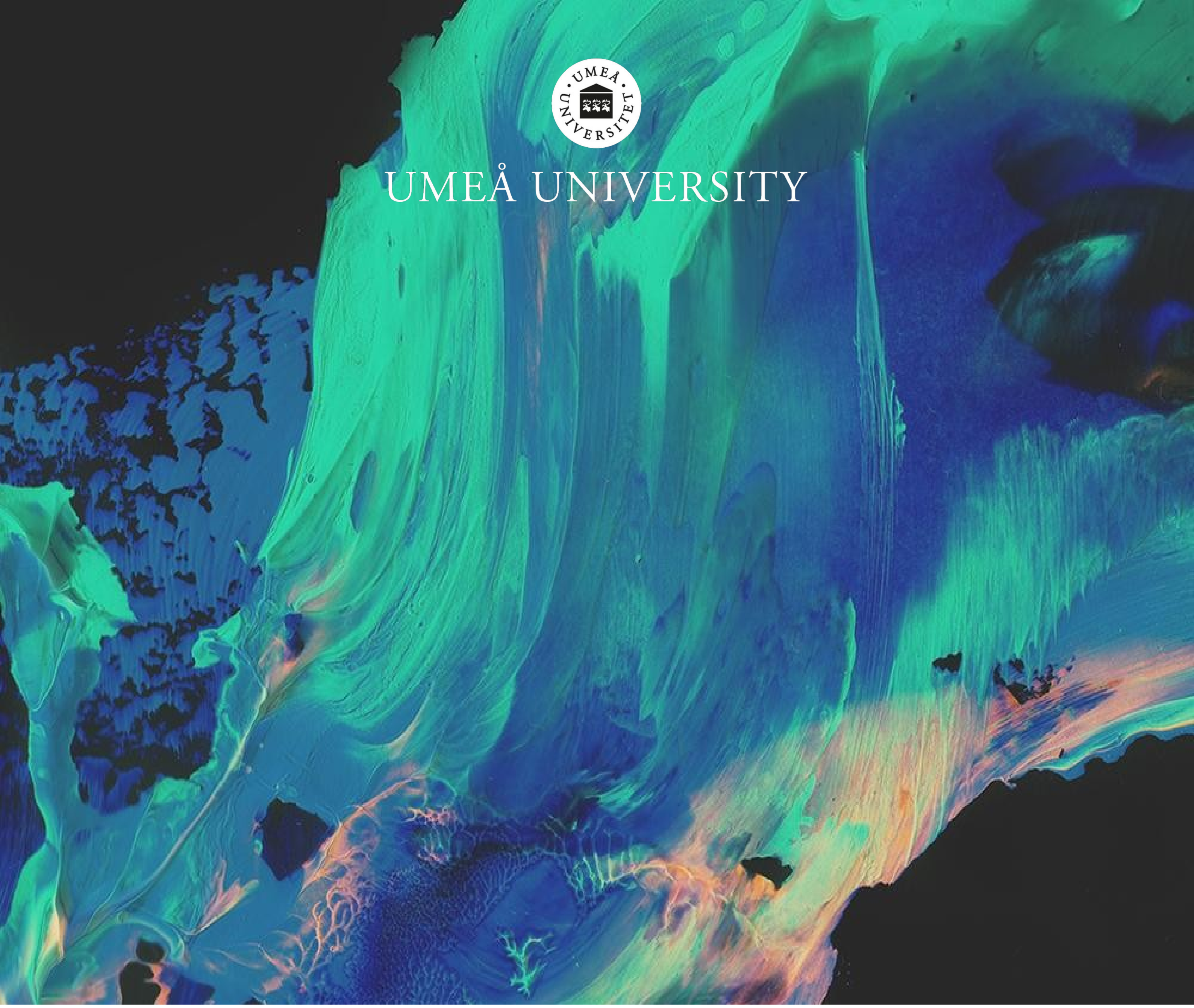


# Effects of parental job loss on children's mental health: the role of latency, timing and cumulative effects

Björn Högberg and Anna Baranowska-Rataj

**CEDAR Working Papers 2023:29**

Centre for Demographic and Ageing Research

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**Abstract**

Crossover effects of critical life events within families have received growing attention in life-course research. A parent losing a job is among the most distressing events that can befall a family, but existing research has reached discrepant conclusions concerning if, and if so how, this affects child mental health. Drawing on insights from models of intra-family influence and life course epidemiological models, we ask if parental job loss have latent or long-term effects on child mental health, if the effects are conditional on the timing of the job loss, and if repeated job losses have cumulative effects.

We use intergenerationally linked Swedish register data combined with entropy balance and structural nested mean models for the analyses. The data allow us to track 400,000 children over 14 years and thereby test different life-course models of crossover effects. We identify involuntary job losses using information on workplace closures, thus reducing the risk of confounding.

Results show that paternal but not maternal job loss significantly increases the risk of mental health problems among children, that the average effects are modest in size (less than 4% in relative terms), that they materialize only after some years, and that they are driven by children aged 6-10 years. Moreover, we find evidence of cumulative effects, but also of declining marginal harm of additional job losses over the life course.

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**Keywords:** job loss; mental health; life course; crossover effects; cumulative effects; sensitive periods.

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## Introduction

The lives and fates of children and their parents are interweaved in complex ways, and critical life course events experienced by one family member can have long-lasting repercussions for others in the family. Life course research and research on linked lives has shown how stressors in the family shape the developmental trajectories of children, including the emergence of mental health problems (Corna, 2013; Elder, 1998; Mari & Keizer, 2021). Such intra-family influence or *crossover effects* have received growing attention across scientific disciplines (Bakker & Demerouti, 2013; Conger et al., 2010; Ruiz-Valenzuela, 2021). Job losses are among the most distressing events that can befall a family provider, with consequences for household finances, social status, relationships, and overall family well-being (Aquino et al., 2022; Brand, 2015). Less is known regarding crossover effects of parental job losses on the mental health of children. The handful studies in the related literatures on job loss and unemployment have reached discrepant conclusions, with many finding negative effects (Bubonya et al., 2017; Mörk et al., 2014; Moustgaard et al., 2018; Schaller & Zerpa, 2019), but others hardly any effects (Mörk et al., 2020). The discrepancies may be due to different methodologies and sample characteristics, or to more substantive heterogeneity in effects depending on the children's age or on family factors (Aquino et al., 2022; Ruiz-Valenzuela, 2021).

Using intergenerationally linked and longitudinal Swedish register data, this study investigates effects of parental job loss on the mental health of children. We complement existing research on crossover effects of parental job loss or unemployment in three ways. First, we identify involuntary job losses objectively using information on workplace closures. As workplace closures are typically beyond the control of the individual worker, this reduces concerns that our results are driven by confounding due reverse causation (if a child's health problems increase the risk of parents losing their jobs) or confounding due to a third factor affecting both parental job loss and child mental health, such as parental health (Burgard et al., 2007; Ruiz-Valenzuela, 2021). Second, we take a life-course and long-term perspective, and combine insights from theoretical models of intra-family influence and life course epidemiological models (Kuh et al. 2003). Specifically, we investigate the role of latent or long-term effects, timing and sensitive periods, and cumulative effects (Kuh et al., 2003; Pearlin, 2010). Most previous studies (see, however, Mörk et al. (2014, 2020)), have been based on short panel surveys, which limits the analysis to short-run effects. Our data follow children for up to 14 years, which allows testing distinct mechanisms that might operate in specific periods of childhood or as a result of repeated exposures to parental job losses. Third, we employ constrained structural nested mean models (Robins, 1994: Wodtke, 2020) to examine cumulative effects of repeated job losses on child mental health. These models are particularly useful for studying how the temporal dynamics critical life events unfold and accumulate over time.

## Background and theoretical framework

### *Life course theory, linked lives, and spillover-crossover effects*

A life course perspective implies among other things (i) attention to long-term temporal processes, including transitions, events and states; (ii) a presumption that earlier transitions, events or states matter for future outcomes; (iii) attention to the timing and duration of these temporal processes within developmental or age-dependent trajectories; and (iv) recognition of the embeddedness of individuals within networks of social relations, not least families (i.e. the notion of "linked lives") (cf. Elder, 1974; Elder, 1998). This set of principles offers a powerful conceptual toolkit and will be essential for deriving the more specific models that are tested empirically in the study. Before outlining these models, we will briefly explicate the notions of linked lives and spillover-crossover effects, as these are key for understanding how parental stressors affect children.

That lives are linked means that the developmental trajectories of individuals who stand in close relationship to one another, such as children and parents, are interdependent. Major life events affecting one individual in a family will have long-lasting repercussions for the lives of the other(s). Likewise, major life decisions cannot be taken in isolation, but require consideration of and deliberation with other family members (Elder, 1998; Koehly & Manalel, 2023). The notion of linked lives, established in demography and sociology, resembles the notion of spillover and crossover-effects studied in psychology (Bakker & Demerouti, 2013; Bubonya et al., 2017). Spillover effects describe how events or processes in one life domain (e.g. work) are transmitted to another life domain (e.g. family life) within an individual (Esche, 2020). Crossover effects concern the transmission, through empathic reactions and social interaction, of feelings and emotional states between individuals in close relationships (Bakker & Demerouti, 2013). Spillover-crossover effects thus describe how spillover effects across different life domains of individuals affect other people, such as their children.

### *Job loss and mental health*

While job loss and unemployment are distinct concepts – job loss does not necessarily result in unemployment and unemployment can come about from other causes than job losses – their impacts on mental health are sufficiently similar to allow discussing both in tandem (Brand, 2015). A large body of research have documented adverse effects of job loss or unemployment on the mental health of the directly affected individual. The underlying mechanisms linking job loss or unemployment with adverse mental health outcomes in the directly affected individual include income loss and resulting financial strain (Jacobson et al., 1993), disruption of time structure

(Jahoda, 1981), stigma and threats to social status (Brand, 2015; Brand & Thomas, 2014), loss of a major social role (Burgard et al., 2007), relationship strain (Blom & Perelli-Harris, 2020; Conger et al., 2010), and restricted agency and life-course control (Fryer, 1986).

The mechanisms linking parental job loss to children's mental health are in many ways similar to those of own job loss explicated above (Brand, 2015), though some may be felt in a particular way, and perhaps more acutely, by a child. For instance, relationship strain or divorces caused by parental job loss (Blom & Perelli-Harris, 2020; Conger et al., 2010; Esche, 2020) may be more disruptive for children, who become at risk of losing an important attachment figure and who may be especially attentive to the emotional climate in the family. Likewise, job loss can force parents to move in search for jobs, and children may be more sensitive to the disruption of own or parental social networks caused by residential mobility (Brand, 2015). Moreover, job loss increases the risk of financial strain in the family, which in turn is linked to harsh, punitive or otherwise inadequate parenting (Conger et al., 2010; Mari & Keizer, 2021). Not least, the notion of emotional crossover effects suggests that the mental health of children may be affected by parent's mental health problems (Bakker & Demerouti, 2013; Brand, 2015; Ruiz-Valenzuela, 2021). In addition to the indirect effects that are transmitted through the parent and the overall family, parental job loss can also affect children more directly by influencing their expectations about their future opportunities in life, which in turn can affect their mental health (Gassman-Pines et al., 2015).

