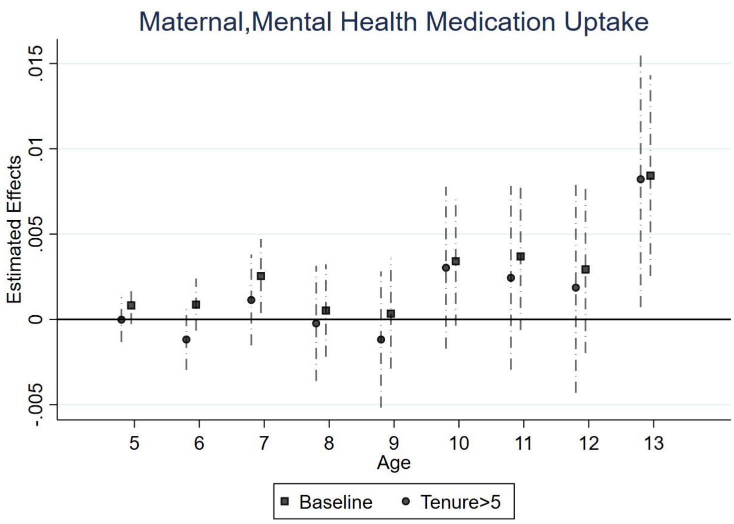

Figure 41: Maternal Job Loss, Estimated Effects on Mental Health Medicines for Higher Tenure Fathers

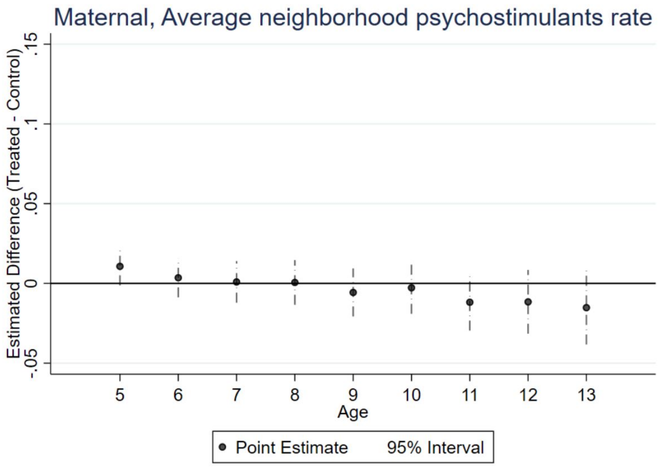

Figure 42: Maternal Job Loss, Neighborhood Psycostimulants Consumption Rate

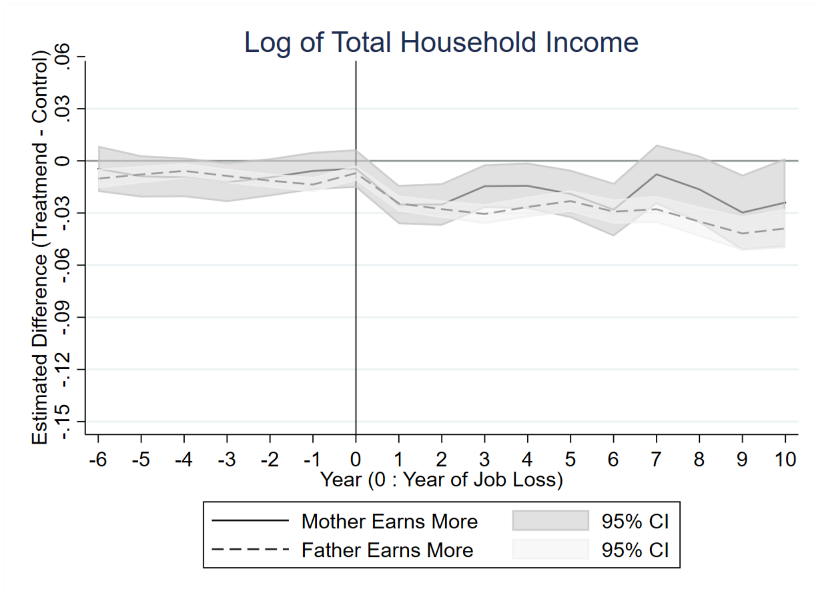

Figure 43: The Effects of Job Loss on Sum of Personal Income of the Parents by the Main Earner, Maternal Job Loss

