The Impact of Children's Health Shocks on Parents' Labor Earnings and Mental Health

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Abstract

We provide novel evidence on the causal impact of a child's health shock on parents' labor market outcomes. Using high-quality Finnish and Norwegian administrative data, we construct counterfactuals for treated households with families who experience the same shock in later years. We find a sharp break in mothers' earnings trajectories after the event. The effect for mothers is persistent, while we do not find significant effects for fathers. Our findings do not align with the hypothesis of household specialization explaining these adjustments. Instead, the evidence suggests that these changes are driven by increased caregiving demands, with mothers bearing the primary burden. Moreover, we also document a substantial impact on parents' mental well-being.

Keywords: Children, health, mortality, parents, earnings, labor supply, mental health.
JEL Codes: I10, I12.

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1 Introduction

Economists have long been interested in understanding the relationship between income and health (Deaton, 2013). The detrimental effect of health shocks on an individual's own labor market outcomes is well documented.[1] However, we know much less about the potential spillover effects of children's health shocks on parents' labor market careers.

This is striking given that the hospitalization of a child is a situation faced by a relatively large number of families. For example, nearly one out of every six discharges from U.S. hospitals in 2012 was for children aged 17 years and younger (Witt et al., 2014). In Finland, if we follow one cohort over time, nearly 50% of children born in 1990 had at least one stay at the hospital before they turned 18.

A child's illness is a stressful event that can have major implications for the well-being of the whole household. Families might incur substantial costs when deciding how to best cope with these health shocks and their associated long-term burden. For example, parents may need to decrease their labor supply to increase the time spent caring for their child, or they might increase their labor supply to make up for the additional medical costs. Moreover, these shocks can also have significant gender inequality repercussions if women are more likely than men to take the bulk of caregiving responsibilities or carry the mental health burden in the household. Understanding the multifaceted ways parenthood can disparately affect women compared to men in the labor market is critical. However, our knowledge of how children's health shocks (both non-fatal and fatal) impact the economic well-being of families is surprisingly limited.

This paper contributes to bridging this gap by providing new evidence on the causal impact of a child's health shock on parental outcomes. We examine the effects of both hospitalizations and fatal health shocks on parents by leveraging long panels of high-quality administrative data from Finland and Norway on families' health and labor market trajectories. We exploit variation in the timing of health shocks among families of otherwise healthy children who had a first health shock

[1] This includes, among others, papers by Bound et al. (1999); Cai et al. (2014); Dobkin et al. (2018); García-Gómez (2011); García-Gómez et al. (2013); Jones et al. (2019); Lindeboom et al. (2016); Lenhart (2019); Maczulskij and Böckerman (2019); Meyer and Mok (2019); Trevisan and Zantomio (2016); Wagstaff (2007).

after school-starting age. Identification comes from comparisons of parents and children in the same respective age cohorts, but whose children experienced the health shock at different ages. In particular, we use a difference-in-differences specification: we construct counterfactuals for treated households with families who experience the same shock a few years later. We show that these families have very similar characteristics and were following very similar trends before the shock. We also complement this approach by estimating a simple event study model with individual fixed effects.

With these data and design, we estimate parents' labor supply responses to children's hospitalization and mortality shocks. We first show that there is no indication that parents' outcomes follow different trends for the treatment and the control group before the health shock of the child. Sharp breaks in the trajectories become visible just after the event for all outcomes. Overall, we find that maternal earnings suffer a substantial and persistent drop after the hospitalization or death of a child. Interestingly, data from two countries allows us to document the strong robustness of our findings: the effect size is strikingly similar, three years after a hospitalization, maternal earnings are 4.6% lower in Finland and 4.7% lower in Norway, compared to two years before the shock. For fathers, the impact is insignificant, and the estimated coefficients are much smaller. For mortality shocks, we find that the mothers' earnings drop by more than 20% three years after the shock, while for fathers, we again see no significant effect. The fact that we find almost identical results for all these outcomes in the context of two different countries that share a similar institutional context strengthens the robustness of our approach and the external validity of our findings.

We also analyze a critical question in this setting: are families insured against such health shocks affecting their children? We show that although transfers offset part of the negative impact, families are not fully insured against these shocks: the drop in maternal income after taxes is around one third smaller than the drop in labor earnings. From a family perspective, in the case of hospitalizations, the impacts on family earnings are, on average, small (around 1.2% in both countries). However, a significant portion of this impact remains uninsured in the contexts of Finland and Norway. For mortality shocks, the drop in family earnings is quite substantial, almost

9%, and the drop in family income is also significant, about 4%. But in this case, we observe a decrease in family allowances, which is consistent with the absence of bereavement support.

Crucially, we exploit the richness and complementarities of the data from both countries to explore several potential mechanisms. We first try to understand if the social insurance attenuates or aggravates the maternal labor supply response in our context of children's health shocks. Using spatial and temporal variation in the allowances received by families after a child's health shock, we do not find evidence that the level of social insurance affects mothers' labor supply decisions. Next, in Finland, we use occupational data to explore whether mothers adjust their labor supply by switching the type of firm they work for. We do not find evidence that mothers move to more family-friendly firms after the shock. We also do not observe changes in the risk of marital dissolution in either country. However, we find that children's health shocks have a substantial impact on the mental well-being of parents. The data from the Norwegian registry allows us to investigate the effect on primary care visits, while for Finland, we use data on specialist visits or hospital admissions. Results from a mediation analysis suggests the mental health shock could be the primary mechanism behind the large effects on maternal labor earnings for mortality shocks, while for hospitalizations it only explains a relatively small part of the variation.

We thus explore if the increased care burden drives the effect for hospitalizations. We show that the impact is stronger for health shocks that require substantial care, as measured by the number of hospital visits in the year after the shock. We also show that the adverse effects are more substantial if the grandparents do not live close to the family. Additionally, we find that household specialization is an unlikely explanation for the (unidirectional) maternal adjustment. We observe that the decline in earnings is larger for women who have more to lose, such as relatively highly educated women with high earning potential or those who are the primary earners in their households. We also find that the adjustment is similar for women whose partner was (relatively) involved in childcare (as proxied by paternity leave take up). Instead, our results align more with these shocks increasing caregiving demands, with women primarily shouldering this burden.

Finally, we analyze which mothers are more affected by this adverse event. We estimate Conditional Average Treatment Effects across families using causal forest algorithms (Athey and Imbens, 2016; Wager and Athey, 2018; Athey et al., 2019). We show that the level declines in earnings are larger among highly educated mothers with higher (pre-event) earnings. However, both in terms of their labor force participation and mental health, the sickness of a child puts a higher strain on mothers from relatively lower socioeconomic backgrounds. This result is consistent with mothers with a lower previous attachment to the labor force, leaving or loosing their jobs after this adverse event. This result is particularly concerning, given that children of mothers from lower socioeconomic backgrounds are almost three times more likely to suffer a hospitalization during childhood.[2] This result highlights the importance of designing policies that support mothers in more vulnerable situations.

This paper contributes to several strands of the literature, including work studying the relationship between children's health and parents' labor market outcomes. Several previous studies find a negative association between childhood disability or illness and maternal employment (e.g, Wasi et al., 2012; Wolfe and Hill, 1995) (see Stabile and Allin (2012) for a review of these papers). A few papers make use of panel data and try to control for previous employment situation (Baydar et al., 2007; Burton et al., 2017; Kvist et al., 2013; Powers, 2003; van den Berg et al., 2017). However, children's health status is unlikely to be randomly distributed across families, meaning that families whose children have poorer health are likely to be different from other families. This makes it difficult to distinguish between the effect of having a child with an illness and that of other confounding characteristics on maternal employment. A recent exception is Eriksen et al. (2021), who focus on a specific diagnosis, childhood diabetes, and match treated and control families on observable characteristics.

This paper advances the existing knowledge by providing credible causal evidence of the spillover effects of child health shocks (broadly defined) by using high-quality administrative data covering the entire population of two different countries. We use a research design that allows us to exploit precisely and objectively identified health shocks and focus on a sample of similar

[2]Own calculation based on administrative data from Finland. In particular, we calculate the hospitalization rate for children by mother's education and occupation. See Figure A1 for more details.

families, differing only in the age at which their child suffered the shock. In addition, our identification strategy allows us to explore all health shocks, thus, studying a broader phenomenon. This also makes it possible to learn what type of hospitalizations drive the negative impacts on maternal labor earnings. Our study shows clear-cut results, and the fact that we use data from Finland and Norway allows us to demonstrate the robustness and magnitude of the effect of this shock on mothers' labor market careers. Finally, we also provide new evidence on three crucial pieces that can guide the design of policies to help mitigate the negative impacts of these disruptions. In particular, we analyze which mothers are more adversely affected, the role of public insurance [3], and the consequences on parental mental well-being.

More broadly, this paper contributes to the literature on the effects of adverse health shocks on labor market outcomes. Most studies focus on the impact of health shocks on the individual's own labor market outcomes (e.g, Bound et al., 1999; Cai et al., 2014; Dobkin et al., 2018; García-Gómez, 2011; García-Gómez et al., 2013; Jones et al., 2019; Lindeboom et al., 2016; Lenhart, 2019; Meyer and Mok, 2019; Trevisan and Zantomio, 2016; Wagstaff, 2007). Using an event study approach, Dobkin et al. (2018) examine the economic consequences of hospitalizations for adults in the US. They find that earnings drop by 20% three years after a hospitalization. Meyer and Mok (2019) use survey data from the US and estimate a similar drop in earnings ten years after the onset of a disability.

Other studies have examined the spillover effects of health shocks, with particular attention paid to how one spouse's health shock affects the other spouse's employment and earnings.[4] Fadlon and Nielsen (2017) analyze the impact of a spouse experiencing a fatal or severe non-fatal shock on household labor supply. Using administrative data from Denmark and exploiting event studies together with a dynamic difference-in-differences approach, they find that fatal health shocks lead to

[3] In subsequent work, Adhvaryu et al. (2023) study if the safety net plays any role in mitigating the impact of childhood cancer shocks on family labor market outcomes using a policy reform. Our work differs in that we exploit a different source of variation: spatial (municipality) and temporal variation in the generosity of the social insurance that families receive. We find very consistent results: the level of social insurance does not seem to affect mothers' labor supply decisions.

[4] See, for example, García-Gómez et al. (2013); Fadlon and Nielsen (2017); Jeon and Pohl (2017); Jiménez-Martín et al. (1999).

an increase in the labor supply of the surviving spouse. In contrast, they do not find any significant response following a non-fatal health shock.[5] García-Gómez et al. (2013) explore the spillover effects of an acute hospitalization using data from the Netherlands. They find gender asymmetries in the response to a spouse's health shock: while wives are more likely to continue—or even start—working when their husbands fall ill, husbands are more likely to withdraw from the labor force when their wives fall ill. Jeon and Pohl (2017) use administrative data from Canada and observe a significant decline in the employment and earnings of individuals whose spouses are diagnosed with cancer.

Rellstab et al. (2019) instead examine the spillover effects of an older parent's unexpected hospitalization[6] on their children's labor supply. Utilizing a difference-in-differences model and administrative data from the Netherlands they do not find significant effects on either employment or earnings. Frimmel et al. (2020) focus on parental health shocks that increase care dependency abruptly and find a significant negative impact on the labor market activities of children.[7]

This study also speaks to the literature that investigates the impact of parenthood on family labor supply, which shows sizeable effects on mothers' labor supply and earnings.[8] The most recent studies estimate that women's earnings decrease considerably following the birth of their first child, and this effect is persistent. The so-called child penalty[9] amounts to around 20% over the long run in the Nordic countries (Kleven et al., 2019b; Sieppi and Pehkonen, 2019), between 30% and 45% in the United Kingdom and the United States, and as high as 50%-60% in Germany and Austria (Kleven et al., 2019a). In addition, Snaebjorn and Steingrimsdottir (2019) find that the child penalty is larger in families in which a child is born with a disability: affected mothers earn

[5] In their study, heart attacks and strokes comprise severe non-fatal health shocks.

[6] They exploit diagnoses classified by physical expert opinion as being unexpected hospitalizations, and thus plausibly exogenous.

[7] Black et al. (2017) study the impact of having a sibling with a disability and find a negative spillover effect on children's test scores.