A majority of studies to date have found at least some adverse effects of parental job loss or unemployment on children's mental health (Bubonya et al., 2017; Ermisch et al., 2004; Moustgaard et al., 2018; Mörk et al., 2014; Nikolova & Nikolaev, 2021; Schaller & Zerpa, 2019), including behavioral outcomes and externalizing problems (Hill et al., 2011; Mari & Keizer, 2021; Peter, 2016), although some studies have found no or very small effects (Mörk et al., 2020). A tentative conclusion is that, in addition to differences in methodology and samples, effects may be conditional on certain child and family characteristics. In particular, life course theory posits that the timing and frequency of different kinds of stressors interact with the developmental processes of the child.

*Latent or long-term effects*

Stress process theory posits that stressful events can bring about a proliferation of subsequent stressors (Pearlin, 2010). In turn, the subsequent stressors can sustain and even augment the harm from the initial event, thus generating long-term negative effects on mental health (Strandh et al., 2014). In a similar vein, latency models in life course epidemiology posit that health effects of stressors early in life can lay dormant and emerge only after some time, often in relation to a specific trigger event (Kuh et al., 2003; Lupien et al., 2009). For instance, there is evidence of delayed onset of mental health problems from earlier stressful events, possibly due to inflammatory responses that affect brain development, the neuroendocrine system, and vulnerability to subsequent stressors (Danese & Baldwin, 2017). On the other hand, set-point theory posits that individual well-being fluctuates around a stable set-point (Diener et al., 2006). Thus, temporary decreases in mental health caused by critical life course events are typically followed by a period of adaptation, after which individuals return to their baseline level of mental health.

Most research to date has found that parental job loss or unemployment during childhood or adolescence has long-term negative effects on mental health that are detectable in young adulthood (Brand & Thomas, 2014; Ermisch et al., 2004; Nikolova & Nikolaev, 2021). Regarding latency, Moustgaard et al. (2018) found that health effects of paternal unemployment are small or non-existent the first year after the unemployment spell but grow stronger over time. Mörk et al. (2020), on the other hand, found no evidence of short- or long-term effects of parental job loss on the risk of hospitalization due to mental and behaviour problems.

*Timing and sensitive periods*

Heterogeneous effects of parental job loss may emerge due to differential timing across sensitive periods (Wheaton & Reid, 2008). A sensitive period can be defined as developmental stages or ages where the effect of a stressor is more pronounced, and where, after the stressor is removed, this effect is more likely to persist (Kuh et al., 2003; Lupien et al., 2009). From a neurobiological perspective, sensitive periods are periods of heightened neuroplasticity, where stress can influence the course of brain development and make the child more sensitive to stress both in the present and later in life. This especially applies to the first years after birth but also to puberty and adolescence (Fuhrmann et al., 2015; Lupien et al., 2009). From a psychological and sociological perspective, however, small children may be sheltered from some negative effects of parental job loss as they lack the cognitive capacity to comprehend the situation, while adolescents may be more cognizant of the loss of status associated with job loss and simultaneously be more vulnerable to stressors as they form their own autonomous identities (Brand & Thomas, 2014). The fact that mental disorders often appear in adolescence also suggests that this may be a sensitive period (Kessler et al., 2007).

Existing results with regard to sensitive periods in relation to parental job loss or unemployment have been mixed. Schaller & Zerpa (2019) found no or small differences in effects on mental health depending on age. Results in Powdthavee & Vernoit (2013) suggest that parental unemployment may have positive effects on well-being in younger children (age 11), but that this effect turns negative as children grow older (until age 15). Ermisch et al. (2004) and Brand & Thomas (2014) found that young adults report poorer mental health when exposed to parental joblessness in later childhood (age 6 to 10/11) or early adolescence (age 11 to 15/17) but not early childhood (age 0-5), while Nikolova & Nikolaev (2021) found that exposure at ages 0-5 and 11-15 but not 6-10 harms well-being later in life.

*Cumulative effects*

A third aspect to consider is the duration and frequency of a stressor over the life-course, which is linked to the concept of cumulative effects in sociology (Corna, 2013; DiPrete & Eirich, 2006). It is known that allostatic load can result from repeated and prolonged exposure to stressors (i.e. chronic stress), and that this in turn is strongly linked with adverse mental health outcomes (Lupien et al., 2009; McEwen, 2012). Cumulative effects can be additive, such that effects increase linearly with the duration or frequency of exposure, or multiplicative, such that there is an added effect of additional exposures. In the case of repeated parental job losses, cumulative effects could arise because of growing despondency, as parents and their families struggle to get a firm foothold in the labour market, or because of growing financial strain resulting from scarring effects of repeated job losses and the gradual depletion of savings (Aquino et al., 2022). Moreover, eligibility to unemployment benefits is often conditional on previous employment, and workers with weak labour market attachment may have to rely on more stigmatizing and less generous means-tested social assistance instead, with negative consequences for their family members. Conversely, repeated job losses may lead to psychological adaptation and thereby weaker effects over time (Aquino et al., 2022; Booker & Sacker, 2012), and set-point theory suggests that individual well-being is largely stable over the long-term and is typically not dependent on the accumulation of stressors occurring possibly several years earlier (Diener et al., 2006).

Previous research on effects of parental job loss or unemployment have generally found that repeated job losses over a shorter follow-up time or longer unemployment spells have more adverse short-term effects on children's mental health (Mörk et al., 2014) or behavioral problems (Hill et al., 2011). However, to the best of our knowledge no study has investigated the cumulative effects of repeated parental job losses throughout childhood on mental health later in life.

Against the background of these life course models, the present study investigates four specific research questions:

RQ1: Does parental job loss have adverse effects on child mental health? This first question considers any short- or long-term effects for all age groups combined.

RQ2: Does parental job loss have latent or long-term effects on child mental health?

RQ3: Are the effects of parental job loss conditional on the timing of the job loss? That is, do the effects of parental job loss on child mental health differ for different age groups?

RQ4: Do repeated job losses have cumulative effects on child mental health?

**Data and methods**

To address our research questions, we need data that allow us to (i) link parents with their children; (ii) follow parents and children over several years; (iii) observe employment as well as health trajectories over these years; and (iv) link workers to workplaces in order to identify job losses due to workplace closures. Intergenerationally linked register data covering close to 400,000 children as well as their parents and their parent's co-workers over 14 years (2005-2018) satisfy these conditions.

We link data from different administrative registers. The Swedish Prescribed Drug Register covers all prescription drugs that have been dispensed at pharmacies in Sweden since 2005. The Medical Birth Register contains health-related information on all births in Sweden since 1973. The Longitudinal integrated database for health insurance and labour market studies (LISA) covers all individuals aged 16 years or older living in Sweden, with data on employment, incomes and workplace identifiers. These registers are matched with basic demographic data regarding family links and family structure from Statistics Sweden. Online supplementary file S1 provides more details about the construction of the analytical sample.

*Outcomes: Drug prescriptions*

We use drugs with the Anatomical Therapeutic Chemical (ATC) Classification codes N05 and N06A as outcomes. N05 refers to psycholeptic drugs (antianxiety agents), the vast majority (>85 %) of which are prescribed for anxiety disorders, while N06A includes antidepressants used to treat mood disorders. These drugs allow us to capture the most salient internalizing disorders among children in Sweden today. Due to the substantial degree of comorbidity between anxiety and mood disorders we combine both types of drugs into one outcome in the analysis.

Completion of the Swedish Prescribed Drug Register is estimated to be close to 100%, although the register does not include information on drugs used in hospitals. The focal drugs can only be bought with a prescription, and only medical doctors are authorized to prescribe drugs in Sweden. Treatment guidelines for children with mood or anxiety disorders are fairly stringent, and drugs are only recommended for more severe cases (National Board of Health and Welfare, 2017). We have data on drug prescriptions from 2005 to 2018, when the children in the sample are, depending on their birth year, between 4-8 and 18-22 years old. Since we want to adjust for lagged values of parental drug prescriptions (see below), we only include observations when the children are at least 6 years old. We estimate effects of parental job losses occurring until age 18, but measure outcomes until age 22 in order to capture long-term effects.

*Treatment: Parental job loss*

Our focal treatment variable is parental job loss due to workplace closure. The use of workplace closures to objectively identify involuntary job loss reduces the risk of confounding due to reverse causation or omitted variables. It also reduces the risk of measurement error compared to self-reported indicators of job loss. We define workplace closures in accordance with Fackler et al. (2018). A workplace is defined as closed if the workplace identifier vanishes between year t+0 and year t+1. In order to avoid misclassifying mergers of two or more workplaces as closures, we in addition require that the maximum clustered outflow of workers between these two years is less than 30% of the workforce in the workplace in year t+0. This means that workplaces where at least 30% of the workers in the original workplace in year t+0 move together to a new workplace in year t+1 are not classified as closed. For workplaces with fewer than four workers, we follow Fackler et al. (2018) and define them as closed if either all workers move to different new workplaces or the new workplace has a larger workforce than the closed one.

Based on these definitions, a child is included in the treatment group in a given year if the focal parent was employed at a workplace that was closed between year t+0 and t+1. A child is included in the control group in a given year if the focal parent was employed at a workplace that was not closed between year t+0 and t+1. If the focal parent cannot be linked to a workplace in year t+0 (i.e. did not work), if the focal parent was self-employed, or if data on covariates are missing (see below), the child is coded as missing in that year. Supplementary file S5 in the Supplementary materials show that, relative to workers in non-closing workplaces, workers in closing workplaces have higher risks of unemployment or non-employment, lower earnings, lower disposable incomes and receives more social assistance following the workplace closure.

*Covariates*

While the use of workplace closures to objectively identify job losses reduces the risk of confounding due to reverse causation or omitted variables, we cannot rule out that characteristics of the child, parent or workplace affects both the risk of workplace closure and child mental health. In order to account for such confounding, we adjust for a range of demographic, employment-related and health-related characteristics of the child and the parents, as well as for workplace characteristics. Child characteristics include health at birth, sex, age, birth year and birth order. Parental demographic characteristics include country of birth, civil status, household status, age, region of residence and educational level. Parental employment-related characteristics include previous job losses and unemployment spells, employment status, wage earnings, disposable income, and receipt of social assistance. Parental health-related characteristics include sickness absence and prescriptions for antianxiety agents and antidepressants. Workplace characteristics include the sector, age and size of the workplace. All time-varying characteristics are measured in the year before the job loss (t-1) in order to avoid overcontrol bias by adjusting for consequences of the job loss. Although we analyse mother's and father's job loss separately, we adjust for characteristics of both parents throughout since the father's (mother's) characteristics may affect both the risk that the mother (father) loses her (his) job and child mental health (Ruiz-Valenzuela, 2021). The exception is work characteristics of the "other" parent, since this information is only available for working parents and adjusting for this would thus imply that we adjust for both parents being employed. We include most continuous covariates as such; the exception is birth year and child age, which are measured with one indicator for each year because of possible non-linear cohort differences and the strong but non-linear correlation between drug prescriptions and age.

A more detailed description of all covariates, as well as summary statistics, are provided in online supplementary files S2-S4.