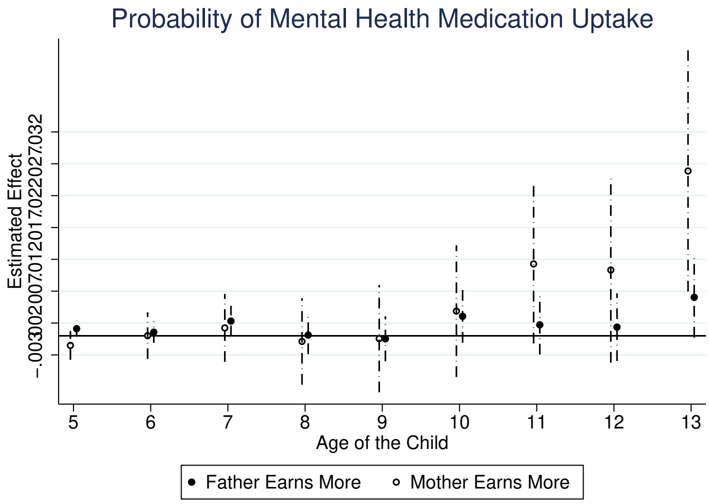

Figure 44: Maternal Job Loss, Estimated Effects on Mental Health Medicines by Main Earner

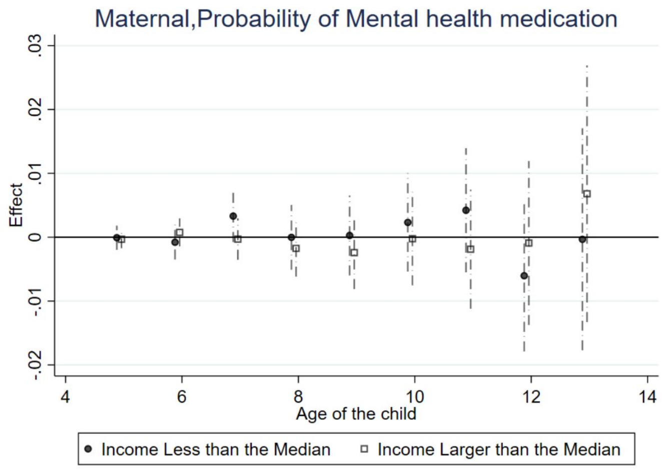

Figure 45: Maternal Job Loss, Estimated Effects on Mental Health Medicines by Household Income

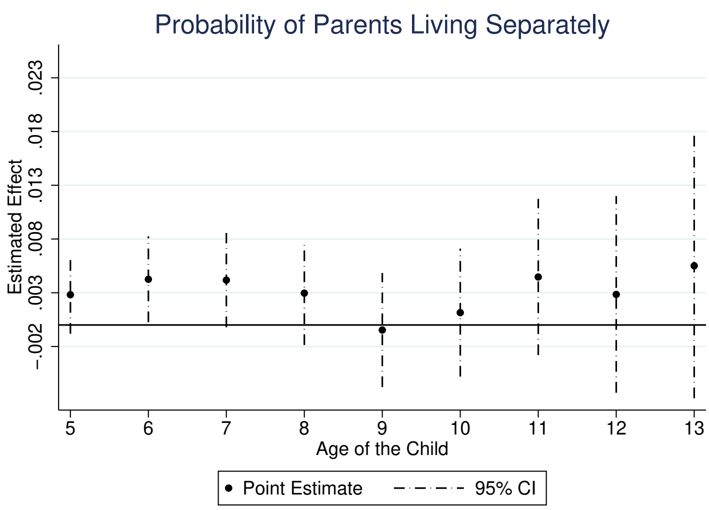

Figure 46: Maternal Job Loss, Estimated Effects on Probability of Parents Living Separately

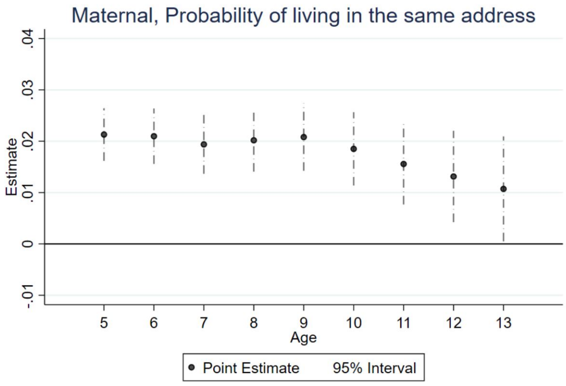

Figure 47: Maternal Job Loss, Probability of Living in the Same Address as Three Years Before the Job Loss Event