[8] This includes, among others, papers by Adda et al. (2017); Angrist and Evans (1998); Angelov et al. (2016); Benard et al. (2007); Bertrand et al. (2010); Bronars and Grogger (1994); Bütikofer et al. (2018); Fernández-Kranz et al. (2013); Hotz et al. (2005); Lundberg and Rose (2000); Lundborg et al. (2017); Paull (2008); Miller (2011); Sigle-Rushton and Waldfogel (2007); Waldfogel (1998).

[9] The earnings child penalty is defined as the percentage in earnings by which women fall behind relative to men due to having children.

13% less in the long run, while affected fathers earn 3% less.

We show here that even in two countries usually seen as leaders in gender equality and considered to have some of the most comprehensive gender and family policies in the OECD (OECD, 2018),[10] health shocks during middle childhood to adolescence still have a disproportionate effect on women's labor market outcomes compared to men. Moreover, the impact on women's labor earnings is substantial: it amounts to around 20% of the estimated drop in maternal earnings three years after childbirth in Finland (Sieppi and Pehkonen, 2019) and 23% in Norway (Andresen and Nix, 2021). We also show that the maternal adjustment is unlikely to be driven by household specialization motives: the drop in earnings is larger for women with high education and high earnings potential. This result can be interpreted in light of studies in the child penalty literature that also find little specialization according to comparative advantage in households (Andresen and Nix, 2022; Artmann et al., 2022; Kleven et al., 2021). These findings are policy-relevant and suggest that the disproportionate costs of children for women's careers do not end with childbirth.

The paper is structured as follows. Section 2 lays out the empirical strategy. Section 3 provides background information about the institutional context and introduces the data. Section 4 reports the main results. Section 5 presents additional evidence to support the main conclusions. Section 6 explores the mechanisms of the effects. The final section concludes.

2 Empirical Strategy

We aim to analyze the impact of a child's health shock on parents' labor market outcomes and well-being. Child hospitalizations are unlikely to be randomly distributed, meaning that the characteristics and trajectories of families whose child suffers a health shock may be different from other families. To illustrate this, Figure 1 plots the coefficients of regressing different family and child characteristics on a dummy equal to one if the child suffered an overnight stay[11]. Having a

[10] Information also available in the OECD brief at: https://www.oecd.org/els/emp/last-mile-longest-gender-nordic-countries-brief.pdf.

[11] Figure A2 shows the same comparison for mortality.

child who was hospitalized predicts almost all characteristics, suggesting that these families are very different from others. Therefore, comparisons between these groups of families are likely to yield biased estimates of the causal impact of children's health shocks.

In order to overcome the potential endogeneity of children's health shocks, we leverage variation in their timing. Focusing on parents who have been exposed to a child's health shock at some point, we exploit variation in the age at which the child experienced the shock, conditional on the age of the parents and children. Importantly, we focus on families of relatively healthy children who experience a first shock after school-starting age.[12] With this sample, we use a simple difference-in-differences framework, by constructing counterfactuals for treated households with families who experience the same shock a few years later. This quasi-experimental design exploits the potential randomness of the timing of a shock within a short period of time, a strategy that has been laid out by Fadlon and Nielsen (2017, 2019). The treatment group is composed of families whose child experiences the shock at a given year τ. The control group is comprised of families from the same age cohorts[13] whose child experienced the same shock in $\tau + \Delta$ (4 years later in our main specification).[14] The treatment effect is identified from the change in the difference in outcomes (i.e., the difference-in-differences) across the two groups over time.

The identifying assumption in this setting is that, in absence of the shock, these two groups of families would have followed similar trends. We provide several pieces of evidence that support the validity of this assumption. First, Figure 2 compares these two groups of affected families and shows that all differences in observable pre-health shock characteristics disappear, in contrast to the previous comparison between affected and unaffected families (Figure 1).[15] The only exception is gender and we control for this in all our specifications.[16] This exercise provides reassuring evidence

[12]School-starting age is 6 and 7 years old in Norway and Finland, respectively.

[13]Families of the treatment and control groups are matched based on the child's and parents' years of birth. For control households, we assign a placebo "shock" at the age at which the children in the matched treatment group undergo their respective shocks. Due to our sample size, fatal shocks are only matched on child's year of birth.

[14]There is a trade-off when choosing Δ, since a larger Δ increases the horizon over which the effect can be observed. However, a smaller Δ is likely to capture more similar households. In our main specification, Δ is equal to 4 years, allowing us to identify effects up to three years after the shock. After this period, the control group also undergoes a shock. In Table A12 we show that our results are robust to alternative choices of Δ.

[15]Similar results for the mortality sample can be found in Panel (b) of Figure A2.

[16]Boys and girls differ in the average age at which they experience a hospital admission. Our results are robust to

that families whose children experience a hospitalization at different ages have very similar predetermined observable characteristics.

We further provide visually clear results of our estimation and show that there is no evidence that the treatment group was following a different trajectory in earnings (or in any other outcomes) before the event (Section 4). In Section 6, we also show that the effect of a health shock on maternal earnings is larger if the child requires substantial and persistent care after the first hospitalization, as measured by the number of specialist visits and later hospital admissions. Finally, we explore two plausibly exogenous health shocks that have very different implications in terms of the care burden imposed on parents. We show that parental earnings do not respond to a health shock that, in general, is not severe (skin conditions), while there is a substantial drop following a hospitalization due to a more serious condition (cancer).

More formally, the estimated equation is a dynamic (period-by-period) difference-in-differences specification that takes the following form:

$$Y_{is} = \alpha + \beta treat_i + \sum_{t \neq -2, t=-5}^{t=3} \gamma_t \times I_t + \sum_{t \neq -2, t=-5}^{t=3} \delta_t \times I_t \times treat_i + \lambda A_{is} + \phi CBY_i + \omega_s + \epsilon_{is} \quad (1)$$

Where Y_{is} denotes the outcome for parent i in calendar year s, $treat_i$ is an indicator for whether a family belongs to the treatment group, and I_t is an indicator variable for the time relative to the assigned treatment year ("event time"). This is the actual treatment year for the treatment group and a placebo treatment year for the control group. The parameter of interest is δ_t, which estimates the period t treatment effect relative to the period -2. A_{is} includes dummies for the age and educational level of both parents and a dummy for the child's gender.[17] CBY_i are child birth year fixed effects, and ω_s calendar-year fixed effects. Finally, we cluster standard errors at the parent level.

In addition, as a complementary estimation, we also use an event study approach. In particular,

controlling for the child's gender.

[17]Due to sample limitations, we only match fatal shocks on a child's birth year, and we control for parent's age and level of education as well as the child's gender.

we estimate the coefficients of indicator variables for years relative to the event ("event time"). We construct a balanced panel of parents with observations dating from five years before and three years after the health shock and we run the following regressions for mothers and fathers separately:

$$Y_{is} = \alpha_i + \sum_{t \neq -2, t=-5}^{t=3} \gamma_t \times I_t + \omega_s + \epsilon_{is} \tag{2}$$

where Y_{is} is the outcome of interest for individual i in calendar year s, α_i are individual fixed effects, I_t are the event time dummies, and ω_s are calendar year dummies. Following Sun and Abraham (2020), we omit two event time dummies to avoid multicollinearity,[18] $t = -2$ and $t = -5$, meaning that the event time coefficients measure the impact of a child's health shock relative to these two periods. An important consideration is that under treatment effect heterogeneity, the two-way fixed effects regression can result in estimates with uninterpretable weights. To take care of this, we implement the interaction weighted (IW) estimator proposed by Sun and Abraham (2020).[19]

3 Institutional Setting and Data

This section describes the institutional context and administrative data for Finland and Norway.

3.1 Institutional Setting

As shown in Table A1, Finland and Norway are similar in size, economic development, and inequality. Both countries also have very similar level of health care expenditure and health indicators (for example, life expectancy, incidence of low-birthweight babies, or child mortality). In

[18] According to Sun and Abraham (2020) and Borusyak et al. (2021): one multicollinearity comes from the relative period indicators summing to one for every unit, and the other multicollinearity comes from the linear relationship between two-way fixed effects and the relative period indicators.

[19] Sun and Abraham (2020) show that in settings with variation in treatment timing across units, the coefficient on a given lead or lag can be contaminated by effects from other periods. They illustrate this and discuss their alternative method via an empirical application that is closely similar to our setting. In particular, they estimate the dynamic effects of a hospitalization following Dobkin et al. (2018).

terms of the organization of the health care system, Finland and Norway have universal public health coverage. Local authorities provide primary healthcare in health centers. General practitioners provide primary healthcare services, such as consultations, preventive care, and drug prescriptions. Specialized medical care consists of specialist examinations and treatment, and usually requires a physician's referral. Emergency medical services, which involve treating acute illnesses or injuries, are provided by hospitals. For some services, there are co-payments in both countries. However, in Finland, children under 18 are exempt from outpatient charges, and only pay co-payments for 7 days inpatient care per year, after that inpatient care is free of charge. Outpatient prescription drugs are free as well (Keskimaki et al., 2019). In Norway, there is no cost-sharing for children and youth for outpatient visits, inpatient care, dental care, and mental health care (Saunes, 2020). Moreover, there are safety-net mechanisms imposing annual caps for out-of-pocket expenditures. So overall, we would expect that medical costs do not play a relevant role in this setting. The private healthcare sector in Finland and Norway is relatively small but has gained importance in recent years. There are only a few such hospitals but the private provision of specialist outpatient care is much more common (OECD, 2017).

In terms of institutional support, Table A1 also shows the different subsidies that parents of ill children can receive. First, in both Finland and Norway, parents can be granted the Special Care Allowance during hospital treatment and subsequent care at home[20]. To be granted this benefit, the attending physician must issue a statement confirming the severity of the illness and the need for the parent to participate in the child's care and treatment. This aid is intended to compensate for lost income while the child is undergoing medical treatment. The amount is based on the earnings of the previous year. Second, in Finland, for disabled or chronically ill children parents can be granted a disability allowance. This is paid when the need for regular care, attention or rehabilitation lasts for more than six months. Finally, in both countries, family members can also be granted an informal care allowance by their municipality if they take care of a severely disabled or chronically ill child at home.[21] The entitlement and the amount of the allowances are determined

[20] Maximum of 60 days in Finland

[21] Information available at: https://www.kela.fi/web/en/if-a-child-gets-ill for Finland. Information for Norway can

on the basis of the care, attention, and rehabilitation that the child requires. The payment period also depends on how long care is needed due to the illness or disability.

Families who face the death of a child are not entitled to receive any allowance in Finland. Survivors' pension only replaces lost income when a family wage earner dies. More in detail, the payment of child benefits ends with the child's death, and recipients need to return the benefits if they have been paid after one month of the child's death.[22] In Norway, parents are allowed to keep the Special Care Allowance up to 6 weeks after a child dies if they were already receiving this allowance (and up to 3 months if they have received 100% care allowance for more than three years).

The social security system of both countries also provides insurances to their population, such as retirement pension and unemployment insurance, and health-related insurances, such as sick pay and disability insurance.

The Nordic countries have long been portrayed as exemplars of gender equality. As shown in Table A1 three out of four women in these two countries participate in the labor force. However, despite having a generous system of social security transfers and progressive gender views that mitigate the unequal impact of parenthood between genders, the literature has found substantial child penalties of around 25% for Finland and 23% for Norway (Sieppi and Pehkonen, 2019; Andresen and Nix, 2021).

3.2 Data

We use rich individual-level administrative data from several sources to link family members, earnings trajectories and health shocks.

In Finland, we merge employer-employee data from the Finnish Longitudinal Survey (FLEED-FOLK) for the period 1988 to 2018, with birth register data to identify families. The FLEED-FOLK records provide information for the entire population (aged between 16 and 70) on year

be accessed here: https://www.nav.no/en/home/benefits-and-services/relatert informasjon/attendance-benefit.

[22] Information available at https://www.kela.fi/web/en/death-of-a-child

of birth, education level, annual labor earnings, and employment status. For health data, we use two different sources. The first is the Finnish Hospital Discharge Register, which contains information on diagnosed medical conditions and the exact date of diagnoses. This register contains all inpatient consultations in Finland from 1988 to 2017. From 1998 onwards, it also includes all outpatient visits to hospitals. In both countries, all diagnoses are recorded using the International Classification of Diseases (ICD) system. The second dataset is the Cause of Death Registry, which includes information on all death dates and causes between 1990 and 2018. The statistics on causes of death are compiled based on the 10th revision of the International Classification of Diseases (ICD-10).