*Analytical strategy*

We use entropy balancing to make treatment and control groups comparable on observed covariates (Hainmueller, 2012). Entropy balancing reweights the control group observations such that the differences in the mean, variance, and skewness of the covariates between the treatment and control groups fall within a pre-specified target. Like other other common pre-processing techniques such as propensity score matching, entropy balance reduces the model dependence for the later analysis. Compared to other common pre-processing techniques, however, entropy balance has two key advantages. First, since the balance constraints (0.01 in our case) can be specified beforehand, it can always marginally improve on the balance that can be obtained by other techniques. Second, it assigns weights to all observations and does not require that unmatched observations are disregarded for the analysis (Hainmueller, 2012). We estimate separate weights for each unit of observation (child-year observations), and match exactly on year (Iacus et al., 2012). Although heterogeneity in effects by parental gender are outside of the life course perspective guiding the formulation of the study's hypotheses, we also balance separately for each parent (Bubonya et al., 2017; Mörk et al., 2020).

We are interested in the overall short- and long-term effects of parental job loss (RQ1), as well as in the temporal dynamics of these effects: if short- vs. long-term effects differ (i.e. latency; RQ2), if effects are conditional on the timing (i.e. sensitive periods; RQ3) and the frequency (i.e. cumulative effects; RQ4) of job losses.

To study overall effects (RQ1), we code the outcome variable such that it takes the value 1 if the respondent is prescribed any drug (anti-anxiety agents or antidepressants) in the same year or in any of the five years following the job loss of the focal parent (cf. Mörk et al., (2020)). We pool all children regardless of age and estimate a weighted linear probability model with parental job loss measured in year t+0 as the treatment and drugs prescriptions measured in years t+1…, t+5 as the outcome. Linear probability models are preferred to e.g. logistic regression models since they facilitate comparison of effect sizes across models (Mood, 2010). We consistently cluster the standard errors at the level of children to account for the panel structure of the data.

To study latent or long-term effects (RQ2), we estimate separate models for all the five years following the job loss. That is, we first estimate effects of parental job loss in t+0 (specifically between t+0 and t+1) on drug prescriptions in t+1, then effects of parental job loss in t+0 on drug prescriptions in t+2, and so on until t+5. The models are otherwise identical to those addressing RQ1 described in the previous paragraph.

To study timing and sensitive periods (RQ3), we split the sample into three age groups: 6-10 years, 11-15 years and 16-18 years. The age groups capture differences between prepubescence, puberty, and later adolescence (Ermisch et al., 2004). As stated, we cannot estimate effects for children younger than 6 years due to data limitations. We balance covariates separately for these age groups and estimate separate weighted regression models with the outcome variable coded 1 if drugs are prescribed in any of the five years following the parental job loss.

To study cumulative effects, we estimate a constrained structural nested mean model using the regression-with-residuals approach (Robins, 1994; Wodtke, 2020). Structural nested mean models enable estimation of the effect of time-varying treatments on an end-of-study outcome in a longitudinal setting, where time-varying and treatment-induced confounding is an issue. In such settings, prior treatments may impact on confounders of future treatments, and confounders at one time point may act as mediators at a later time point. An example may clarify the point. A parent who loses a job due to workplace closure may get re-employed at a less productive workplace. Because of its lower productivity, the new workplace pays less and simultaneously has a higher risk of closing down. Lower earnings are a confounder of future treatments since it is correlated with “workplace productivity” (which we cannot directly observe), but it is also a mediator since it may harm child mental health (Conger et al., 2010). As is well known, not adjusting for time-varying confounders will lead to omitted variable bias. However, adjusting for time-varying confounders that are also mediators through conventional methods such as regression or balancing will in this setting remove the part of the effect of the treatment that runs through these time-varying confounders, thus introducing over-control (endogenous selection) bias.

Regression-with-residuals overcomes this problem by adjusting for residualized instead of untransformed values of the confounders. In the first stage, all covariates (i.e. potential confounders) are residualized at each time point. At the first time point, the covariates are centred at their mean. At subsequent time points, each covariate is regressed on lagged values of the covariates, lagged outcomes, and lagged treatments, and the residuals from these regression are extracted. In the second stage, the end-of-study outcome is regressed on the residualized confounders and cumulative treatments (Wodtke, 2020). The residualized confounders generated in the first step are by construction not associated with prior treatments, thus avoiding over-control bias, but their association with variables measured at a later time point – notably the outcome and future treatments – is not affected by the residualization, thus avoiding omitted variable bias (Wodtke et al., 2019).

We restrict the first stage to one-year lags, and regress confounders measured in t-1 on confounders and treatment in t-2. In the second stage, we measure the outcome at age 18, and sum the number of treatments (parental job losses) for each year until age 18. Unlike in the analyses addressing RQ1-RQ3, we sum the total number of job losses of both parents since there are no theoretical reasons to expect that cumulative effects would be restricted to job losses of either parent. Due to the low number of children experiencing more than four job losses, we sum four or more job losses into one category.

The results reported in in this study will suffer from omitted variable bias if there are unobserved confounding that affects both the risk of parental job loss and child mental health. Although the use of workplace closures to identify job losses, in combination with adjustment of a rich set of pre-treatment covariates, reduces the risk of such confounding, we investigate if the main estimates are robust to more stringent definitions of the treatment variable in supplementary analyses. Moreover, the results will only apply to children with employed parents since these are the only ones at risk of being treated (i.e. structural or deterministic non-positivity). In addition, regression-with-residuals may be biased if there is effect modification due to treatment-confounder interactions, or if the association between confounders and confounders and treatments are not linear and additive (Wodtke et al., 2019). We investigate these issues further in supplementary analyses.

**Results**

Table 1 shows overall effects within five years of the parental job loss (right-most column), thus addressing RQ1, and also compare short term with latent or long-term effects (columns 1-5), thus addressing RQ2. The overall effects are positive for both maternal and paternal job loss, but only for paternal job loss are the estimates statistically significant at the 5% level, while the estimates for maternal job loss are close to zero and not significant. Substantively, the estimates mean that maternal job loss increases the risk of mental health problems (drug prescriptions) within five years of the job loss by 0.16 percentage points, or by 1.5% compared to the sample mean, with the corresponding numbers for paternal job loss being 0.39 percentage points or 3.6%. Thus, while both estimates are positive and that for paternal job loss is significant, they are fairly small in both absolute and in relative terms. Note that the conventional 5% significance threshold may not be a meaningful indicator of substantively important effects given the sample size of more than three million person-year observations.

Table 1 also shows that the short-run effects – in the first year following the job loss – of both maternal and paternal job loss are very small and not statistically significant. More noticeable effects in absolute terms only emerge after two years, although no consistent temporal pattern is visible after that: for maternal job loss, the largest effect is observed five years after the job loss, while for paternal job loss the largest effect is three years after the job loss. The latter estimate is also the only one that is statistically significant. It should be noted that the long-run effects are mechanically larger in absolute terms since the risk of drug prescriptions increase strongly with age. The largest effects in relative terms are 3.5% (after five years) for maternal job loss and 6.6% (after three years) for paternal job loss.

**Table 1. Short-term, long-term and overall effects of parental job loss on drug prescriptions of children.**

| | | t+1 | t+2 | t+3 | t+4 | t+5 | t+1,…,t+5 |
|---|---|---|---|---|---|---|---|
| **Mothers** | | | | | | | |
| Mother’s job loss | B | -0.0009 | 0.0011 | 0.0013 | 0.0011 | 0.0021 | 0.0016 |
| | SE | (0.0012) | (0.0014) | (0.0015) | (0.0016) | (0.0018) | (0.0021) |
| Sample mean of outcome | | 0.0327 | 0.0417 | 0.0480 | 0.0540 | 0.0593 | 0.1072 |
| N person-years (controls) | | 3431801 | 3431801 | 3236390 | 2975835 | 2645014 | 3431801 |
| N person-years (treated) | | 23057 | 23057 | 21948 | 20387 | 18542 | 23057 |
| **Fathers** | | | | | | | |
| Father’s job loss | B | -0.0001 | 0.0020 | 0.0032* | 0.0025 | 0.0028 | 0.0039* |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | SE | (0.0010) | (0.0011) | (0.0013) | (0.0014) | (0.0015) | (0.0018) |
| Sample mean of outcome | | 0.0334 | 0.0425 | 0.0488 | 0.0549 | 0.0604 | 0.1089 |
| N person-years (controls) | | 3299235 | 3299235 | 3120985 | 2882669 | 2580610 | 3299235 |
| N person-years (treated) | | 36739 | 36739 | 35053 | 32873 | 29945 | 36739 |

*Notes: B = regression slope. SE = standard errors, clustered at the child level. * p<0.05; ** p<0.01; *** p<0.001. Table shows estimates from weighted linear probability models*.

Table 2 examines the role of timing and sensitive periods by showing separate estimates for different age groups, thus addressing RQ3. The pattern is similar for both maternal and paternal job loss: absolute effect sizes are clearly largest for the youngest age group (age 6-10), diminish for the middle age group (age 11-15), and then diminish further and turn negative (maternal job loss) or essentially reach zero (paternal job loss) for the oldest age group (age 16-18). Only for the youngest age group are the estimates statistically significant. Again, since the baseline risks of drug prescriptions increase strongly with age, the age differences are even more striking if we consider relative effect sizes. For the 6-10 age group, maternal job loss increases the risk by 15.3% and paternal job loss by 17.1% compared to the mean for the age group. The corresponding relative effects for the 11-15 age group are 0.6% and 2.6%, respectively, and for the 16-18 age group -1.6% and 0.6%, respectively.

**Table 2. Overall effects of parental job loss on drug prescriptions of children within five years. Heterogeneity by age.**

| | | Age 6-10 | Age 11-15 | Age 16-18 |
|---|---|---|---|---|
| **Mothers** | | | | |
| Mother's job loss | B | 0.0058* | 0.0007 | -0.0027 |
| | SE | (0.0026) | (0.0033) | (0.0057) |
| Sample mean of outcome | | 0.0379 | 0.1208 | 0.1646 |
| N person-years (controls) | | 983028 | 1655156 | 793617 |
| N person-years (treated) | | 7189 | 11278 | 4590 |
| **Fathers** | | | | |
| Father's job loss | B | 0.0068*** | 0.0033 | 0.0010 |
| | SE | (0.0021) | (0.0027) | (0.0048) |
| Sample mean of outcome | | 0.0398 | 0.1247 | 0.1708 |
| N person-years (controls) | | 1006679 | 1569346 | 723210 |
| N person-years (treated) | | 12103 | 17641 | 6995 |

*Notes: B = regression slope. SE = standard errors, clustered at the child level. * p<0.05; ** p<0.01; *** p<0.001. Table shows estimates from weighted linear probability models. The outcome variable is defined as any drugs prescribed in the same year or within five years of the job loss.*

Table 3 turns to the role of cumulative effects by showing estimates from regression-with-residuals models with the cumulative number of job losses as the treatment and drug prescriptions at age 18 as the outcome, thus addressing RQ4. Note that the table now shows results for the cumulative job losses of both parents. We present two sets of results. The first column shows results adjusted for all (residualized) covariates except for workplace characteristics: workplace sector, size and age. This is because information on workplaces is only available for working parents, meaning that adjusting for these variables would imply that we condition on both parents working. The second column shows results adjusted for all (residualized) covariates including workplace characteristics of both parents. The two columns show very similar results for the first three job losses. The effect of two job losses (0.93 percentage points) are more than twice as large as the effect of one job loss (0.44-0.40 percentage points). Experiencing a third job loss is more harmful still (1.11-1.02 percentage points), but the additional harm of going from two to three is smaller than that of going to one to two. In relative terms, three job losses increase the risk of drug prescriptions by around 12% compared to the sample mean. With regard to four or more job losses, the point estimates are somewhat smaller than for two or three job losses in the model not adjusting for workplace characteristics (0.69 vs. 0.93-1.11 percentage points), but similar in the model adjusted for workplace characteristics (0.91

vs. 0.93-1.02 percentage points). However, both estimates for four or more job losses are fairly imprecise and we cannot rule out neither weaker nor stronger effects compared with fewer job losses. In sum, we find some evidence for cumulative effects in the sense that the point estimates increase until three job losses, but there simultaneously seem to be a declining marginal effect of additional job losses in the sense that the additional harm of more job losses grows smaller after two job losses and disappears at four or more job losses.