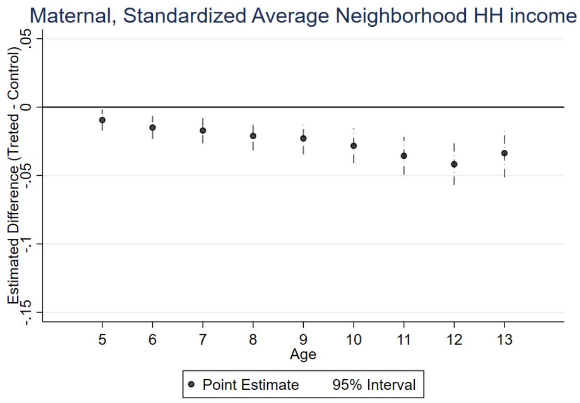

Figure 48: Maternal Job Loss, Standardized Average Neighborhood Income

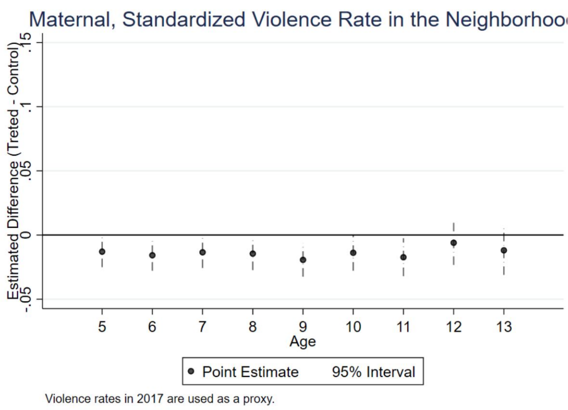

Figure 49: Maternal Job Loss, Standardized Average Neighborhood Violence Rate

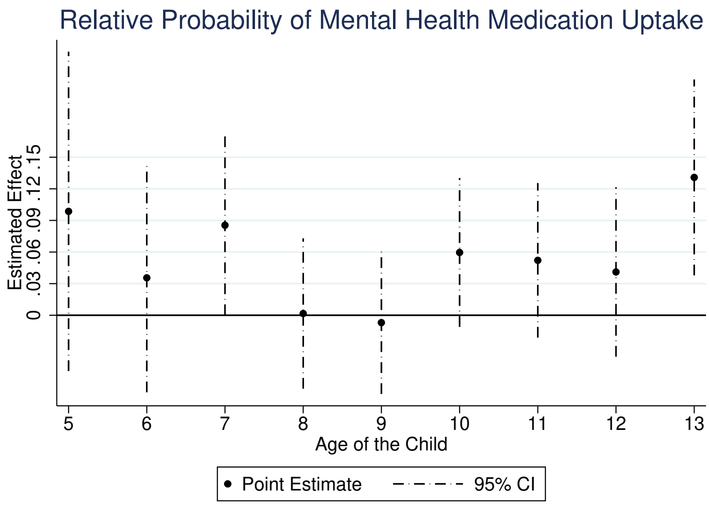

Figure 50: Maternal Job Loss, Estimated Effects on Mental Health Medicines Relative to the Mean of Control Group (to see the means, check Table 4)

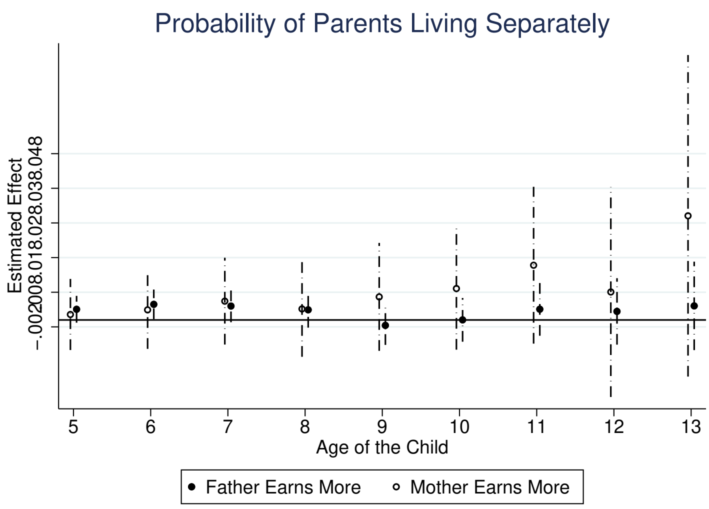

Figure 51: Maternal Job Loss, Estimated Effects on Probability of Parents Living Separately by the Main Earner