For Norway, data on labor market outcomes comes from registers provided by Statistics Norway, which contain information on individual labor and capital income, as well as welfare benefits from 1993–2014. Individual characteristics, such as birth year, educational level and marital status are also available. For health data we use the Norwegian Patient Registry (NPR) from 2008 to 2014. It includes all hospital admissions, both inpatient and outpatient stays. In addition, in Norway we also observe primary health care services use from 2006 to 2014 in the Control and Distribution of Health Reimbursement database (KUHR).[23]

In each family, we focus on the first child that suffered a health shock. For hospitalizations in Finland, the sample includes families whose child suffered a first inpatient stay in an acute care hospital between ages seven and eighteen.[24] For fatal shocks, the sample consists of all families whose child died between ages seven and eighteen. In Norway, due to data availability,[25] we focus on the first hospitalization observable in the data after age six. We further restrict the sample to children that did not suffer any hospitalization in the year before the health shock. Figure A3 shows the number of observations by age between seven and eighteen. Hospitalizations and fatalities

[23]For each visit, this provides a report of procedures used and the main diagnosis codified using The International Classification of Primary Care (ICPC). It classifies the patient's reason for the visit and the related diagnosis, as well as the procedures done by the primary healthcare service.

[24]We focus on children that are relatively healthy and experience the health shock after school starting age. In Finland, children start school during the calendar year they turn seven years old. In Norway, they start at age six.

[25]In Norway, we only have data on hospitalizations from 2008–2014, we therefore do not have enough cohorts to use the same restriction as in the Finnish data. Instead, we exclude children who had a hospital visit at all in the year before the health shock, and all children that had a health shock before age six.

show considerable variation in the age at which they occur.

Tables A2 and A3 show summary statistics for the final samples used in the analysis. The matched sample for the difference-in-differences analysis consists of 48274 children who suffered their first inpatient admission between ages seven and eighteen during the period 1995 to 2014 in Finland (Column (1)).[26] We use mortality data from the Finnish administrative register. The final matched sample for the mortality analysis consists of 2369 children (Column (3) in Table A2). In Norway, the final matched sample includes 24316 children's hospitalizations (Column (1), Table A3).

3.3 Incidence of health shocks

How common are these health shocks? In this subsection, we shed some light on this question and show that these shocks (particularly the hospitalization of a child) affect a considerable number of families.

We analyze first some descriptive statistics for a specific cohort in Finland that can be followed until adulthood: children born in 1990. In Figure A4, we show the percentage of children who suffered a hospitalization by age group. Around 50% of the children born in 1990 suffered the first hospitalization in their lives at or before turning 18. However, most hospitalizations are concentrated in the first years of life. If we focus on ages 7 to 18, 14% of children born in 1990 suffered their first hospitalization during this age range. In Panel (b) we observe that 0.9% of children born in 1990 suffered a fatal shock from ages 0 to 18. This corresponds to 9 deaths per 1,000 children. For ages 7 to 18, the numbers are 2.4 per 1,000 children or 0.24% of all children born in 1990.

In Panel (c) of Figure A4, we plot how many of these first hospitalizations were followed by at least another hospital stay by age. For all ages, at least around 50% of the children who suffered a first hospital stay had to be hospitalized again. Children who experienced an early hospitalization (ages 0-4) were most likely to experience a recurrent hospitalization, nearly 75% of those who

[26] Similarly to Fadlon and Nielsen (2019) the same household may appear both in the treatment and in the control group for earlier treated units (before they receive the treatment). We note, however, that a household is never used as a control to itself.

had their first hospitalization at age 0 experienced recurrence. In Panel (d), we zoom in on the health shocks occurring after school starting age, and we calculate the number of future stays after the first hospitalization. Again, around 50% of the sample only suffered the first hospital stay. However, more than 20% of children suffered a second stay after the first one, and more than 10% of children had more than five stays.

In terms of the causes for these hospitalizations, in Figure A5 we show for our main sample the number of observations by primary diagnosis (for Finland in Panel (a), and Norway in Panel (b)) and by mortality cause (in Panel (c)). In both Finland and Norway, the main category is injury, poisoning, and other external causes for hospitalizations. These are followed by diseases of the respiratory and digestive systems, and symptoms, signs, and abnormal clinical and laboratory findings. Similarly, for the mortality sample, the largest category is injuries and other external causes, followed by deaths due to neoplasms.

4 Results

4.1 Hospitalizations

Figure 3 presents the estimates for the impact of a child's hospital admission on maternal labor earnings from our difference-in-differences estimation. There is no indication that maternal earnings follow a different trend for the treatment group compared to the control group before the child's hospital admission. A sharp break in the trajectory becomes visible just after the event. Strikingly, the magnitude of the effects is very similar for Finland and Norway: just one year after the child experiences the hospitalization maternal earnings drop by about 2.4% and 2.0%, respectively, compared to earnings in $t-2$. The negative effect is persistent and appears to become larger over time.

Table 1 provides further details about the estimates. One year after the shock mothers' earnings have dropped by more than €515 and €620 for Finland and Norway, respectively.[27] In Finland,

[27]The estimate for $t-1$ in Norway is marginally significant and negative. This is likely to be driven by the less

three years after the shock mothers earn, on average, about €1000 less than two years before the event. In Norway, the drop in earnings is €1450.[28] This represents a drop of about 4.6% and 4.7% for Finland and Norway, respectively (Column (2)). Column (3) shows the results for the probability of employment. For Finland, the drop in the probability of working also becomes visible just after the shock occurs. For Norway, the estimates for one and two years after the shock are negative but not significant. Three years after the shock the probability of working is significantly lower in both countries: about 2 percentage points lower in Finland and about 1.4 percentage points lower in Norway. This amounts to a 2.2% and 1.6% decrease in a mother's working probability with respect to the mean level of employment before the event. Similar to the results for labor earnings, there is a snowball effect on employment: the probability of leaving the workforce seems to increase over time.[29]

To investigate the impact on mothers' earnings distribution, we construct dummy variables that take value of one if a mother's earnings fall below a specified percentile of the income distribution. The results are presented in Figure A6. For both countries, we observe that a child's health shock increases the probability of maternal earnings falling below various thresholds, except for the highest percentile. Specifically, in Finland, the probability of earnings falling below the tenth percentile increases by approximately 1.7 percentage points, while in Norway, it increases by 0.7 percentage points. This represents a 17% and 7% increase in probability, respectively. For the twenty-fifth percentile, there is a 10% increase in probability for Finland and a 7% increase for Norway. At the fiftieth percentile, the probability increases by 5.4% for both countries, and at the seventy-fifth percentile, it increases by 1.3% for Finland and 1.6% for Norway. Interestingly, we find no effects at the highest percentile. These results suggest that a health shock has a wide-

restrictive definition of health shocks for this country. See Section 3 for further details.

[28] We convert NOK to EUR using the yearly conversion rate provided by the Norwegian Central Bank (https://www.norges-bank.no/tema/Statistikk/valutakurser/?tab=currency&id=EUR).

[29] To assess how much of the decline in earnings can be attributed to the decrease in the labor force, we can perform a back-of-the-envelope calculation. In Finland, three years post-shock, we observe a reduction in employment of 0.020 percentage points, which translates to a 2.17% decrease. This 2.17% of mothers have zero earnings, and considering that average earnings in t-2 is €23322, this implies a total reduction in earnings of €506 due to the decline in employment. This suggests that the extensive margin adjustment accounts for approximately half of the overall decline. For Norway, the extensive margin adjustment explains around one-third of the earnings decrease.

ranging impact across the income distribution, with a stronger effect on the probability of falling into the lower percentiles of the earnings distribution.

We apply the event study method as a complementary technique to estimate the impact of a child's hospitalization on maternal earnings (Table A4). In this case, we regress maternal earnings on the event time dummies, including individual and calendar year fixed effects and implement the IW estimator proposed by Sun and Abraham (2020) (see Equation 2). The results of this exercise are consistent with those obtained using the difference-in-differences approach. Although the coefficients are slightly bigger, the magnitude of the effects is very similar: we find that three years after a child's hospitalization maternal labor earnings have decreased by 7.4% in Finland and by 5.2% after two years in Norway.[30] This finding strengthens our interpretation of the results and the validity of both approaches to estimate the impact of children's health shocks on parents' labor careers.

The results for fathers are presented in the second Panel of Figure 3. We do not observe any visible negative impact immediately after the shock in either country. However, there is some suggestive evidence that the situation deteriorates over time but the drop is not significant and the magnitude is small (see Column (1) in Table A5). Notably, the point estimates for mothers are more negative than for fathers in all periods after the event. We formally test if the effect on maternal earnings shown in Figure 3 is statistically different from the impact on fathers. For Finland, we can confidently reject the null hypothesis that the estimated effects for mothers are the same as those for fathers in all periods after the shock. The same pattern is visible in Norway, where we can reject the hypothesis of equal impact across gender for two and three years after the shock. This evidence suggests that health shocks which occur during middle childhood to teenage years also have a disproportionate effect on women's labor market outcomes compared to men.

[30] Note that for Norway, our cohorts are children hospitalized from 2008 to 2011. Given that we use the 2011 cohort as control, we can only estimate the impacts up to two years after the shock.

4.2 Mortality

Figure 4 presents the results for the impact of a child's fatal health shock on parents' labor earnings. In Panel (a), we include all fatal shocks, regardless of the cause of death. We again observe a decline in maternal earnings, but there is evidence of an anticipation effect in the case of these shocks. This is likely to be driven by the child's death being predated by a deterioration in their health. This anticipation effect means that the control group experiences a decrease in earnings the year before the shock, thus potentially biasing the effect towards zero for the last period. In spite of this, we observe a huge drop in maternal earnings after the fatal shock occurs. In particular, in the year of the shock maternal earnings drop by around 16%.

To reduce this anticipation effect, for the rest of the mortality analysis, we concentrate on fatal shocks due to injuries, poisonings, or other consequences of external causes (from now on referred to as "injuries").[31] The results using this sample of mortality shocks are displayed in Panel (b) of Figure 4. These shocks are less likely to be predated by a deterioration in the child's health. Consistent with this, we do not see any evidence of an anticipation effect when focusing on this mortality sample. Similar to the results based on all fatal shocks, we find that a child's death has an enormous and long-lasting impact on maternal earnings. The effect is much larger than that estimated after a hospitalization. In particular, one year after the fatal shock, the mother's earnings are more than €3,600 lower compared to her earnings two years before the shock (Table 2 column (1)). This represents a decrease of about 18%. Three years after the death of a child, mothers' earnings follow the same negative trend with a 21% reduction in labor earnings.[32] Moreover, mothers also have a higher probability of being out of employment, with a drop of 8.2 percentage points in their working probability (Table 2 column (3)). This is a 9.5% decrease in their working probability three years after the event.[33]

[31] Codes S00-T88 from the 10th revision of the International Classification of Diseases (ICD-10).

[32] Comparing these estimates (Figure 4 Panel (b)) in the last periods with the estimates that include all fatal shocks (Panel (a)), we see that the effects are larger in the former. This is likely to be driven by the control group experiencing a decrease in labor earnings before the fatal shock when we do not restrict the sample of shocks.

[33] Figure A6c illustrates the impact on mothers' earnings distribution. Our findings indicate that a mortality shock raises the probability of falling into the tenth percentile by 25%, the twenty-fifth percentile by 19%, the fiftieth percentile by 19%, and the seventy-fifth percentile by 8.5%. Again, there are no discernible effects on the ninetieth

The lower Panel of Figure 4 shows the results for fathers. We do not observe any effect on the father's labor earnings (more details on labor market outcomes in Table A6). The coefficients are insignificant, relatively small in magnitude (except the coefficient on the period of the shock), and for some periods even positive. In the case of mortality shocks, we can also reject the null hypothesis that the coefficients on maternal and on paternal labor earnings are equal for all periods after the shock.