**Table 3. Cumulative effects of parental job losses on drug prescriptions of children at age 18.**

| | | **Not adjusted for workplace characteristics** | **Adjusted for workplace characteristics** |
|---|---|---|---|
| **Cumulative number of job losses of both parents** | | | |
| 1 | B | 0.0044*** | 0.0040** |
| | SE | (0.0012) | (0.0012) |
| 2 | B | 0.0093*** | 0.0093*** |
| | SE | (0.0024) | (0.0025) |
| 3 | B | 0.0111* | 0.0102* |
| | SE | (0.0048) | (0.0050) |
| 4 or more | B | 0.0069 | 0.0091 |
| | SE | (0.0085) | (0.0092) |
| Sample mean of outcome | | 0.0880 | 0.0857 |
| N person-years (total) | | 3582020 | 3226416 |

*Notes: B = regression slope. SE = standard errors, clustered at the child level. * p<0.05; ** p<0.01; *** p<0.001. Table shows estimates from weighted linear probability models. The outcome variable is defined as drug prescription when the child is 18 years old.*

*Supplementary and sensitivity analyses*

Supplementary files S6-S8 show results of sensitivity analyses where we restrict the sample to workers with at least three consecutive years of employment before the workplace closure (S6), restrict the sample to workplaces with at least 10 workers (S7), or restrict the sample to families that ever experience job loss during the studied period (S8) (Ruiz-Valenzuela, 2021). The results are largely similar to the main results presented in the paper, although the estimates are larger (more positive) when we restrict the sample to larger workplaces. Supplementary file S9 shows that the effects for paternal job loss are similar or somewhat stronger, but the effects of maternal job loss are weaker and even negative, when use ADHD medication (as an indicator of externalizing problems) instead of antianxiety drugs and antidepressants as the outcome. It also shows that only one and three cumulative job losses increase the risk of ADHD medication at age 18. Supplementary file S10 shows effects for sensitive periods not adjusted for parental drug prescriptions, meaning that we can include children younger than 6 years old. The results show that neither maternal nor paternal job loss at age 0-5 affects drug prescriptions during the first five years, but that paternal job loss at that age increases the risk of drug prescriptions at age 18, indicating that this may be a sensitive period for very long-term effects (cf. Nikolova & Nikolaev, 2021). Supplementary file S11 shows that the results are not affected by adjusting for lagged drug prescriptions. Supplementary file S12 shows that the estimates of cumulative effects are larger, and that there may also be an additional effect of four or more job losses, when we allow for effect modification due to treatment-confounder interactions.

## Discussion

Against the background of life course research, this study investigated if parental job loss resulting from workplace closure has crossover effects on child mental health (RQ1). Following calls to disentangle heterogeneous effects of critical events (Aquino et al., 2022; Brand, 2015), we examined if the effects are latent and/or long-term (RQ2), how the effects depend on the timing of the job loss (RQ3), and if these effects accumulate such that repeated job losses are more harmful than a single job loss (RQ4).

With regard to the overall effects (RQ1), we found that paternal job loss increases the risk of mental health problems (measured by prescriptions for anti-anxiety agents or antidepressants) by 3.6%, while maternal job losses have very small or no effects. The findings are qualitatively consistent with the related previous literature, most of which report at least some negative effects of parental job loss or unemployment on child mental health (Ermisch et al., 2004; Moustgaard et al., 2018; Nikolova & Nikolaev, 2021; Schaller & Zerpa, 2019), although, contrary to our findings, some have found maternal job loss or unemployment to be most harmful (Bubonya et al., 2017; Mörk et al., 2014). Direct comparisons of effect sizes are difficult since most of the previous literature has investigated continuous measures of mental health. Compared with the effect sizes reported in studies using binary measures similarly as ours, our estimates are larger in relative terms than those reported by Mörk et al. (2014, 2020), also using Swedish register data but with a more rare and severe outcome, namely hospitalization. On the other hand, our estimates are about a quarter as large as those reported by Moustgaard et al. 2018), based on Finnish register data but using a very similar outcome measure, and about a tenth as large as estimates based on American survey data reported by Schaller & Zerpa (2019). The relatively modest average effects found in our study may reflect the fact that job losses in Sweden have mild economic consequences in a comparative perspective (OECD, 2013), and that the Swedish welfare state buffers much of the negative impact of job loss on families. This conclusion is tentative, however, and we echo the call of Corna (2013) for more cross-country comparative research to understand how inequalities in health over the life course are shaped by social policy configurations.

Our results regarding latent or long-term effects (RQ2) showed that the negative effects of parental job loss on child mental health were only visible after two to three years. This is very similar to what Moustgaard et al. (2018) found, and suggests that crossover effects of family-based stressors such as parental losses can take time to materialize in the form of deteriorated mental health among children and adolescents. Thus, future research on parental employment dynamics and child outcomes should, if possible, avoid relying solely on measures of immediate consequences of critical life course events occurring within families. Our research highlights the importance of taking a longer time perspective in studies of child outcomes.

With regard to timing (RQ3), previous studies have found that parental job loss or unemployment is most harmful when experienced during adolescence (Brand & Thomas, 2014; Ermisch et al., 2004), although early childhood may also be a sensitive period (Nikolova & Nikolaev, 2021). However, these studies have only measured mental health in young adulthood, meaning that sensitive periods cannot be disentangled from the time elapsed between treatment and outcome. Using approaches more similar to ours, Powdthavee & Vernoit (2013) found that unemployment is positive for the well-being of children aged 11 but grows more harmful for older children (until age 15), while Schaller & Zerpa (2019) found no systematic differences across age groups. Our results instead highlights later childhood (age 6-10) as a sensitive period. While neurobiological studies have not identified this as a particularly sensitive age in terms of mental health (Fuhrmann et al., 2015; Lupien et al., 2009), a possible explanation for this results is that the family has a more dominant position in the lives of younger children, while adolescents have already begun to construct their own independent social networks and may therefore be less dependent on their parents for their well-being. Alternatively, adolescents may be better able to cope with family-based stressors such as parental job losses, for instance by seeking support outside of the family. Overall, our assessment is that the evidence to date do not allow for strong conclusions regarding sensitive periods in the context of parental job loss or unemployment and child mental health.

Our study presented novel evidence on cumulative effects (RQ4). Consistent with theoretical expectations, our findings indicate that two or three job losses are more harmful than one job loss, which is also broadly consistent with related research showing that “more is worse” (Bubonya et al., 2017; Hill et al., 2011; Kalil & Ziol-Guest, 2005; Mörk et al., 2014). This suggests that the most vulnerable children in terms of parental employment status also run the greatest risks of experiencing mental health problems and thus should be in focus of preventive interventions. However, our finding that there seem to be a declining marginal harm of additional job losses also indicates that the most exposed families may find ways to cope with and adjust to difficult circumstances. Thus, future research should investigate the coping strategies adopted in families or children’s social environments that may foster resilience against economic shocks such as job losses.

*Limitations*

The results of the study should be view in light of its limitations. The outcome measure used in the study only allows us to capture more severe cases that lead to a medical diagnosis and treatment, but the results may not generalize to milder mental health problems that are more prevalent among children or to mental health problems that were undetected or unrecognized by medical services. Moreover, using drugs as the outcome makes it difficult to disentangle effects on underlying mental health from effects on help-seeking behaviour. Although health care in Sweden is universal and generally free of charge for minors, there is nonetheless a socio-economic gradient in utilization (Nordin et al., 2013) and we cannot rule out that families are more likely to abstain from seeking care if a parent loses his or her job. Related to this, we only have data on drugs over a 14-year period, meaning that we are not able to investigate effects during the possibly sensitive period of early childhood (before age 6), nor investigate life course dynamics over the full childhood from birth. Another limitation is that we only have yearly data, but the temporal dynamics may operate on a shorter timescale that is only possible to capture with more granular data. It should also be noted that only around 1% of the total sample experience more than two, and less than 0.3% experience more than three, job losses by age 18, and that the estimates of cumulative effects thus reflect the situation for a very selected group of children.

*Conclusions*

In this study, we showed that parental job loss following workplace closures has negative crossover effects on child mental health as measured by prescriptions of anti-anxiety agents and antidepressants. The effects, estimated using Swedish register data, are on average small to modest in size and are only significant for paternal job loss. This study adds to life course research showing that the same life event can have profound consequences for some population groups but minor, or even no impact on others (Aquino et al., 2022), and that temporal aspects of exposure to stressors such as job losses can be the driver of such heterogeneity (Wheaton & Reid, 2008). We show that the effects only materialize after some time, and are driven by children aged 6-10 years, with the effects for adolescents being small or non-existent. The latter finding contradicts some previous studies and calls for more research to identify developmentally sensitive periods in relation to parental employment dynamics and child outcomes. We also found that effects are stronger for children experiencing repeated parental job losses during their childhood, suggesting that children in families with weak labour market attachment and recurrent exposure to economic stressors are at particularly high risk of developing mental health problems. Since mental health problems, in turn, can undermine children's educational attainment and in extension future employment prospects (Mikkonen et al., 2020), preventive interventions may be required to avoid reproduction of labour market disadvantage and mental health problems across generations.

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# Supplementary materials for Effects of parental job loss on children's mental health: the role of latency, timing and cumulative effects

**Contents**

**Supplementary file S1 – Construction of the analytical sample**

We link three different sets of data. The first consists of all children born in Sweden between 1996 and 2000. For this dataset, we have data on mental health outcomes (drug prescriptions)[1], and child covariates (e.g. birth year and health at birth). The second dataset consists of the mothers and fathers of these children, with data on employment, workplace, incomes, demographic characteristics and parental mental health. The third dataset consists of the co-workers of the children's parents, with data on workplace and employment status. The first dataset is used to observe mental health outcomes of children, the second for adjusting for parent-level confounders, and the third to identify workplace closures among parents. The first dataset contains the analytical sample, and data from the parents are linked to this through unique personal identifiers.

| | N individuals | N person-years |
|---|---|---|
| Children born 1996-2000 | 440,792 | 10,579,008 |
| + Can be linked to both mother and father | 438,267 | 10,518,408 |
| + Complete data on outcomes, treatment and covariates (models for maternal job loss) | 390,852 | 3,404,238 |
| + Complete data on outcomes, treatment and covariates (models for paternal job loss) | 386,442 | 3,285,777 |

Note that only observations from 2006 can be used, since (lagged) data on parental drug prescriptions are not available before 2005.

[1] Completion of the Swedish Prescribed Drug Register is estimated to be close to 100%, although the register does not include information on drugs used in hospitals (Wettermark et al., 2007).

**Supplementary file S2 – Prevalence of drug prescriptions (in t+0) by age, gender and treatment status**

| Age | Boys (full sample) | Girls (full sample) | Maternal job loss=0 (analytical sample) | Maternal job loss=1 (analytical sample) |
|---|---|---|---|---|
| 5 | 0.3% | 0.3% | 0.3% | 0.5% |
| 6 | 0.4% | 0.4% | 0.4% | 0.1% |
| 7 | 0.5% | 0.4% | 0.4% | 0.4% |
| 8 | 0.5% | 0.4% | 0.5% | 0.5% |
| 9 | 0.7% | 0.4% | 0.6% | 0.7% |
| 10 | 0.9% | 0.6% | 0.7% | 0.8% |
| 11 | 1.2% | 0.7% | 0.9% | 1.0% |
| 12 | 1.6% | 0.9% | 1.2% | 1.4% |
| 13 | 2.0% | 1.3% | 1.6% | 1.1% |
| 14 | 2.5% | 2.5% | 2.4% | 2.6% |
| 15 | 3.3% | 4.4% | 3.7% | 3.6% |
| 16 | 4.1% | 6.4% | 5.1% | 4.8% |
| 17 | 5.2% | 9.1% | 6.9% | 7.5% |
| 18 | 6.5% | 11.9% | 8.5% | 8.3% |
| 19 | 6.4% | 12.5% | 8.9% | 8.3% |
| 20 | 6.7% | 13.0% | 9.2% | 9.7% |
| 21 | 7.4% | 13.7% | 10.0% | 11.0% |
| 22 | 8.3% | 14.6% | 10.9% | 11.8% |

**Supplementary file S3 – Information on variables used in the analysis.**

| Variable | Description |
|---|---|
| *Child Outcomes* | |
| Drug prescriptions | Was prescribed drugs (ATC-codes N05 or N06A) in t+0…,t+5 |
| | |
| *Treatment* | |
| Parental job loss | 1 = Job loss due to workplace closure. Workplace closes between year t+0 and t+1. |
| | |
| *Conditions* | Only workers with paid employment as main source of income in t+0 are included. Self-employed and non-employed are excluded.<br>Only children with complete data on covariates included in the final analytical sample. |
| | |
| *Child covariates* | |
| Birth weight, in grams | Birth weight, in grams |
| Low birth weight (LBW) | Dummy coded. Birth weight < 2500 grams |
| Preterm birth (PTB) | Dummy coded. Born before week 37 |
| Small for gestational age (SGA) | Small for gestational age |
| Birth order of child | Birth order of child, 4 categories.<br>1,2,3 = 1,2,3.<br>>4 = 4 |
| Age | Age of child, in years |
| Birth year | Child birth year, categorical. Range 1996-2000 |
| Birth month | Child birth month, categorical. Range 1-12 |
| Gender | Child gender. 0=boy, 1=girl |
| | |
| *Parent data – Socio-demographics*[2] | |
| Age | Age of parent, in years |
| Country of birth | Four categories: Sweden, Nordic, Europe, outside Europe |
| NUTS region | 8 categories, one for each NUTS3 region. |
| Household status (single) | Dummy coded. 1 = Does not live with anyone aged 18 or more. |
| Civil status | Three categories: Not Married=0, Married=1, Divorced or widowed=2. |
| Education level | Three categories: ISCED ≤ 2, ISCED 3-4, ISCED ≥ 5. |
| | |
| *Parent data – Employment* | |

[2] All parental and workplace variables are measured for both mothers and fathers.

| | |
|---|---|
| Registered unemployed | Dummy coded: 1=Registered at unemployment office. |
| Days registered unemployed | Number of days registered at unemployment office. |
| Job loss | Job displacement due to workplace closure between t-1 and t+0 |
| Employment status | Three categories: Not employed, employed, self-employed. |
| | |
| *Parent data – Income* | |
| Wage income, in SEK | Income from paid employment, in SEK. Deflated with consumer price index to 1996 prices. |
| Social assistance, in SEK | Income from social assistance, in SEK. Deflated with consumer price index to 1996 prices. |
| Disposable income, in SEK | Total disposable income, in SEK (net of transfers and taxes). Individualized from household disposable income. Deflated with consumer price index to 1996 prices. . |
| | |
| *Parent data – Workplace* | |
| Industry sector (NACE code) | Industry sector of workplace, 10 NACE categories. |
| Age of workplace, in years | Age of workplace (current year – year of establishment). |
| No. workers at workplace | Number of workers at workplace. |
| | |
| *Parent data – Health* | |
| Drug prescriptions | Was prescribed drugs (ATC-codes N05 or N06A). |
| Sickness days | Number of days on paid sickness leave. |

**Supplementary file S4 – Summary statistics for all covariates**

We only show summary statistics by treatment status for maternal job loss here. The patterns are similar for paternal job loss. Note that the table shows unadjusted summary statistics.

| | Control group (maternal job loss) | | | Treatment group (maternal job loss) | | |
|---|---|---|---|---|---|---|
| | N | Mean or proportion | SD | N | Mean or proportion | SD |
| *Child data* | | | | | | |
| Birth weight | 3,431,801 | 3,551 | 589 | 23,057 | 3,530 | 594 |
| Low birth weight | 3,431,801 | 0.04 | 0.20 | 23,057 | 0.04 | 0.21 |
| Preterm birth | 3,431,801 | 0.06 | 0.23 | 23,057 | 0.06 | 0.24 |
| Small for gestational age | 3,431,801 | 0.02 | 0.14 | 23,057 | 0.02 | 0.15 |
| Birth order | 3,431,801 | 1.8 | 0.9 | 23,057 | 1.9 | 0.9 |
| Age | 3,431,801 | 12.6 | 3.2 | 23,057 | 12.4 | 3.2 |
| Birth month | 3,431,801 | 6.3 | 3.3 | 23,057 | 6.3 | 3.4 |
| Birth year | 3,431,801 | 1998.1 | 1.4 | 23,057 | 1998.1 | 1.4 |
| *Parent data – Socio-demographics* | | | | | | |
| Age – mother | 3,431,801 | 41.5 | 5.7 | 23,057 | 41.0 | 5.9 |
| Age – father | 3,431,801 | 44.2 | 6.5 | 23,057 | 43.9 | 6.8 |
| Country of birth – mother | | | | | | |
| Sweden | 2,993,983 | 87.24 | | 19,059 | 82.66 | |
| Nordic | 72,487 | 2.11 | | 511 | 2.22 | |
| Europe | 145,670 | 4.24 | | 1,260 | 5.46 | |
| Other | 219,661 | 6.40 | | 2,227 | 9.66 | |
| Country of birth – father | | | | | | |
| Sweden | 2,967,754 | 86.48 | | 18,872 | 81.85 | |
| Nordic | 71,770 | 2.09 | | 542 | 2.35 | |
| Europe | 165,199 | 4.81 | | 1,390 | 6.03 | |
| Other | 227,078 | 6.62 | | 2,253 | 9.77 | |
| NUTS region – mother | | | | | | |
| 11 | 723,935 | 21.09 | | 5,620 | 24.37 | |
| 12 | 584,990 | 17.05 | | 3,861 | 16.75 | |
| 21 | 316,650 | 9.23 | | 1,735 | 7.52 | |
| 22 | 474,261 | 13.82 | | 3,355 | 14.55 | |
| 23 | 707,798 | 20.62 | | 4,356 | 18.89 | |
| 31 | 295,833 | 8.62 | | 2,012 | 8.73 | |
| 32 | 136,077 | 3.97 | | 983 | 4.26 | |
| 33 | 192,257 | 5.60 | | 1,135 | 4.92 | |
| NUTS region – father | | | | | | |
| 11 | 729,003 | 21.24 | | 5,707 | 24.75 | |
| 12 | 581,688 | 16.95 | | 3,839 | 16.65 | |
| 21 | 315,981 | 9.21 | | 1,726 | 7.49 | |
| 22 | 474,721 | 13.83 | | 3,334 | 14.46 | |
| 23 | 708,390 | 20.64 | | 4,366 | 18.94 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| 31 | 295,055 | 8.60 | | 2,005 | 8.70 | |
| 32 | 135,823 | 3.96 | | 954 | 4.14 | |
| 33 | 191,140 | 5.57 | | 1,126 | 4.88 | |
| Household status (single) - mother | 3,431,801 | 0.21 | 0.41 | 23,057 | 0.26 | 0.44 |
| Household status (single) - father | 3,431,801 | 0.21 | 0.41 | 23,057 | 0.26 | 0.44 |
| Civil status – mother | | | | | | |
| Not married | 963,499 | 28.08 | | 6,428 | 27.88 | |
| Married | 2,042,592 | 59.52 | | 13,055 | 56.62 | |
| Divorced or widowed | 425,710 | 12.40 | | 3,574 | 15.50 | |
| Civil status – father | | | | | | |
| Not married | 950,574 | 27.70 | | 6,458 | 28.01 | |
| Married | 2,052,592 | 59.81 | | 13,010 | 56.43 | |
| Divorced or widowed | 428,635 | 12.49 | | 3,589 | 15.57 | |
| Education – mother | | | | | | |
| ISCED ≤ 2 | 208,325 | 6.07 | | 2,700 | 11.71 | |
| ISCED 3-4 | 1,635,204 | 47.65 | | 12,530 | 54.34 | |
| ISCED ≥ 5 | 1,588,272 | 46.28 | | 7,827 | 33.95 | |
| Education – father | | | | | | |
| ISCED <3 | 393,426 | 11.46 | | 3,354 | 14.55 | |
| ISCED 3-4 | 1,827,649 | 53.26 | | 12,645 | 54.84 | |
| ISCED >4 | 1,210,726 | 35.28 | | 7,058 | 30.61 | |
| *Parent data – Employment* | | | | | | |
| Registered unemployed – mother | 3,431,801 | 0.10 | 0.30 | 23,057 | 0.21 | 0.41 |
| Registered unemployed – father | 3,431,801 | 0.08 | 0.27 | 23,057 | 0.10 | 0.30 |
| Days registered unemployed - mother | 3,431,801 | 7.9 | 37.7 | 23,057 | 20.2 | 60.7 |
| Days registered unemployed - father | 3,431,801 | 9.1 | 42.9 | 23,057 | 12.1 | 49.5 |
| Job loss t-1 – mother | 3,431,801 | 0.01 | 0.09 | 23,057 | 0.03 | 0.16 |
| Job loss t-1 – father | 3,431,801 | 0.02 | 0.13 | 23,057 | 0.02 | 0.16 |
| Employment status t-1 – mother | | | | | | |
| Not employed | 72,708 | 2.12 | | 1,470 | 6.38 | |
| Employed | 3,342,677 | 97.40 | | 20,470 | 88.78 | |
| Self-employed | 16,416 | 0.48 | | 1,117 | 4.84 | |
| Employment status t-1 – father | | | | | | |
| Not employed | 205,703 | 5.99 | | 2,103 | 9.12 | |
| Employed | 2,922,912 | 85.17 | | 18,199 | 78.93 | |
| Self-employed | 303,186 | 8.83 | | 2,755 | 11.95 | |
| *Parent data – Income* | | | | | | |
| Wage income – mother | 3,431,801 | 224,889 | 138,47 | 23,057 | 173,265 | 145,607 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | 7 | | | |
| Wage income – father | 3,431,801 | 303,339 | 252,380 | 23,057 | 271,965 | 264,256 |
| Social assistance – mother | 3,431,801 | 226 | 2,672 | 23,057 | 706 | 4,987 |
| Social assistance – father | 3,431,801 | 563 | 5,757 | 23,057 | 827 | 6,740 |
| Disposable income – mother | 3,431,801 | 209,833 | 149,429 | 23,057 | 199,242 | 429,884 |
| Disposable income – father | 3,431,801 | 273,193 | 469,838 | 23,057 | 279,803 | 614,746 |
| *Parent data – Workplace* | | | | | | |
| Age of workplace – mother | 3,431,801 | 18.1 | 8.6 | 23,057 | 6.5 | 8.1 |
| Age of workplace – father | 3,108,164 | 16.4 | 9.0 | 20,112 | 14.1 | 9.4 |
| No. workers at workplace – mother | 3,431,801 | 527.6 | 1,498 | 23,057 | 36.2 | 187 |
| No. workers at workplace – father | 3,118,613 | 408.6 | 1,355 | 20,226 | 270.8 | 1,052 |
| Industry sector (NACE code) – mother | | | | | | |
| 1 | 14,023 | 0.41 | | 548 | 2.38 | |
| 2 | 302,251 | 8.81 | | 1,595 | 6.92 | |
| 3 | 39,760 | 1.16 | | 634 | 2.75 | |
| 4 | 497,731 | 14.50 | | 6,428 | 27.88 | |
| 5 | 81,157 | 2.36 | | 802 | 3.48 | |
| 6 | 90,217 | 2.63 | | 373 | 1.62 | |
| 7 | 39,252 | 1.14 | | 601 | 2.61 | |
| 8 | 355,867 | 10.37 | | 5,067 | 21.98 | |
| 9 | 1,878,992 | 54.75 | | 4,486 | 19.46 | |
| 10 | 132,551 | 3.86 | | 2,523 | 10.94 | |
| Industry sector (NACE code) – father | | | | | | |
| 1 | 64,043 | 2.06 | | 551 | 2.74 | |
| 2 | 787,183 | 25.34 | | 4,323 | 21.51 | |
| 3 | 325,457 | 10.47 | | 2,280 | 11.34 | |
| 4 | 710,779 | 22.88 | | 5,315 | 26.44 | |
| 5 | 171,096 | 5.51 | | 1,092 | 5.43 | |
| 6 | 70,767 | 2.28 | | 451 | 2.24 | |
| 7 | 54,716 | 1.76 | | 450 | 2.24 | |
| 8 | 366,131 | 11.78 | | 2,681 | 13.34 | |
| 9 | 457,409 | 14.72 | | 2,223 | 11.06 | |
| 10 | 99,510 | 3.20 | | 733 | 3.65 | |
| *Parent data – Health* | | | | | | |
| Drug prescriptions – mother | 3,431,801 | 0.14 | 0.35 | 23,057 | 0.18 | 0.38 |
| Drug prescriptions – father | 3,431,801 | 0.09 | 0.29 | 23,057 | 0.10 | 0.30 |
| Sickness days – mother | 3,431,801 | 10.6 | 43.7 | 23,057 | 14.4 | 52.5 |
| Sickness days – father | 3,431,801 | 6.5 | 36.2 | 23,057 | 7.9 | 40.8 |