4.3 Institutional Support

4.3.1 Impacts on Income after Transfers, Transfers, and Family Allowances

As discussed in Section 3, parents who take time off from work to care for a sick child can apply for various types of allowances. Therefore, the crucial question is, to what extent are these families insured? In the administrative data, we have three pieces of information that can help shed some light on this question. First, we have data on total income for both countries. This is a measure of disposable income consisting of earned income, entrepreneurial income, property income, current transfers, and tax-deductible expenses. Second, for both countries, we also have information on total transfers received.[34] Individuals receive transfers from the employment pension, social security payments, sickness benefits, unemployment benefits, etc. And third, for Finland, we also have information on the combined benefits received by families with underage children. This variable contains information on parental allowances, child home care allowances, child benefits, child's disability allowance and special care allowance (which includes care and rehabilitation allowance for a sick child). Note that the benefits received depend on their previous earnings and the severity of the sickness. We compute the average effects, but there might be heterogeneity in the level of insurance. To ease the comparisons, we quantify the average effect over the three years after the shock.

Table 3 shows the results for children's hospitalization shocks. In column (1), we show the

percentile.

[34] For Finland, this data is only available starting from 2000.

average effect on earnings for the sample for which we have information on transfers. Column (2) shows the results for mothers' disposable income. The magnitude of the effects is substantially smaller: over the three years after the hospitalization of a child the mother's disposable income is €374 and €504 lower relative to before the shock, in Finland and Norway, respectively. This is a decrease of about 1.8% and 1.3% for Finland and Norway, respectively. It reveals that the impact of a shock on labor earnings is partly offset through transfers. In fact, compared to the decrease in maternal labor earnings, the drop in disposable income is around 37.7% smaller for Finland and 45.0% smaller in Norway.[35] This further highlights that the institutional support provided to these families in both countries is highly similar, as discussed in Section 3.

In column (3), we analyze the impact on total transfers and observe an increase in the transfers received. During this period families in both Finland and Norway receive 2.3% more in transfers. It is important to note that this variable includes unemployment benefits.

Finally, in column (4), we explore the impact on family allowances. Similarly, we find that families receive more child benefits after their child suffers a hospitalization. Mothers receive 81 additional euros to take care of their children. This means that around 20% of the drop on maternal labor earnings is insured solely through targeted child benefits and allowances.

Similar to the analysis on labor earnings, the impact of children's hospitalizations on fathers' disposable income is negligible (see results in Table A7 in the Appendix). We also do not observe any significant increase in the transfers or the child allowances received by fathers.

To examine the magnitude of the overall effect, we also explore the impact from the household perspective. The results are in Table A8 in the Appendix. As one would expect, the effects on family earnings are relatively smaller, given that there is only a negative impact for mothers, and overall family earnings are considerably higher. Nevertheless, it is noteworthy that the decline is still significant in both countries, with a 1.2% drop in Finland and a 1.2% drop in Norway. In terms of family income after transfers, there is a significant decrease in Finland, albeit around 1%, while for Norway, the point estimate is negative but no longer statistically significant. Both countries

[35]For Finland: (1-((374/21194)/(622/21959)))*100, for Norway: (1-((504/38228)/(737/30722)))*100.

exhibit an increase in family transfers (significant in Finland). Similarly, family allowances see an increase of approximately 1.8%. These findings indicate that, although the average overall impact on family earnings is small, around 80% and 70% of the earnings decline in Finland and Norway, respectively, remains uninsured. It is crucial to note that the effects on family earnings can be substantial in the case of more severe shocks (as we explore in Section 6.1).

Overall, in the case of hospitalizations, the impacts on family earnings are, on average, small, but still, a significant part of this impact remains uninsured in the contexts of Finland and Norway. And importantly, there is an unequal gendered distribution of this negative impact within households.

In Table A9, we carry out the same exercise for mortality shocks. Again, we find that the drop in the mother's total income is smaller than the impact on labor earnings, but follows the same pattern: during the first three years after a child's death the mother's disposable income is approximately €1789 lower than her earnings before the shock. This represents an 8% reduction in maternal total income that is not compensated through transfers. The drop in maternal disposable income is 53% smaller[36] than the drop in maternal labor earnings. We also observe a (marginally) significant increase in the transfers received. However, we do not observe any increase in child benefits. All the coefficients are negative after the child's fatal shock, suggesting that families lose their parental and child allowances after their child's death. These results are consistent with the lack of special bereavement support for families who lose a child.

We also perform the analysis at the family level for the case of fatal shocks. Table A10 shows that the drop in family earnings is quite substantial, almost 9%. The drop in family income is also significant, around 4%.

4.3.2 The Role of Social Insurance

Does social insurance mitigate or aggravate the maternal labor supply response in our context of children's health shocks? To answer this question, we follow the approach in Fadlon and Nielsen

[36]For the mortality sample, we calculate this number as follows: (1-((1789/21412)/(3088/19995))*100

(2021) and exploit spatial and temporal variation in the allowances received by the family after a child's health shock.[37]

We capture municipality leniency (or generosity) using a leave-out residualized measure based on all children's health shocks that occurred in a municipality in a given year. We first regress at the individual level, the allowances received in the post period on ICD10 diagnosis code fixed effects (to use variation within diagnosis only) and predict the residuals. For each family, we then construct the leave-out average (adjusted) family allowances in a given municipality in a given year. This consists of the sum of all the (adjusted) individual family allowances divided by the number of children who suffered a health shock, in a given municipality-year. Leaving out a child's own family allowance from this measure allows us to eliminate the mechanical bias from the child's own case entering into the municipality generosity measure.

Figure A7 in the Appendix shows the variation in this instrument. We can see that there is substantial heterogeneity. In a given-municipality-year, the average family allowances provided in our sample amounts to €20100. From the figure, we can observe that the variation in the instrument goes from approximately €20000 more to €20000 less (conditional on the type of health shock).

When we use this variation as an instrument, the identifying assumption in this setting is that, given our set of controls, the average (residualized) allowances transferred to other mothers whose children suffered a health shock in a municipality in a given year ("the generosity" of the municipality in terms of social assistance), affects a mother's labor market outcomes only through its influence on her own family allowances. Note that the source of variation that we use is within municipalities over time since we will include municipality and calendar year fixed effects as controls.

The results of this analysis are in Table A11 below. Column (1) shows the reduced form effects, where we interact the $treat_i \times post_{i,t}$ with the municipality measure of generosity, and in column (2) the IV estimates. For the IV estimates, we report the relevant diagnostic statistics at the bottom

[37] Note that we do not have data on disability or special care allowances separately. However, we can use the variable family allowances, which includes benefits for families with children. In particular, the variable consists of parental allowances, child home care allowances, child benefits, child's disability allowance, and special care allowance (care and rehabilitation allowance for a sick child). This information is available since 1995

of the table. The F-Statistic is 87.79, so following Stock and Yogo (2005) critical values with one endogenous variable and one IV (16.38), we can reject the null hypothesis that our instrument is weak.

Overall, we do not find evidence that the level of social insurance affects mothers' labor supply decisions. The estimates of the coefficients on the triple interactions in all the specifications are small and close to zero. This indicates that social insurance provisions do not appear to explain the reductions in maternal labor earnings observed after a child's health shock. In particular, in this context, the generosity of the safety net does not seem to create disincentives to work. This finding is in line with concurrent work for Denmark (Adhvaryu et al., 2023), which finds very similar results for the case of cancer, using variation in the generosity of the benefits caused by a policy change.

5 Robustness Checks

In this section we perform a number of robustness checks to support the validity of the methodology and the required identification assumptions.

5.1 Delta Choice

In our main specification, Δ is equal to 4 years, allowing us to identify effects up to three years after the shock. After this period, the control group also undergoes a shock. Thus, there is a clear trade-off when choosing the control group: a bigger Δ increases the horizon over which the effect can be observed, while a smaller Δ is likely to capture more similar households. In Table A12 we explore the robustness of our results to different choices of the control group. In particular, we run the regression in Equation 1 again with the control group defined as families whose children suffered a hospitalization two years after (column (1) of Table A12), and three years after the treated group (column (2)). For comparison, column (3) shows the results of our main specification.

The results demonstrate that the coefficients are fairly similar across specifications. For example, if we focus on the results for Finland one year after the shock and select families who experience the shock two years later as a control group, mothers' earnings drop by €516 during the first year. For the same time period following the shock the drop is €516 when Δ equals three years, and €517 in our main specification. Furthermore, all the estimates are contained within one another's confidence intervals.

The same holds for the mortality sample as displayed in Table A14. One year after the fatal shock mothers' earnings have dropped by €3632 in our main specification (Δ = 4). The corresponding drop is €3538 for Δ = 2, and €3704 for Δ = 3. This evidence demonstrates that our results are very robust to different choices of the control group.

5.2 Mutual Shocks

One potential threat to the identification strategy could be simultaneous mutual shocks to both the parents and the child. This could potentially explain both the observed drop in maternal earnings and the child's health shock. Therefore, we re-estimate our main equation for both hospitalizations and fatal shocks excluding, first, child shocks where either of the parents were hospitalized one week before or one week after the child suffered the shock, and second, hospitalizations with a mutual shock one month before or after the child's shock.

Table A13 shows the results of this exercise for hospitalizations (Table A15 shows the same estimation for the mortality sample). The coefficients on the interactions between the event time dummies and the treat dummy remain unchanged across these specifications, suggesting that mutual shocks do not play any relevant role in explaining the drop in maternal earnings. In Section 6 we present additional evidence in favor of this interpretation. In particular, we explore cancer and skin conditions, because these two diagnoses are unlikely to be the result from joint health shocks or be driven by a previous deterioration of parents' labor earnings.

6 Mechanisms

This section investigates potential mechanisms underpinning the observed impact of children's health shocks on maternal earnings. We exploit the same variation as before, following the estimation of Equation 1. To ease the comparisons across groups, we quantify the average effect over the three years after the shock.

6.1 Burden of Care

If the reduction in labor earnings is partly due to the child's need for care, we would expect to find that the effect is stronger for hospitalizations that impose a substantial and persistent burden of care on family members. We investigate this question using information about the persistence of the shock as well as exploiting variation in the potential support for the caregiving activities from family members.[38]

6.1.1 Recurrent health shocks

We first analyze if the effect is driven by persistent hospitalizations that impose a high burden of care. To do this, we empirically estimate a child's need for care in the year of the shock, as measured by inpatient and outpatient visits to the hospital. This measure can also be interpreted as capturing the severity of the health shock.

Figure A8 plots the average number of hospital admissions or specialist visits for the period ranging from five years before to three years after a child's hospitalization. The number of visits jumps to over 4 in the year of the shock. We thus define high-burden hospitalizations as those requiring more visits in the year of the shock than this average over the entire sample (i.e., requiring a relatively high burden of care). Hospital admissions that require fewer visits in the year of the event are defined as low-burden hospitalizations. We estimate Equation 1 separately for these two distinct samples.

[38] We do this exercise for Finland, as the panel for Norway is significantly shorter and we lose precision.

Column (1) of Table 4 presents the results for maternal earnings. As expected, we find that health shocks that are more severe or invoke a higher burden of care have a larger negative impact on the mothers' labor earnings. We can reject the null hypothesis that the average effects of high-burden and low-burden hospitalizations are equal to each other after the shock.

6.1.2 By diagnosis: Skin conditions vs. Cancer

Another potential approach to exploring conditions with a different burden of care and severity implications is to exploit the exact diagnosis made by physicians. In particular, we explore the impact of cancer and skin conditions diagnoses.[39] These two conditions are interesting to study given that the implications in terms of care are very different.[40] While a skin condition is expected to generate a need for timely care, cancer is a condition with a much more complicated prognosis. According to the medical literature, in the case of cancer, the involvement of family caregivers is very relevant to ensure compliance with treatments, continuity of care, and social support (Glajchen, 2004). Moreover, cancer diagnoses have previously been used in the literature as exogenous health shocks (Gupta et al., 2017; Jeon and Pohl, 2017).

Column (2) of Table 4 shows the results for cancer and skin conditions. Due to sample limitations, we focus this part of the analysis on Finland. As expected, mothers' earnings suffer a significant drop following a child's cancer diagnosis. During the three years after a cancer diagnosis, the average effect is a drop in maternal earnings of more than €2,000 lower. However, we do not observe such a decline when focusing on skin conditions. We can reject the null hypothesis that the effects of cancer are equal to those of skin conditions.