**Supplementary file S5 – Descriptive statistics on parents who do and do not experience job displacement.**

The table shows statistics for the full sample of parents in the years 2005-2017.

| | | Maternal sample | | Paternal sample | |
|---|---|---|---|---|---|
| **Variable** | **Year** | **No job loss** | **Job loss** | **No job loss** | **Job loss** |
| Registered unemployed | t-1 | 0.157 | 0.288 | 0.110 | 0.240 |
| Registered unemployed | t+1 | 0.126 | 0.407 | 0.092 | 0.368 |
| Days registered unemployed | t-1 | 11 | 25 | 11 | 28 |
| Days registered unemployed | t+1 | 9 | 43 | 10 | 48 |
| Employment status: Not employed | t+1 | 0.033 | 0.081 | 0.018 | 0.067 |
| Employment status: Not employed | t+1 | 0.026 | 0.183 | 0.015 | 0.160 |
| Wage earnings, in SEK | t-1 | 182115 | 128021 | 289903 | 209896 |
| Wage earnings, in SEK | t+1 | 199709 | 111398 | 308821 | 180116 |
| Social assistance, in SEK | t-1 | 388 | 1064 | 506 | 1450 |
| Social assistance, in SEK | t+1 | 262 | 916 | 327 | 1282 |
| Disposable income, in SEK | t-1 | 180216 | 158995 | 237049 | 207594 |
| Disposable income, in SEK | t+1 | 194745 | 161813 | 256416 | 203011 |
| N (person-year observations) | | 5,430,486 | 53,894 | 5,468,206 | 78,752 |

t = year of job displacement. SEK = Swedish kronor. Total number of mothers = 344,145. Total number of fathers = 341,165

**Supplementary file S6 – Restrict sample to workers employed for at least 3 consecutive years.**

By restricting the sample to workers with stable employment for at least three years, we reduce the risk that the results are driven by workers with unstable employment histories who may disproportionally be selected into workplaces with higher probability of closing down. This restriction also decrease the risk that the results are distorted by selectivity concerning which workers leave workplaces prior to the workplaces closing down (Carneiro et al., 2022; Ruiz-Valenzuela, 2021). This may in turn increase the internal validity of the estimates.

**Table S6a. Short-term, long-term and overall effects of parental job loss on drug prescriptions.**

| | | **t+1** | **t+2** | **t+3** | **t+4** | **t+5** | **t+1,…,t+5** |
|---|---|---|---|---|---|---|---|
| **Mothers** | | | | | | | |
| Mother's job loss | B | -0.0008 | 0.0015 | 0.0016 | 0.0014 | 0.0020 | 0.0021 |
| | SE | (0.0013) | (0.0015) | (0.0016) | (0.0018) | (0.0020) | (0.0023) |
| Sample mean of outcome | | 0.0327 | 0.0417 | 0.0479 | 0.0537 | 0.0590 | 0.1066 |
| N person-years (controls) | | 3257167 | 3257167 | 3068977 | 2817751 | 2498854 | 3257167 |
| N person-years (treated) | | 18634 | 18634 | 17727 | 16444 | 14922 | 18634 |
| | | | | | | | |
| **Fathers** | | | | | | | |
| Father's job loss | B | -0.0002 | 0.0018 | 0.0031* | 0.0028 | 0.0021 | 0.0030 |
| | SE | (0.0011) | (0.0012) | (0.0013) | (0.0015) | (0.0016) | (0.0019) |
| Sample mean of outcome | | 0.0331 | 0.0421 | 0.0484 | 0.0544 | 0.0600 | 0.1079 |
| N person-years (controls) | | 3149636 | 3149636 | 2979932 | 2753061 | 2465012 | 3149636 |
| N person-years (treated) | | 29490 | 29490 | 28173 | 26468 | 24200 | 29490 |

Notes: B = regression slope. SE = standard errors, clustered at the child level. * p<0.05; ** p<0.01; *** p<0.001. Table shows estimates from weighted linear probability models.

**Table S6b. Overall effects of parental job loss on drug prescriptions within five years. Heterogeneity by age.**

| | | **Age 6-10** | **Age 11-15** | **Age 16-18** |
|---|---|---|---|---|
| **Mothers** | | | | |
| Mother's job loss | B | 0.0093** | 0.0001 | -0.0036 |
| | SE | (0.0029) | (0.0035) | (0.0062) |
| Sample mean of outcome | | 0.0372 | 0.1194 | 0.1633 |
| N person-years (controls) | | 913704 | 1578333 | 765130 |
| N person-years (treated) | | 5678 | 9187 | 3769 |
| | | | | |
| **Fathers** | | | | |
| Father's job loss | B | 0.0064** | 0.0021 | -0.0011 |
| | SE | (0.0022) | (0.0029) | (0.0054) |
| Sample mean of outcome | | 0.0395 | 0.1233 | 0.1701 |
| N person-years (controls) | | 961112 | 1499664 | 5430 |
| N person-years (treated) | | 9864 | 14196 | 0.1826 |

Notes: B = regression slope. SE = standard errors, clustered at the child level. * p<0.05; ** p<0.01; *** p<0.001. Table shows estimates from weighted linear probability models. The outcome variable is defined as any drugs prescribed in the same year or within five years of the job loss.

**Table S6c. Cumulative effects of parental job losses on drug prescriptions of children at age 18.**

| | | **Not adjusted for workplace characteristics** | **Adjusted for workplace characteristics** |
|---|---|---|---|
| **Cumulative number of job losses of both parents** | | | |
| 1 | B | 0.0025 | 0.0024 |
| | SE | (0.0013) | (0.0013) |
| 2 | B | 0.0080** | 0.0076** |
| | SE | (0.0029) | (0.0029) |
| 3 | B | 0.0076 | 0.0076 |
| | SE | (0.0065) | (0.0067) |
| 4 or more | B | 0.0119 | 0.0146 |
| | SE | (0.0129) | (0.0136) |
| Sample mean of outcome | | 0.0880 | 0.0857 |
| N person-years (total) | | 3582020 | 3226416 |

Notes: B = regression slope. SE = standard errors, clustered at the child level. * p<0.05; ** p<0.01; *** p<0.001. Table shows estimates from weighted linear probability models. The outcome variable is defined as drug prescription when the child is 18 years old.

**Supplementary file S7 – Restrict sample to workers in workplaces with at least 10 workers.**

Smaller workplaces are more likely to close down than larger ones. By restricting the sample to workers in larger workplaces (in this case, at least 10 workers), we reduce the risk that the results are driven by workers who self-select into small workplaces with a higher risk of closing down. Restricting the sample to workers in larger workplaces also reduces the risk that individual worker characteristics affect the probability of workplace closure, which could generate bias (Carneiro et al., 2022; Ruiz-Valenzuela, 2021). This may in turn increase the internal validity of the estimates.

**Table S7a. Short-term, long-term and overall effects of parental job loss on drug prescriptions.**

| | | **t+1** | **t+2** | **t+3** | **t+4** | **t+5** | **t+1,…,t+5** |
|---|---|---|---|---|---|---|---|
| **Mothers** | | | | | | | |
| Mother’s job loss | B | -0.0007 | 0.0014 | 0.0012 | 0.0001 | 0.0094* | 0.0096* |
| | SE | (0.0023) | (0.0026) | (0.0028) | (0.0031) | (0.0037) | (0.0043) |
| Sample mean of outcome | | 0.0330 | 0.0422 | 0.0484 | 0.0543 | 0.0597 | 0.1077 |
| N person-years (controls) | | 3027140 | 3027140 | 2852293 | 2620046 | 2325738 | 3027140 |
| N person-years (treated) | | 5896 | 5896 | 5673 | 5294 | 4917 | 5896 |
| | | | | | | | |
| **Fathers** | | | | | | | |
| Father’s job loss | B | 0.0014 | 0.0040 | 0.0064* | 0.0015 | 0.0050 | 0.0071 |
| | SE | (0.0020) | (0.0023) | (0.0026) | (0.0027) | (0.0031) | (0.0037) |
| Sample mean of outcome | | 0.0338 | 0.043 | 0.0493 | 0.0555 | 0.061 | 0.1094 |
| N person-years (controls) | | 2763205 | 2763205 | 2610272 | 2406043 | 2147738 | 2763205 |
| N person-years (treated) | | 8673 | 8673 | 8312 | 7891 | 7282 | 8673 |

Notes: B = regression slope. SE = standard errors, clustered at the child level. * $p<0.05$; ** $p<0.01$; *** $p<0.001$. Table shows estimates from weighted linear probability models.

**Table S7b. Overall effects of parental job loss on drug prescriptions within five years. Heterogeneity by age.**

| | | Age 6-10 | Age 11-15 | Age 16-18 |
|---|---|---|---|---|
| **Mothers** | | | | |
| Mother's job loss | B | 0.0081 | 0.0133* | 0.0017 |
| | SE | (0.0052) | (0.0065) | (0.0119) |
| Sample mean of outcome | | 0.0381 | 0.1211 | 0.1649 |
| N person-years (controls) | | 859414 | 1460701 | 707025 |
| N person-years (treated) | | 1952 | 2915 | 1029 |
| | | | | |
| **Fathers** | | | | |
| Father's job loss | B | 0.0179*** | 0.0098 | -0.0132 |
| | SE | (0.0049) | (0.0054) | (0.0098) |
| Sample mean of outcome | | 0.0398 | 0.1243 | 0.1699 |
| N person-years (controls) | | 821820 | 1322187 | 619198 |
| N person-years (treated) | | 2682 | 4489 | 1502 |

Notes: B = regression slope. SE = standard errors, clustered at the child level. * $p<0.05$; ** $p<0.01$; *** $p<0.001$. Table shows estimates from weighted linear probability models. The outcome variable is defined as any drugs prescribed in the same year or within five years of the job loss.

**Table S7c. Cumulative effects of parental job losses on drug prescriptions of children at age 18.**

Very few children (around 0.4% of the sample) experience two or more, and extremely few (0.04 % of the sample) experience three or more, job losses in workplaces with at least 10 workers. We have therefore collapsed three or more into one category, but the estimates for even for this broader category are still very imprecise.

| | | Not adjusted for workplace characteristics | Adjusted for workplace characteristics |
|---|---|---|---|
| **Cumulative number of job losses of both parents** | | | |
| 1 | B | 0.0072*** | 0.0068*** |
| | SE | (0.0020) | (0.0021) |
| 2 | B | 0.0208** | 0.0225** |
| | SE | (0.0075) | (0.0079) |
| 3 or more | B | -0.0044 | -0.0045 |
| | SE | (0.0211) | (0.0216) |
| Sample mean of outcome | | 0.0880 | 0.0857 |
| N person-years (total) | | 3582020 | 3226416 |

Notes: B = regression slope. SE = standard errors, clustered at the child level. * $p<0.05$; ** $p<0.01$; *** $p<0.001$. Table shows estimates from weighted linear probability models. The outcome variable is defined as drug prescription when the child is 18 years old.

**Supplementary file S8 – Restrict sample to families that ever experience job loss**

By restricting the sample to children in families where at least one parent experience a job loss during the studied period, we can make the treatment and control groups more similar ex ante. This can reduce the risk of omitted variable bias, since unobserved factors that affect both job loss and mental health are more likely to be balanced in a sample where all children experience parental job loss at some point. This sensitivity analysis is particularly useful for comparisons of the role of differential timing (sensitive periods), since the only treatment-related variation left in the sample is the timing of the job loss.

We do not show results for cumulative effects this sensitivity analysis, since the idea with investigating cumulative effects is to compare if treatment effects differ between different numbers of treatment, and all children with at least one job loss are by definition included in the subsample of families that ever experience job loss.

**Table S8. Short-term, long-term and overall effects of parental job loss on drug prescriptions.**

| | | **t+1** | **t+2** | **t+3** | **t+4** | **t+5** | **t+1,…,t+5** |
|---|---|---|---|---|---|---|---|
| **Mothers** | | | | | | | |
| Mother's job loss | B | 0.0003 | 0.0023 | 0.0023 | 0.0020 | 0.0032 | 0.0029 |
| | SE | (0.0012) | (0.0014) | (0.0015) | (0.0016) | (0.0019) | (0.0021) |
| Sample mean of outcome | | 0.0345 | 0.0435 | 0.0500 | 0.0562 | 0.0618 | 0.1129 |
| N person-years (controls) | | 470970 | 470970 | 444191 | 408241 | 362007 | 470970 |
| N person-years (treated) | | 23057 | 23057 | 21948 | 20387 | 18542 | 23057 |
| | | | | | | | |
| **Fathers** | | | | | | | |
| Father's job loss | B | -0.0006 | 0.0017 | 0.0029* | 0.0023 | 0.0026 | 0.0029 |
| | SE | (0.0010) | (0.0011) | (0.0013) | (0.0014) | (0.0015) | (0.0018) |
| Sample mean of outcome | | 0.0357 | 0.0451 | 0.0518 | 0.0583 | 0.064 | 0.1171 |
| N person-years (controls) | | 628045 | 628045 | 594945 | 550240 | 492892 | 628045 |
| N person-years (treated) | | 36739 | 36739 | 35053 | 32873 | 29945 | 36739 |

Notes: B = regression slope. SE = standard errors, clustered at the child level. * p<0.05; ** p<0.01; *** p<0.001. Table shows estimates from weighted linear probability models.

**Table S8b. Overall effects of parental job loss on drug prescriptions within five years. Heterogeneity by age.**

| | | **Age 6-10** | **Age 11-15** | **Age 16-18** |
|---|---|---|---|---|
| **Mothers** | | | | |
| Mother's job loss | B | 0.0045 | 0.0016 | 0.0022 |
| | SE | (0.0026) | (0.0034) | (0.0059) |
| Sample mean of outcome | | 0.0414 | 0.1266 | 0.1695 |
| N person-years (controls) | | 131235 | 226799 | 112936 |
| N person-years (treated) | | 7189 | 11278 | 4590 |
| | | | | |
| **Fathers** | | | | |
| Father's job loss | B | 0.0057** | 0.0026 | -0.0009 |
| | SE | (0.0021) | (0.0027) | (0.0050) |
| Sample mean of outcome | | 0.0439 | 0.1337 | 0.1817 |
| N person-years (controls) | | 190057 | 296830 | 141158 |
| N person-years (treated) | | 12103 | 17641 | 6995 |

Notes: B = regression slope. SE = standard errors, clustered at the child level. * p<0.05; ** p<0.01; *** p<0.001. Table shows estimates from weighted linear probability models. The outcome variable is defined as any drugs prescribed in the same year or within five years of the job loss.

**Supplementary file S9 – Psychostimulants (ADHD medication) as the outcome.**

Switching the outcome variable to psychostimulants (ADHD medication; ATC-code NB06) has two benefits. First, it can be seen as a way to test the external validity of the results presented in the main manuscript. While the main analysis in the manuscript focuses on outcomes related to anxiety and mood disorders (or internalizing problems), in this additional analysis we test if our results hold also with regard to other common mental health problems, such as attention-deficit/hyperactivity disorder, which exemplifies externalizing problems (Kauten & Barry, 2020). Second, it contributes with new knowledge concerning the social determinants of externalizing problems. It is well known that externalizing problems are more common in socially disadvantaged families, but only a handful of studies have examined the role of parental employment dynamics for this using methods for causal inference (Hill et al., 2011; Mari & Keizer, 2021; Peter, 2016).

**Table S9a. Short-term, long-term and overall effects of parental job loss on drug prescriptions.**

| | | **t+1** | **t+2** | **t+3** | **t+4** | **t+5** | **t+1,…,t+5** |
|---|---|---|---|---|---|---|---|
| **Mothers** | | | | | | | |
| Mother’s job loss | B | -0.0027* | -0.0019 | -0.0009 | 0.0013 | 0.0021 | -0.0006 |
| | SE | (0.0011) | (0.0012) | (0.0012) | (0.0014) | (0.0015) | (0.0016) |
| Sample mean of outcome | | 0.0253 | 0.0277 | 0.0294 | 0.0309 | 0.0325 | 0.0483 |
| N person-years (controls) | | 3431801 | 3431801 | 3236390 | 2975835 | 2645014 | 3431801 |
| N person-years (treated) | | 23057 | 23057 | 21948 | 20387 | 18542 | 23057 |
| | | | | | | | |
| **Fathers** | | | | | | | |
| Father’s job loss | B | 0.0019* | 0.0030** | 0.0023* | 0.0028* | 0.0031* | 0.0029* |
| | SE | (0.0010) | (0.0010) | (0.0011) | (0.0012) | (0.0012) | (0.0013) |
| Sample mean of outcome | | 0.0264 | 0.0289 | 0.0307 | 0.0324 | 0.0341 | 0.0503 |
| N person-years (controls) | | 3299235 | 3299235 | 3120985 | 2882669 | 2580610 | 3299235 |
| N person-years (treated) | | 36739 | 36739 | 35053 | 32873 | 29945 | 36739 |

Notes: B = regression slope. SE = standard errors, clustered at the child level. * p<0.05; ** p<0.01; *** p<0.001. Table shows estimates from weighted linear probability models.

**Table S9b. Overall effects of parental job loss on drug prescriptions within five years. Heterogeneity by age.**

| | | Age 6-10 | Age 11-15 | Age 16-18 |
|---|---|---|---|---|
| **Mothers** | | | | |
| Mother's job loss | B | 0.0041 | 0.0009 | -0.0115*** |
| | SE | (0.0025) | (0.0024) | (0.0031) |
| Sample mean of outcome | | 0.0352 | 0.0564 | 0.0474 |
| N person-years (controls) | | 983028 | 1655156 | 793617 |
| N person-years (treated) | | 7189 | 11278 | 4590 |
| | | | | |
| **Fathers** | | | | |
| Father's job loss | B | 0.0034 | 0.0039 | -0.0005 |
| | SE | (0.0020) | (0.0021) | (0.0029) |
| Sample mean of outcome | | 0.0373 | 0.0589 | 0.0498 |
| N person-years (controls) | | 1006679 | 1569346 | 723210 |
| N person-years (treated) | | 12103 | 17641 | 6995 |

Notes: B = regression slope. SE = standard errors, clustered at the child level. * p<0.05; ** p<0.01; *** p<0.001. Table shows estimates from weighted linear probability models. The outcome variable is defined as any drugs prescribed in the same year or within five years of the job loss.

**Table S9c. Cumulative effects of parental job losses on drug prescriptions of children at age 18.**

| | | Not adjusted for workplace characteristics | Adjusted for workplace characteristics |
|---|---|---|---|
| **Cumulative number of job losses of both parents** | | | |
| 1 | B | 0.0042*** | 0.0038*** |
| | SE | (0.0008) | (0.0009) |
| 2 | B | 0.0021 | 0.0014 |
| | SE | (0.0016) | (0.0016) |
| 3 | B | 0.0083* | 0.0068 |
| | SE | (0.0034) | (0.0035) |
| 4 or more | B | -0.0029 | -0.0020 |
| | SE | (0.0054) | (0.0057) |
| Sample mean of outcome | | 0.0378 | 0.0363 |
| N person-years (total) | | 3582020 | 3226416 |

Notes: B = regression slope. SE = standard errors, clustered at the child level. * p<0.05; ** p<0.01; *** p<0.001. Table shows estimates from weighted linear probability models. The outcome variable is defined as drug prescription when the child is 18 years old.