Additionally, we conducted a second classification exercise. We followed the Healthcare Cost

[39] We use the following ICD10 diagnoses codes: C00-D49 Neoplasms, and L for skin related problems

[40] We also estimate the effects by categorizing all health shocks according to the child's diagnosis (ICD-10 codes). Figure A9, panel (a) shows significant adverse effects for several health shock categories, including infectious diseases, neoplasms (tumors), endocrine, nutritional, and metabolic conditions (encompassing conditions such as diabetes), mental, behavioral, and neurodevelopmental disorders, as well as injuries, poisonings, and certain other consequences of external causes. It is worth mentioning that the injuries category stands out as the most common type of shock in our dataset (see Figure A5). Infections, endocrine issues, and mental health conditions are relatively prevalent diagnoses. Conversely, we are able to precisely estimate null impacts for respiratory and digestive diagnoses, which rank as the second and third most frequent reasons for child hospitalization in these age groups. Nevertheless, it is important to acknowledge that there is considerable variability in the severity of conditions within the ICD-10 diagnosis groups.

and Utilization Project (HCUP) Chronic Condition Indicators (CCI) for the International Classification of Diseases, which categorizes diagnosis codes into chronic and non-chronic conditions.[41] In this classification, a condition is considered chronic if it typically lasts twelve months or longer and meets one or both of the following criteria: it necessitates ongoing medical intervention with medical products, services, and special equipment, or it imposes limitations on self-care, independent living, and social interactions. The results of this analysis can be found in panel (b) in Figure A9. We find that maternal earnings decrease by €792 (equivalent to 3.9%) following a child's chronic condition diagnosis. In contrast, the impact is smaller for acute conditions, averaging €399 (or 1.85%).

This evidence further suggests that the impact on maternal earnings is driven by severe and persistent conditions that require substantial care and support from caregivers. Moreover, the results of this exercise also show that our main findings are unlikely to be explained by mutual shocks or child hospitalizations brought about by a deterioration in maternal earnings.

6.1.3 Grandparents' support

Grandparents can play an essential role as caregivers for their grandchildren. For example, Frimmel et al. (2020) find that the first grandchild's birth increases the grandmother's probability of leaving the labor market. They also document that the effect is more substantial when grandmothers live close to their grandchild.

In Finland, we can link three generations and exploit the residence location information. We split the sample into two groups based on the grandparents living close to the family or not. The results of this exercise are presented in Table 4. In line with aforementioned work, we find that the negative impact of a child hospitalization is stronger if the grandparents live in a different region suggesting that grandparents provide support to mothers, helping alleviate the impact of the increased burden of care derived from the shock.

[41] More information available here.

6.2 Mental Health

Some studies find that parents of children with poor health or disabilities report higher stress levels and worse sleep quality. In particular, some of these papers have documented that maternal self-reported health is negatively associated with parenting a child with a severe disability or a chronic condition (Burton et al., 2008; Stabile and Allin, 2012). In contrast, they do not find the same association for fathers. Burton et al. (2008) hypothesize that the division of responsibilities according to traditional gender roles might be a factor behind this differential gender effect.

Additionally, mental health has been found to impact labor market outcomes (Biasi et al., 2018; Salokangas, 2021).[42]

We explore this potential mechanism by looking at the number of contacts with the health care system due to mental health conditions. We only observe visits to specialists or inpatient hospital admissions for Finland, thus capturing the most severe cases. In Norway, on the other hand, we observe diagnoses in primary care, which should include milder cases.[43]

Table 5 shows the results of the impact of a child's hospitalization on parents' medical visits with a mental health diagnosis. After the child's health shock, there is a substantial deterioration in the parents' mental well-being. Relative to two years before the shock, mothers visit specialists or hospitals at a higher rate for issues related to mental health conditions. For Finland, one year after the shock, the number of visits increases by over 55%.[44] For Norway, the estimated increase in the number of visits is around 14%.[45] For fathers, we also observe an increase in their number of visits, marginally significant in the year of the shock for Finland. The coefficient for Norway is

[42]In particular, Biasi et al. (2018) use data from Denmark and find that there is a large drop in labor earnings after a depression diagnosis, and earnings never recover to pre-diagnosis levels. Two years after the diagnosis, people with depression earn 29 percent less compared with two years before the diagnosis. Salokangas (2021) finds an association of similar size in Finland: relative to the healthy controls, those who are treated for any psychiatric reason earn 37 percent less during their lifetime.

[43]Note that for Norway we only have health data from 2006 to 2014, and thus, we cannot estimate all the event time dummies. For this reason, we exclude $t = -5$ from the estimation.

[44]The number of visits increases by 0.075, and the average number of visits two years before the shock is 0.135. Thus, the effect in percentage terms is 0.075/0.135 $\cdot$100 = 55.5%.

[45]The coefficient is 0.068, and the mean two years before the shock is 0.487. The effect in percentage terms is 0.068/0.487 $\cdot$100 = 14.0%.

also positive but insignificant.[46] Table A16 shows the results on mental health for families whose child suffers a fatal shock. We observe a large and significant increase in mothers' number of visits with a mental health diagnosis for all periods after the shock. For fathers, only the coefficient for the year of the shock is large in magnitude and significant. Overall, our results suggest that this stressful event leaves parents, and especially mothers, in a vulnerable position in terms of mental health.

6.2.1 Mediation Analysis

To provide insights about how much of the effect on maternal labor earnings is driven by the mental health shock, we perform a mediation analysis in the spirit of Gelbach (2016) and Sorrenti et al. (2020). Given that we rely on a single source of exogenous variation, and both of these outcomes are determined during the same time-period, we lack specific variation to disentangle the impact of the mental health shock. Thus, the mediation analysis should be interpreted with caution. Despite this limitation, the analysis is still helpful to understand if this mechanism can potentially explain the treatment effects.

We assume that the child's health shock has both direct and indirect effects on maternal labor market outcomes. The indirect effects run through the impact of the child's hospitalization or fatal shock on mental health, and are obtainable by decomposing the unconditional effect of the health shock δ_t (the period t treatment effect) in Equation (1) in the following way:

$$\frac{dY}{d(I_t \times treat)} = \frac{\partial Y}{\partial M} \frac{\partial M}{\partial (I_t \times treat)} + R_t, \tag{3}$$

where Y is maternal labor earnings, $I_t \times treat$ is the treatment indicator, *M* indicates if a mother experienced at least one mental health visit in a given calendar year, and R_t is the unexplained part

[46] We can reject the null hypothesis that the estimated effects for mothers one year after the shock are the same as those for fathers.

of the health shock effect. First, $\frac{\partial Y}{\partial M}$ is estimated by augmenting (1) with mediator *M*:

$$Y_{is} = \alpha + \beta treat_i + \sum_{t \neq -2, t=-5}^{t=3} \gamma_t \times I_t + \sum_{t \neq -2, t=-5}^{t=3} \delta_t^{m_1} \times I_t \times treat_i + \eta M_{is} + \lambda A_{is} + \phi CBY_i + \omega_s + \epsilon_{is}. \tag{4}$$

Note that here we capture the association between mental health and labor earnings in a given year (conditional on controls). Next, we estimate the effect of a child's hospitalization or fatal shock on the probability of a mental health visit, $\frac{\partial M}{\partial(I_t \times treat)}$, as in section 6.2:

$$M_{is} = \alpha + \beta treat_i + \sum_{t \neq -2, t=-5}^{t=3} \gamma_t \times I_t + \sum_{t \neq -2, t=-5}^{t=3} \delta_t^{m_2} \times I_t \times treat_i + \lambda A_{is} + \phi CBY_i + \omega_s + \epsilon_{is}. \tag{5}$$

The contribution of *M* to the health shock effect in each period $t \in \{0, 1, 2, 3\}$ (i.e., during and after the health shock) is then calculated as the following ratio $\frac{\eta \times \delta_t^{m_2}}{\delta_t}$. The unexplained part, R_t, is subsequently computed as $R_t = 1 - \frac{\eta \times \delta_t^{m_2}}{\delta_t}$.

Results of this exercise are in Figure A10. Panel (a) shows the results for children's hospitalization shocks. We find that the mental health shock drives around 10% of the impact on maternal labor earnings. The explanatory power of this channel decreases over time, suggesting that other factors are playing a more critical role. For mortality shocks, the picture is very different: in the year of the shock, the impact on mental health can explain more than half of the drop in maternal labor earnings. This result suggests that the mechanisms behind the effects of non-fatal and fatal shocks are very different: while for fatal shocks, the mental health shock is the primary driver of the negative impact, for hospitalization shocks, it is more plausible that the decrease in earnings results from the combination of the increased time needed to care for the child (discussed in Section 6.1) and the worsening of maternal mental health.

6.3 Household specialization vs preferences/norms

An important question is whether the adjustments in maternal supply come from a household specialization decision. To investigate this dimension, we construct a dummy variable that captures if the mother was the primary earner in the pre-period ($t-2$ to $t-5$), or if she, otherwise, was the secondary earner. We then estimate our DiD specification by splitting our data into these two subsamples. Results are in Table 6.

Two things are worth noticing. First, for both Finland and Norway, we observe significant negative effects for both primary and secondary earner mothers. Second and perhaps even more surprisingly, the impacts in both countries are larger for primary earners: in Finland, the negative impact is more than four times larger (5.6% compared to 1.2%), for Norway, more than double the size (4.21% vs 1.88%). This is consistent with the results from the Conditional Average Treatment Effects estimated using causal forest algorithms in Section 7, where we show that the earning losses are larger among highly educated mothers with higher (pre-event) earnings. All together, this evidence provides suggestive evidence that the observed effects are unlikely to be driven by specialization within the household.

This result can be interpreted in light of studies in the child penalty literature that also find little specialization according to comparative advantage in households (Andresen and Nix, 2022; Artmann et al., 2022; Kleven et al., 2021). In particular, men's labor market trajectories seem to be largely unaffected by parenthood, irrespective of their relative earnings potential in the household. In fact, this result is more in line with strong preferences or norms playing an important role in women's decisions about childcare provision and labor supply. It is crucial to recognize that, in the event of a health shock, relying on external childcare may not be a viable or practical option for many families. Thus, given that this unidirectional adjustment in maternal labor supply will take place (given social norms or preferences), this can be especially harmful for women with high earnings potential.

Another way to measure this is to examine heterogeneity by the father's previous involvement in childcare activities. To proxy for this household dynamics, we exploit the share of parental leave in the child's first years of life taken by the father, using data from Norway. Figure A11 plots the share of parental leave taken by the father during the first year after birth. The distribution is very right-skewed, with most fathers taking a very low share of the total parental leave in the household.

In our sample, the average father's leave share is 7.3%. Only 27% of fathers take any leave, and around 4.8% of fathers take at least 10% of all the parental leave taken by the household.

We thus split our sample by whether the father was involved in the household during parental leave or not. The first columns in Table A17 show the results for families whose father either took any leave (father's leave share > 0), and by whether the father took at least 10% of the total parental leave taken in the household. In the next two columns, we show the coefficients for families whose father was not involved in the household care measured again by these two indicators. Although the coefficients are more imprecisely estimated due to the smaller sample size, the effects are similarly sized, suggesting that even in households where the father was relatively more involved in childcare (as proxied by paternity leave take-up), mothers are the ones who suffer the negative shock.

Again, together with the previous results, this suggests that household specialization is unlikely to be the main driver of these results. Instead, preferences or social norms seem to be a more relevant mechanism behind the effects.

6.4 Family Stability

Previous papers find that having a child with a disability is associated with a higher probability of relationship dissolution (Stabile and Allin, 2012). While marital dissolution is an outcome in itself, it may also affect parents' labor supply decisions (e.g, Ananat and Michaels, 2008; Bargain et al., 2012; Leopold, 2018; Page and Stevens, 2004). We have information on marital status for both countries. Figure 5 shows the results (in Panel (a) for Finland and Panel (b) for Norway). We do not find evidence of an increased risk of divorce after the child's hospitalization, suggesting that these shocks do not significantly impact family stability.

We also analyze the impacts of children's health shocks separately for married women and for divorced women. We can observe in columns (1) and (2) in Table A18 that the effects are very similar across these two groups, and if something, larger for divorced women. It is worth considering that divorced women in these countries may still receive significant financial support from their former spouses.[47] Therefore, these two groups might possess a financial cushion to adjust their responses if they have strong preferences or cultural norms favoring in-family care during shocks.

For Finland and Norway, the unmarried women category consists of both women who are cohabitating with their partner and single women. We observe a similar effect size for Norway but find no significant effect for Finland (see columns (3)). This difference could stem from variations in family structure composition between the two countries, complicating the interpretation of the results. However, in the case of Finland, we can directly identify single mothers from our data registry. Column (4) in the table presents results for this subgroup, revealing a notably smaller coefficient. It is important to note that this estimate is less precise due to a smaller sample size.