**Supplementary file S10 – Sensitive periods, including age 0-5**

We could not investigate effects of job losses occurring when the child is younger than 6 years in the main analysis since data on key covariates (lagged parental drug prescriptions) are not available for these children. However, the first years after birth have previously been identified as a sensitive period for child development (Almond et al., 2018; Lupien et al., 2009). Supplementary file S10 therefore shows results without adjustment for lagged parental drug prescriptions, thus enabling inclusion of the youngest children.

Table S10a shows results with drug prescriptions within five years after the job loss as the outcome. However, drug prescriptions are very rare among children aged 0-5 years. We therefore also show results for drug prescriptions at age 18, but with the treatment measured at ages 0-5, 6-10, 11-15 and 16-18 years. The results in Table S10b are thus comparable to those of Brand & Thomas (2014), Ermisch et al. (2004) and Nikolova & Nikolaev (2021), who compare effects of differential timing of treatment on mental health in young adulthood.

**Table S10a. Overall effects of parental job loss on drug prescriptions within five years. Heterogeneity by age.**

| | | Age 0-5 | Age 6-10 | Age 11-15 | Age 16-18 |
|---|---|---|---|---|---|
| **Mothers** | | | | | |
| Mother’s job loss | B | -0.0005 | 0.0028 | 0.0015 | -0.0013 |
| | SE | (0.0008) | (0.0016) | (0.0033) | (0.0057) |
| Sample mean of outcome | | 0.0085 | 0.0300 | 0.1208 | 0.1646 |
| N person-years (controls) | | 1252772 | 1643234 | 1655156 | 793617 |
| N person-years (treated) | | 12885 | 13025 | 11278 | 4590 |
| | | | | | |
| **Fathers** | | | | | |
| Father’s job loss | B | 0.0010 | 0.0044** | 0.0037 | 0.0020 |
| | SE | (0.0007) | (0.0014) | (0.0027) | (0.0048) |
| Sample mean of outcome | | 0.0088 | 0.0316 | 0.1247 | 0.1708 |
| N person-years (controls) | | 1366891 | 1695278 | 1569346 | 723210 |
| N person-years (treated) | | 18671 | 21233 | 17641 | 6995 |

Notes: B = regression slope. SE = standard errors, clustered at the child level. * $p<0.05$; ** $p<0.01$; *** $p<0.001$. Table shows estimates from weighted linear probability models. The outcome variable is defined as any drugs prescribed in the same year or within five years of the job loss.

**Table S10b. Effects of parental job loss on drug prescriptions at age 18. Heterogeneity by age.**

| | | Age 0-5 | Age 6-10 | Age 11-15 | Age 16-18 |
|---|---|---|---|---|---|
| **Mothers** | | | | | |
| Mother’s job loss | B | 0.0037 | 0.0022 | -0.0002 | 0.0036 |
| | SE | (0.0021) | (0.0026) | (0.0029) | (0.0044) |
| Sample mean of outcome | | 0.0894 | 0.0883 | 0.0878 | 0.0832 |
| N person-years (controls) | | 1820421 | 1643234 | 1655156 | 793617 |
| N person-years (treated) | | 20919 | 13025 | 11278 | 4590 |
| | | | | | |
| **Fathers** | | | | | |
| Father’s job loss | B | 0.0080*** | 0.0044* | 0.0055* | -0.0025 |
| | SE | (0.0018) | (0.0022) | (0.0024) | (0.0035) |
| Sample mean of outcome | | 0.0918 | 0.0909 | 0.0914 | 0.0873 |
| N person-years (controls) | | 2032513 | 1695278 | 1569346 | 723210 |
| N person-years (treated) | | 29505 | 21233 | 17641 | 6995 |

Notes: B = regression slope. SE = standard errors, clustered at the child level. * $p<0.05$; ** $p<0.01$; *** $p<0.001$. Table shows estimates from weighted linear probability models. The outcome variable is defined as any drugs prescribed in the same year or within five years of the job loss.

**Supplementary file S11 – Adjustment for lagged drug prescriptions.**

Adjusting for lagged outcomes may reduce the risk of bias due to omitted variables such as past health problems of the child (Allison, 1990; Angrist & Pischke, 2009). In addition, adjusting for a variable with a strong effect on the outcome (which is often the case with lagged outcomes) can improve precision (Cinelli et al., 2022). However, adjustment for lagged outcomes may be problematic due to correlation between residuals and the lagged dependent variable (Angrist & Pischke, 2009), and lagged outcomes can also be colliders (Morgan & Winship, 2007). In the main analysis, we did not adjust for lagged outcomes since we regard the risk that child mental health problems affects the probability that their parent's workplace closes to be low. Supplementary file S11 shows results where we include one-year lags of child drug prescriptions in the set of covariates to be balanced.

**Table S11a. Short-term, long-term and overall effects of parental job loss on drug prescriptions.**

| | | **t+1** | **t+2** | **t+3** | **t+4** | **t+5** | **t+1,…,t+5** |
|---|---|---|---|---|---|---|---|
| **Mothers** | | | | | | | |
| Mother's job loss | B | -0.0004 | 0.0016 | 0.0017 | 0.0014 | 0.0023 | 0.0022 |
| | SE | (0.0012) | (0.0014) | (0.0015) | (0.0016) | (0.0018) | (0.0021) |
| Sample mean of outcome | | 0.0327 | 0.0417 | 0.0480 | 0.0540 | 0.0593 | 0.1072 |
| N person-years (controls) | | 3431801 | 3431801 | 3236390 | 2975835 | 2645014 | 3431801 |
| N person-years (treated) | | 23057 | 23057 | 21948 | 20387 | 18542 | 23057 |
| | | | | | | | |
| **Fathers** | | | | | | | |
| Father's job loss | B | -0.0002 | 0.0019 | 0.0031* | 0.0024 | 0.0027 | 0.0037* |
| | SE | (0.0010) | (0.0011) | (0.0013) | (0.0014) | (0.0015) | (0.0018) |
| Sample mean of outcome | | 0.0334 | 0.0425 | 0.0488 | 0.0549 | 0.0604 | 0.1089 |
| N person-years (controls) | | 3299235 | 3299235 | 3120985 | 2882669 | 2580610 | 3299235 |
| N person-years (treated) | | 36739 | 36739 | 35053 | 32873 | 29945 | 36739 |

Notes: B = regression slope. SE = standard errors, clustered at the child level. * p<0.05; ** p<0.01; *** p<0.001. Table shows estimates from weighted linear probability models.

**Table S11b. Overall effects of parental job loss on drug prescriptions within five years. Heterogeneity by age.**

| | | **Age 6-10** | **Age 11-15** | **Age 16-18** |
|---|---|---|---|---|
| **Mothers** | | | | |
| Mother's job loss | B | 0.0053* | 0.0021 | -0.0027 |
| | SE | (0.0026) | (0.0033) | (0.0057) |
| Sample mean of outcome | | 0.0379 | 0.1208 | 0.1646 |
| N person-years (controls) | | 983028 | 1655156 | 793617 |
| N person-years (treated) | | 7189 | 11278 | 4590 |
| | | | | |
| **Fathers** | | | | |
| Father's job loss | B | 0.0067** | 0.0032 | 0.0009 |
| | SE | (0.0021) | (0.0027) | (0.0048) |
| Sample mean of outcome | | 0.0398 | 0.1247 | 0.1708 |
| N person-years (controls) | | 1006679 | 1569346 | 723210 |
| N person-years (treated) | | 12103 | 17641 | 6995 |

Notes: B = regression slope. SE = standard errors, clustered at the child level. * p<0.05; ** p<0.01; *** p<0.001. Table shows estimates from weighted linear probability models. The outcome variable is defined as any drugs prescribed in the same year or within five years of the job loss.

**Table S11c. Cumulative effects of parental job losses on drug prescriptions of children at age 18.**

| | | **Not adjusted for workplace characteristics** | **Adjusted for workplace characteristics** |
|---|---|---|---|
| **Cumulative number of job losses of both parents** | | | |
| 1 | B | 0.0041*** | 0.0037** |
| | SE | (0.0012) | (0.0012) |
| 2 | B | 0.0087*** | 0.0088*** |
| | SE | (0.0023) | (0.0024) |
| 3 | B | 0.0103* | 0.0093 |
| | SE | (0.0047) | (0.0049) |
| 4 or more | B | 0.0056 | 0.0076 |
| | SE | (0.0082) | (0.0089) |
| Sample mean of outcome | | 0.088079 | 0.0857 |
| N person-years (total) | | 3582020 | 3226416 |

Notes: B = regression slope. SE = standard errors, clustered at the child level. * $p<0.05$; ** $p<0.01$; *** $p<0.001$. Table shows estimates from weighted linear probability models. The outcome variable is defined as drug prescription when the child is 18 years old.

**Supplementary file S12 – Adjustment for treatment-confounder interactions in the stage 2 regression**

Constrained structural nested means models estimated through regression of residuals rely on three basic assumptions: (1) No treatment-effect modification by confounders, meaning that the time-varying effects of the treatment does not vary across levels of the confounders; (2) the associational effects of the confounders is additive and linear; and (3) no unobserved confounding of the association between treatment and outcome (Wodtke, 2020; Wodtke et al., 2019). The second assumption – that the associational effects of the confounders is additive and linear – is difficult to test given the immense number or possible two- or higher-order interactions between the 45 included covariates, many of which contain several nominal categories. The third assumption – no confounding of the association between treatment and outcome – is also difficult to test since the confounding is by definition unobserved. However, the use of workplace closures as an exogenous cause of job loss, and the large number of covariates, should reduce the risk of such confounding in our case. Note that the second and third assumptions also apply to the other analyses in the paper. The first assumption – no treatment-effect modification by confounders – can, however, be tested by including all two-by-two interactions between the treatment and the residualized confounders in the stage 2 regressions. The results of this sensitivity analysis are presented in Table S12.

**Table S12c. Cumulative effects of parental job losses on drug prescriptions of children at age 18.**

| | | **Not adjusted for workplace characteristics** | **Adjusted for workplace characteristics** |
|---|---|---|---|
| **Cumulative number of job losses of both parents** | | | |
| 1 | B | 0.0044** | 0.0039* |
| | SE | (0.0016) | (0.0017) |
| 2 | B | 0.0104** | 0.0093** |
| | SE | (0.0033) | (0.0034) |
| 3 | B | 0.0175* | 0.0145* |
| | SE | (0.0071) | (0.0074) |
| 4 or more | B | 0.0198 | 0.0244 |
| | SE | (0.0129) | (0.0140) |
| Sample mean of outcome | | 0.0880 | 0.0857 |
| N person-years (total) | | 3582020 | 3226416 |

Notes: B = regression slope. SE = standard errors, clustered at the child level. * p<0.05; ** p<0.01; *** p<0.001. Table shows estimates from weighted linear probability models. The outcome variable is defined as drug prescription when the child is 18 years old.

**Supplementary file S13 – References for the supplementary materials**


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