In summary, these findings suggest that the impact on women is relatively consistent across different family structures, with a possible tendency for smaller effects among single women. One plausible interpretation of this result is that single women in these contexts may face greater economic constraints, making it less possible for them to reduce their labor supply in response to shocks.

6.5 Choice of Work Environment

Other studies have indicated that after childbirth women prefer jobs that are more "family-friendly" (e.g, Goldin and Katz, 2016; Lundborg et al., 2017). In particular, Pertold-Gebicka et al. (2016) and Kleven et al. (2019b) find that mothers have a higher probability of moving to an occupation in the public sector following parenthood, which is known to have more flexible working conditions.

Similarly, after the hospitalization of a child, mothers may also seek a more family-friendly job in order to provide care. We take advantage of the availability of rich occupational data in Finland to explore this margin of adjustment. In Panel (a) of Figure 6, we examine whether mothers have a higher probability of working in the public sector after their child undergoes a health shock. We

[47] In Finland, in 2017 a median-income single parent with one child would receive 300 USD in child support from the non-resident parent, and about 420 USD if she has two children. In Norway, the same parent with one child would receive around 220 USD, and sightly less than 500 USD for two children (Hakovirta et al. (2022)).

do not find this to be the case, which suggests that mothers do not adjust their labor supply in this manner. More generally, Panel (b) in Figure 6 looks at whether mothers have a higher probability of moving to a different job after their child's health shock. For each year, we define an indicator variable equal to one if the mother is not working in the same company as in the previous period. Again, we do not find evidence that mothers have a higher probability of switching to a different job after the health shock.

7 Who is More Negatively Impacted? Heterogenous Treatment Effects Using Causal Forests

One crucial question is, which mothers are more negatively affected by their child's sickness? The average effects presented in Table 1 could mask substantial heterogeneity. Given the richness of our administrative data, we characterize this heterogeneity by using causal forests estimators (Athey and Imbens, 2016; Athey et al., 2019; Wager and Athey, 2018). The intuition behind this approach is to split the data to maximize the difference in treatment effects across subsamples while preserving the accurate estimation of the treatment effect. There are two main advantages of using this approach. First, it limits the researcher's discretion when selecting which splits and variables to consider for the heterogeneity analysis. This is particularly important when the potential covariates list is very large, as in this setting. Second, using the "honest" approach, that is, having mutually exclusive training and estimation samples, this method preserves the validity of confidence intervals constructed on treatment effects within subgroups (Athey and Imbens, 2016).

We estimate CATE (Conditional Average Treatment Effects) on a large set of observable characteristics of the child, mother, and family, as well as type of shock (using the hospital diagnosis).[48] We follow the approach in Britto et al. (2021) and run the causal forest over first-differences.[49]

[48]The algorithm starts by building trees. Each of the trees stratifies the set of characteristics into a number of regions, often referred as leafs. Within each leaf, it calculates the mean outcome for those who are treated, and then subtracts the mean outcome for those in the control group. We require that each leaf contains at least 100 observations. This procedure is repeated until we reach 5000 trees. The final causal forest prediction is a weighted average over the predictions in each tree.

[49]In this way, the treatment group indicator is orthogonal to the covariates, so the unconfoundness assumption in

We first examine the heterogeneous treatment effects for maternal labor earnings. We focus on Finland given the larger sample size. The predicted CATE is negative and statistically significant for all mothers, showing the ubiquitous effect of a child's health shock for mothers' labor careers. Figure A12a shows the distribution of the effect size in our sample. The loss in earnings (during the three years after the shock) ranges from €116 to €1407. Table A19 compares the characteristics of mothers with below- and above-median treatment effects and formally tests for the difference in means. Although most of the differences are statistically significant, their magnitude is large (above 0.2) only for four characteristics. In particular, more affected mothers are less likely to have lower education (highest maternal education level being upper secondary education or equivalent), more likely to have higher education (master's degree), more likely to be among the highest (pre-event) earning group (Q4), and more likely that their household earnings gap is small (Q1). To explore these features further, Figure A13a shows how the treatment effect varies along the earnings and education dimension while keeping the other variable constant. We see that there is substantial variation in the CATE by educational level for a given income quartile, suggesting again that the impacts are concentrated among highly educated women. We also see larger impacts for mothers in the highest income quartile. Another simple metric of the importance of each variable in explaining CATE relates to the share of data-driven sample splits over a given characteristic (Athey et al., 2019). Mother's education and ICD10 diagnosis codes rank first and second, driving 22.7% and 17.8% of the sample splits, respectively. They are followed by the mother's pre-shock earnings, which drives 11.0% of the sample splits.

If we just consider the absolute drop in labor earnings after the shock, these patterns suggest that mothers who are hurt the most are the ones who have more to lose. In particular, the sickness of a child seems to be a particularly detrimental situation (in terms of the earnings drop) for relatively highly educated women with high earnings potential and whose earnings gap relative to their partner's earnings is relatively small.

We next examine the heterogeneity in the employment probability. Figure A12b shows that

Wager and Athey (2018) holds. See Britto et al. (2021) for more details. In addition, we do not allow the same observation to appear in both the treatment and control group.

there is also substantial variation in the impact of a child's health shock on the probability of being employed. Crucially, at the extensive margin, mothers who make the biggest adjustment in terms of labor supply are those with lower earnings before the shock and larger earnings gap with their partners (Table A20). Interestingly, there is no educational gradient here, suggesting that it is driven by both mothers from low and high educational backgrounds but with lower earnings before the shock (see heatmap in Figure A13b). This pattern could be explained by mothers with a lower attachment to the labor force (for example, working part-time) leaving the labor force after this adverse event.

Finally, we examine the heterogeneity in the impact on a mother's mental health. Specifically, we analyze the probability of visiting a specialist or a hospital due to a mental health condition. Figure A12c shows the distribution of the effect size. Again, there is substantial heterogeneity: the probability of being diagnosed with a mental health condition ranges from a very slight drop of 0.5 percentage points to an increase of 2.5 percentage points. Strikingly, we observe here the same income gradient as in the results for employment: from Table A21 we can see that among the most affected mothers, there are more women with low incomes (Q1, Q2) and big household earnings gaps (Q4). In contrast, less affected mothers tend to have a higher income (Q3, Q4) and a smaller household earnings gap (Q1). The pattern is depicted in the heatmap in Figure A13c.

Overall, our results indicate that the declines in earnings are more substantial among relatively highly educated women with high earning potential and a relatively small earnings gap with their partners. Consequently, this adjustment appears to be particularly detrimental to women who have more to lose.

Conversely, when a child falls ill, it places a greater burden on mothers with lower pre-event earnings in terms of their labor force participation and mental health. This pattern aligns with mothers who have weaker ties to the labor force (e.g., working part-time) leaving it after encountering this adverse event. This finding is of particular concern, especially considering that children of mothers from lower socioeconomic backgrounds are nearly three times more likely to experience a hospitalization[50] during childhood. This is illustrated in Figure A1, where we present the hospitalization rates for our cohorts categorized by educational and occupational factors.

8 Conclusions

This paper provides new evidence on the impact of children's health shocks on parental labor market outcomes. To identify the causal effect, we compare families whose children are exposed to health shocks at varying ages, conditional on the parents' and children's ages. This allows us to focus on a sample of very similar families and abstract from differences across households who suffer the illness or death of a child and those who do not.

In particular, we use long panels of high-quality administrative data from two different countries, Finland and Norway, on family income and health trajectories. We construct counterfactuals for treated households through families who experience the same shock a few years later. Our analysis addresses both the impact of hospitalizations and fatal health shocks.

The results show that children's health shocks have a persistent negative impact on mothers' careers. We find that mothers' earnings are 4.6% and 4.7% lower three years after a hospitalization, while we do not find evidence of an effect for fathers. Additionally, we show that the impact is stronger for severe hospitalizations or health shocks that require substantial and persistent care after the event. To put the magnitude of the effects into context, the effect on maternal earnings is approximately one-fourth of the estimated impact of a health shock on an individual's own labor earnings (Dobkin et al., 2018; Meyer and Mok, 2019; Fadlon and Nielsen, 2017), and around 20% the estimated drop in maternal earnings 3 years after childbirth in Finland (Sieppi and Pehkonen, 2019), and 23% in Norway (Andresen and Nix, 2021). Our estimates are strikingly similar for Finland and Norway. These two Nordic countries share many characteristics in terms of institutional context, culture, and gender norms. The fact that we find almost identical results strengthens the robustness of our approach and the external validity of our findings.

[50] The same socioeconomic gradient is evident for fatal shocks. Results can be found in Panel b and d of Figure A1

In addition, we use data from Finland to study fatal shocks. The impact of losing a child on maternal labor earnings is much larger than for hospitalizations: three years after the death of a child mothers' earnings are about 20% lower than two years before the shock. For fathers, we do not find evidence of any significant impact.

We study if these families are insured through transfers and benefits linked to these shocks. We show that although transfers and other tax-deductible expenses offset part of the negative impact, families are not fully insured against these shocks.

Children's health shocks also adversely affect parents' mental well-being. We document this using data on hospital and specialist diagnoses (from Finland) and primary care data (from Norway). Our findings suggest that this is the primary mechanism underlying the impact of fatal shocks, whereas for hospitalizations, it only explains a relatively small portion of the variation.

Subsequently, we delve into the mechanisms that can explain the adjustments in maternal labor market outcomes. First, we attempt to discern whether social insurance mitigates or exacerbates the maternal labor supply response in the context of children's health shocks. Utilizing spatial and temporal variation at the municipality level, in the allowances provided to families following a child's health shock, we do not find evidence that the level of social insurance significantly influences mothers' labor supply decisions, meaning that the generosity of the safety net does not seem to explain the reductions in maternal labor supply in this context.

Next, we explore the role of increased caregiving demands. We show that the decline in maternal earnings is more pronounced for health shocks requiring substantial care, as measured by the number of hospital visits in the year following the shock or for chronic health conditions. Additionally, we also find suggestive evidence that the adverse effects are more substantial when grandparents do not reside close to the family.

Furthermore, household specialization is an improbable explanation for the one-sided maternal adjustment. We observe that the decline in earnings is more significant for women with more at stake, such as relatively highly educated women with high earning potential or those serving as primary earners in their households. Instead, our results align more with these shocks increasing caregiving demands, and with women primarily bearing this burden.

Overall, our results highlight the importance of assisting families whose child experiences a health shock, especially by providing mental health support. Moreover, these results also have important implications concerning gender equality. Our evidence shows that the disproportionate costs of children for women's labor market careers compared to that for men do not end with childbirth. We demonstrate that in two countries usually portrayed as exemplars of gender equality, and with very generous family policies, health shocks that occur during middle childhood to adolescence also disproportionately affect women's labor market outcomes.

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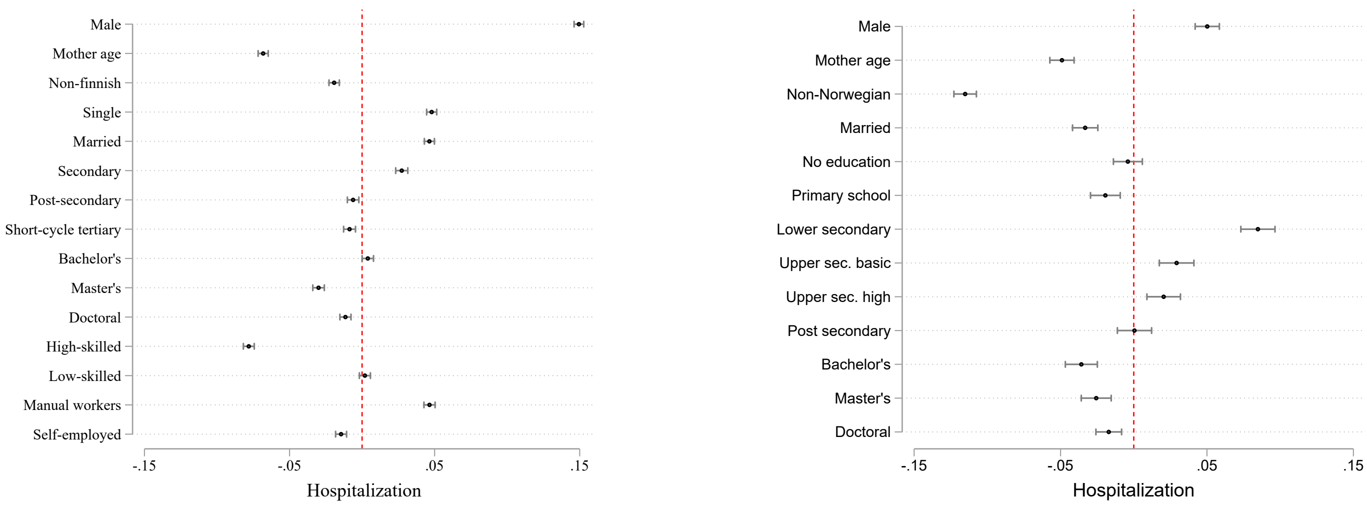
Figures and Tables

Figures

Figure 1: Differences in Characteristics: Across Families

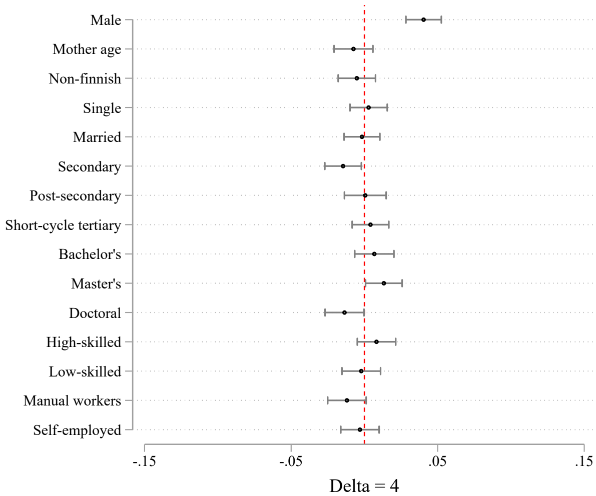


(a) Finland

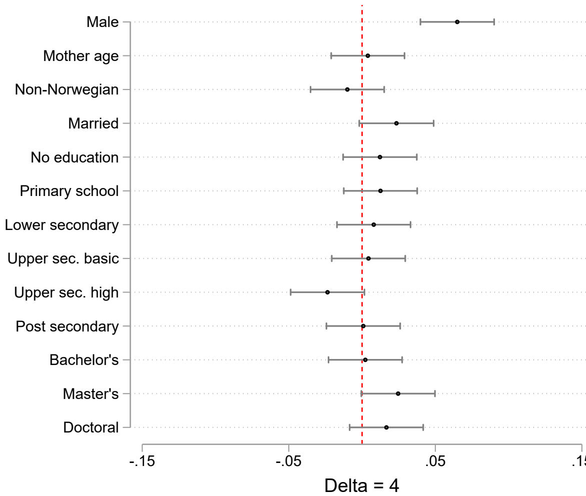
(b) Norway

Notes: The figure shows the coefficients and 95% CI from separate regressions of each (standardized) variable on an indicator that takes a value of 1 if the child suffered at least one hospitalization from ages 0 to 18. Panel (a) shows the results for Finland, and panel (b) for Norway. All specifications include year-of-birth fixed effects. Standard errors are clustered at the mother level.

Figure 2: Differences in Characteristics: Within Affected Families



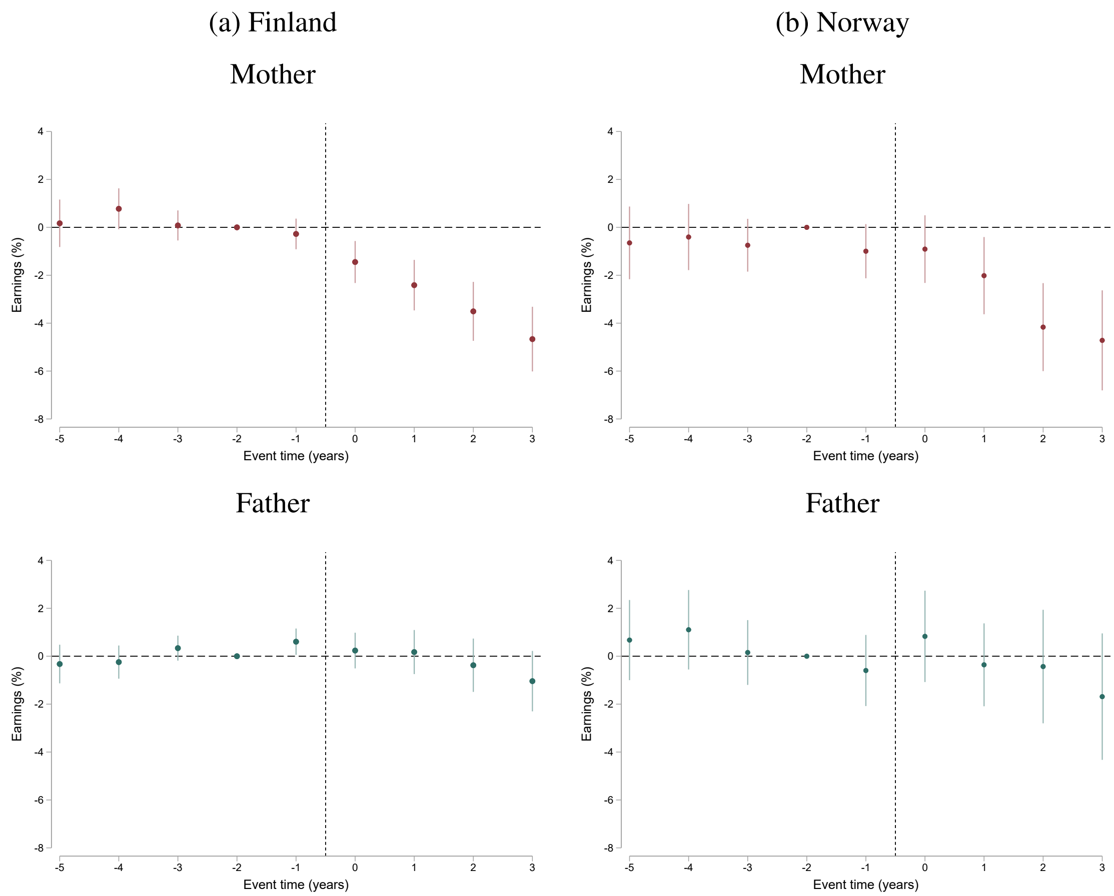
(a) Finland



(b) Norway

Notes: The figure shows the coefficients and 95% CI from separate regressions of each (standardized) variable on an indicator that takes a value of 1 if the family is in the treatment group, and 0 for the control group (the child experiences the shock 4 years later). Panel (a) shows the results for Finland, and panel (b) for Norway. All specifications include year-of-birth fixed effects. Standard errors are clustered at the mother level.

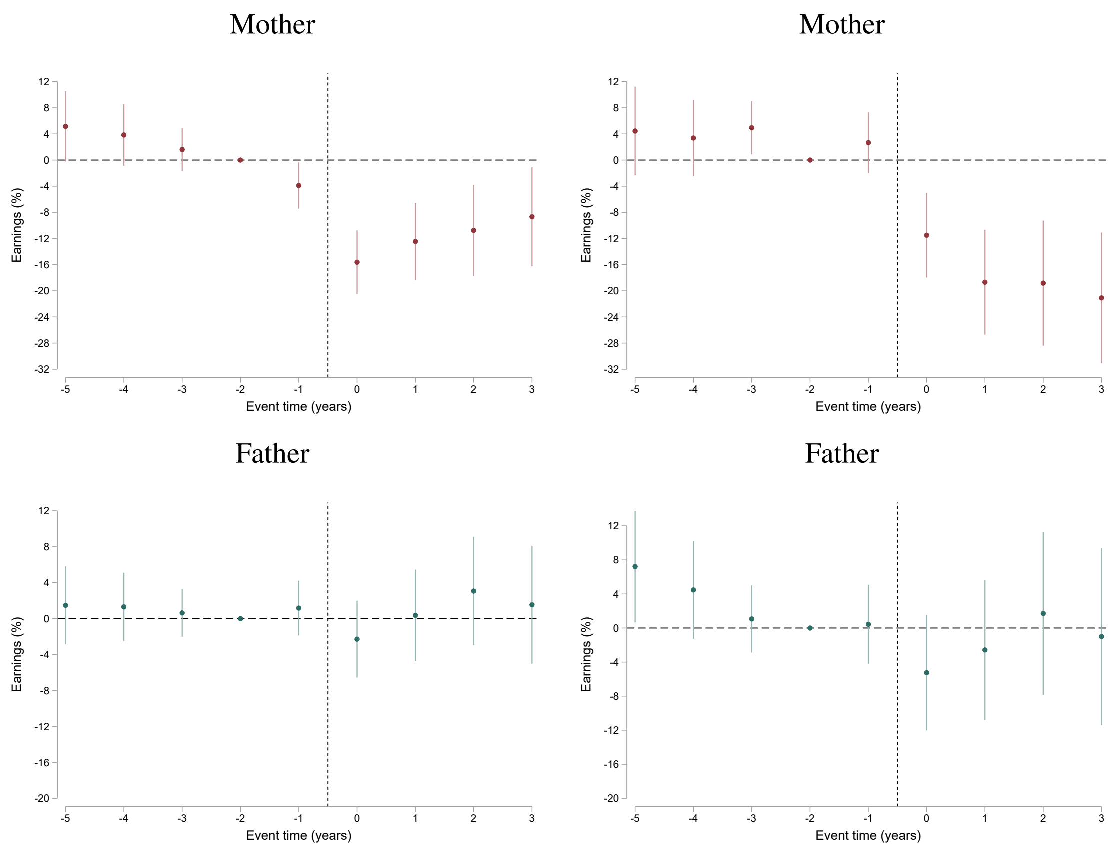
Figure 3: Hospitalizations: Mothers' and Fathers' Labor Earnings



Notes: This figure shows the impact of a child's hospitalization on the mother's and father's labor earnings (as a percentage of their earnings in $t-2$). We plot the coefficients for the interaction between the event time dummies and the treat dummy in Equation (1), with the corresponding 95 percent confidence intervals. Panel (a) plots the results for Finland. Panel (b) plots the results for Norway. All specifications include controls for calendar year, child's year of birth, child's gender, and each parent's age and educational level. Standard errors are clustered at the parent level.

Figure 4: Impact of a Child's Fatal Shock on Mothers' and Fathers' Labor Earnings

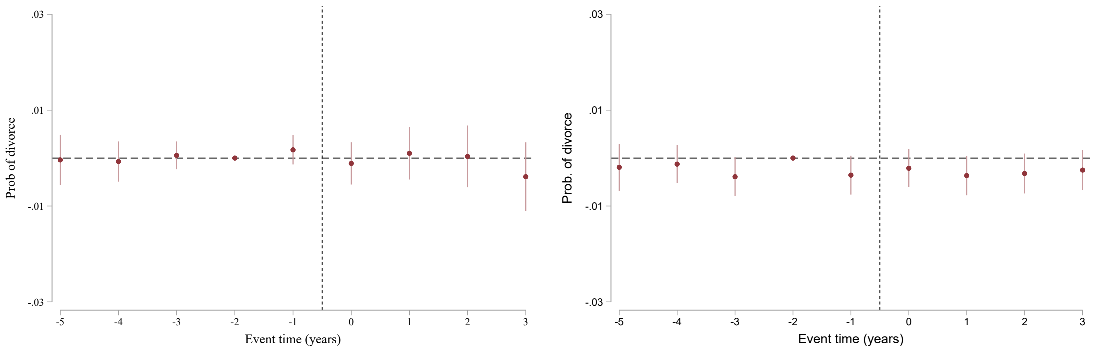
(a) All | (b) Injuries



Notes: This figure shows the impact of a child's fatal shock on the mother's and father's labor earnings (as a % of their earnings in $t-2$). We plot the coefficients for the interaction between the event time dummies and the treat dummy in Equation 1, with the corresponding 95 percent confidence intervals. Panel (a) plots the results of all mortality shocks, regardless of the cause of death. Panel (b) restricts the sample to fatal shocks due to injuries, poisonings, or other consequences of external causes. All specifications include controls for calendar year, child's year of birth, child's gender, and one parent's age depending on the outcome variable. We use administrative data from Finland. Standard errors are clustered at the parent level.

Figure 5: Hospitalizations: Probability of Divorce

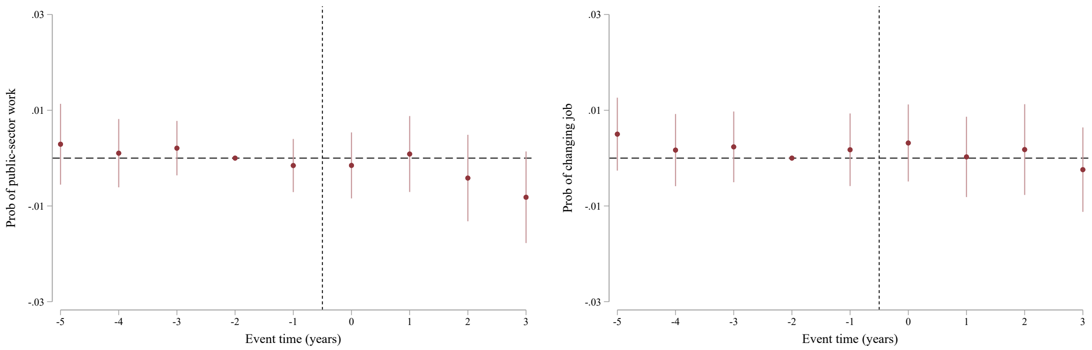
(a) Finland (b) Norway



Notes: This figure shows the impact of a child's hospitalization on the probability of relationship dissolution. We plot the coefficients for the interaction between the event time dummies and the treat dummy in Equation 1, with the corresponding 95 percent confidence intervals. Panel (a) plots the results for Finland. Panel (b) plots the results for Norway. All specifications include controls for calendar year, child's year of birth, child's gender, and each parent's age and educational level. Standard errors are clustered at the parent level.

Figure 6: Hospitalizations: Choice of Work Environment

(a) Public-sector work (b) Changing jobs



Notes: This figure shows the impact of a child's hospitalization on the probability of working in the public sector (panel (a)) and the probability of switching jobs (panel (b)). We plot the coefficients for the interaction between the event time dummies and the treat dummy in Equation 1, with the corresponding 95 percent confidence intervals. We use administrative data from Finland. All specifications include controls for calendar year, child's year of birth, child's gender, and each parent's age and educational level. Standard errors are clustered at the parent level.

Tables

Table 1: Hospitalizations: Mothers' Labor Outcomes

	(1) Earnings (€)		(2) Earnings (%)		(3) Employment	
	Finland	Norway	Finland	Norway	Finland	Norway
-5	36.260	-199.724	0.169	-0.649	0.005	0.001
	(108.398)	(237.686)	(0.505)	(0.774)	(0.003)	(0.004)
-4	166.305*	-123.308	0.775*	-0.405	0.008***	0.002
	(93.366)	(216.523)	(0.435)	(0.705)	(0.003)	(0.004)
-3	17.047	-229.748	0.079	-0.748	-0.000	0.003
	(68.632)	(172.738)	(0.320)	(0.562)	(0.002)	(0.003)
-1	-59.126	-307.845*	-0.276	-0.997*	-0.002	0.005*
	(69.882)	(177.189)	(0.326)	(0.557)	(0.002)	(0.003)
0	-310.543***	-283.37	-1.448***	-0.909	-0.007**	0.002
	(95.867)	(221.354)	(0.447)	(0.72)	(0.003)	(0.003)
1	-517.681***	-620.884**	-2.413***	-2.017**	-0.011***	-0.003
	(115.358)	(252.637)	(0.538)	(0.822)	(0.003)	(0.004)
2	-752.394***	-1279.759***	-3.508***	-4.166***	-0.015***	-0.006
	(134.557)	(287.903)	(0.627)	(0.937)	(0.003)	(0.004)
3	-1000.763***	-1450.364***	-4.665***	-4.718***	-0.020***	-0.014***
	(147.714)	(327.171)	(0.689)	(1.065)	(0.003)	(0.004)
Observations	401787	212688	401787	212688	401787	212688
Controls	YES	YES	YES	YES	YES	YES
Mean Y_{t-2}	21450.555	30722.236	100	100	0.920	0.878

Notes: This table shows the impact of a child's hospitalization on maternal earnings (Euro) (in column (1)), maternal earnings as a % of mean earnings in $t-2$ (in column (2)), and maternal working probability (in column (3)), for both Finland and Norway, respectively. The table shows the estimated coefficients for the interaction between the event time dummies and the treat dummy in Equation 1. All specifications include controls for calendar year, child's year of birth, child's gender, and each parent's age and educational level. Standard errors are clustered at the parent level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Mortality: Mothers' Labor Outcomes

	(1) Earnings (€)	(2) Earnings (%)	(3) Employment
-5	863.707	4.442	0.012
	(673.499)	(3.464)	(0.024)
-4	656.534	3.377	0.036*
	(580.610)	(2.986)	(0.021)
-3	961.383**	4.944**	0.025
	(403.634)	(2.076)	(0.016)
-1	518.002	2.664	0.012
	(460.415)	(2.368)	(0.017)
0	-2234.341***	-11.491***	-0.036*
	(642.672)	(3.305)	(0.020)
1	-3632.357***	-18.681***	-0.047**
	(796.163)	(4.095)	(0.023)
2	-3659.945***	-18.823***	-0.062**
	(949.352)	(4.883)	(0.027)
3	-4099.865***	-21.086***	-0.082***
	(991.618)	(5.100)	(0.027)
Observations	10562	10562	10562
Controls	YES	YES	YES
Mean Y_{t-2}	19443.969	100	0.859

Notes: This table shows the impact of a child's fatal shock on maternal earnings (Euro) (in column (1)), maternal earnings as a % of mean earnings in $t-2$ (in column (2)), and maternal working probability (in column (3)). The table shows the estimated coefficients for the interaction between the event time dummies and the treat dummy in Equation 1. We use administrative data from Finland, and the sample includes all fatal shocks due to injuries, poisonings, or other consequences of external causes. All specifications include controls for calendar year, child's year of birth, child's gender, and the mother's age. Standard errors are clustered at the parent level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Hospitalizations: Mothers' Institutional Support

	(1) Earnings (€)		(2) Total Income (€)		(3) Transfers (€)		(4) Allowance (€)
	Finland	Norway	Finland	Norway	Finland	Norway	Finland
$Post_t * Treat_i$	-622.479***	-737.453***	-374.277***	-504.595***	110.375***	184.033*	81.635***
	(103.951)	(214.287)	(65.403)	(191.099)	(36.302)	(98.592)	(23.279)
Observations	376612	212688	376612	212688	376612	212688	376612
Controls	YES	YES	YES	YES	YES	YES	YES
Mean Y_{t-2}	21959.513	30722.236	21194.231	38228.001	4692.090	7884.261	3485.605

Notes: This table shows the impact of a child's hospitalization on maternal earnings (in column (1)) total income (in column (2)), transfers received by the mother (in column (3)), and family allowance (in column (4)), for both Finland and Norway, respectively. The table shows the coefficient for the interaction between a post dummy (year of the hospitalization and all subsequent years) and the treat dummy in equation 1. All specifications include controls for calendar year, child's year of birth, child's gender, age of the parent, and parent's education level. Clustered standard errors at the parent level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Hospitalizations: Burden of Care and Severity

	(1) By Burden of Care		(2) By Diagnosis		(3) Grandparent's Region	
	High	Low	Cancer	Skin	Different	Same
$Post_t * Treat_i$	-978.616***	-508.561***	-2213.941***	293.468	-914.446***	-574.952***
	(181.333)	(146.754)	(751.530)	(762.139)	(269.118)	(121.656)
Observations	124781	178262	8327	8553	65589	248361
Controls	YES	YES	YES	YES	YES	YES
Mean Y_{t-2}	22140.138	20705.836	23498.052	19632.313	22408.158	19265.829

Notes: This table shows the impact of a child's hospitalization on maternal earnings (Euro) for different subsamples of hospitalizations. In column (1), we split the sample by burden of care, measured by the number of visits and hospitalizations in the year of the shock. In column (2), we analyze cancer and skin conditions. In column (3), we split the sample by whether the grandparents live close to the family or not. The table shows the estimated coefficients for the interaction between the event time dummies and the treat dummy in Equation 1 for columns (1) and (3), and the estimated coefficients for the event time dummies in Equation 2 for column (2). We use administrative data from Finland. All specifications include controls for calendar year, child's year of birth, child's gender, and each parent's and educational level. Standard errors are clustered at the parent level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Hospitalizations: Parents' Number of Mental Health Visits

	(1) Mother		(2) Father	
	Finland	Norway	Finland	Norway
-5	-0.019		-0.042*	
	(0.023)		(0.022)	
-4	-0.041*	0.000	-0.031*	-0.034
	(0.021)	(0.041)	(0.017)	(0.06)
-3	-0.019	0.031	-0.019	-0.015
	(0.016)	(0.027)	(0.014)	(0.028)
-1	0.014	-0.005	0.004	0.012
	(0.019)	(0.022)	(0.011)	(0.02)
0	0.059***	0.079***	0.026*	0.031
	(0.023)	(0.026)	(0.015)	(0.025)
1	0.075***	0.068**	0.016	0.013
	(0.026)	(0.027)	(0.018)	(0.025)
2	0.043	0.01	0.022	0.016
	(0.029)	(0.029)	(0.019)	(0.028)
3	0.031	0.014	0.018	0.02
	(0.029)	(0.029)	(0.020)	(0.027)
Observations	387856	162922	387856	162922
Controls	YES	YES	YES	YES
Mean Y_{t-2}	0.135	0.487	0.079	0.289

Notes: This table shows the impact of a child's hospitalization on the mother's (column (1)) and father's (column (2)) mental health, for both Finland and Norway, respectively. The outcome measures the number of mental-health related visits to a hospital or specialist (in Finland) or a primary care physician (in Norway). The table shows the estimated coefficients for the interaction between the event time dummies and the treatment dummy in Equation 1. All specifications include controls for calendar year, child's year of birth, child's gender, and each parent's age and educational level. Standard errors are clustered at the parent level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Hospitalizations: By Mothers' Specialization within the Household

	(1) Primary Earner		(2) Secondary Earner	
	Finland	Norway	Finland	Norway
$Post_t * Treat_i$	-1669.608***	-1934.053***	-228.938**	-518.431**
	(234.045)	(658.393)	(106.436)	(228.680)
Observations	88175	35298	306512	164916
Controls	YES	YES	YES	YES
Mean Y_{t-2}	29501.611	45923.087	19098.422	27541.731

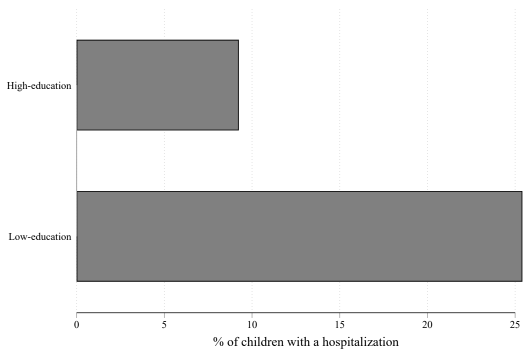
Notes: This table shows the impact of a child's hospitalization on maternal earnings for primary earner mothers (in column (1)) and secondary earner mothers (in column (2)) (defined from average earnings from -2 to -5), for both Finland and Norway, respectively. The table shows the coefficient for the interaction between a post dummy (after hospitalization) and the treat dummy in equation 1. All specifications include controls for calendar year, child's year of birth, child's gender, age of the parent, and parent's education level. Clustered standard errors at the parent level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

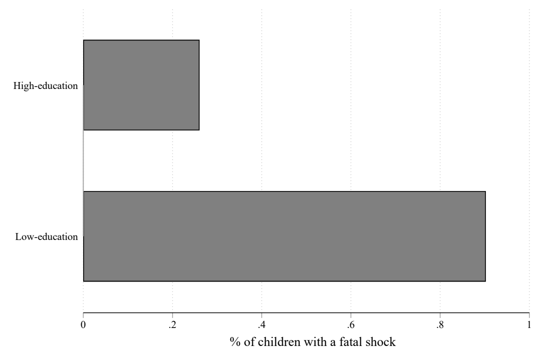
Appendix (For Online Publication)

Figure A1: Descriptive: Maternal Socioeconomic Background and Children's Health Shocks

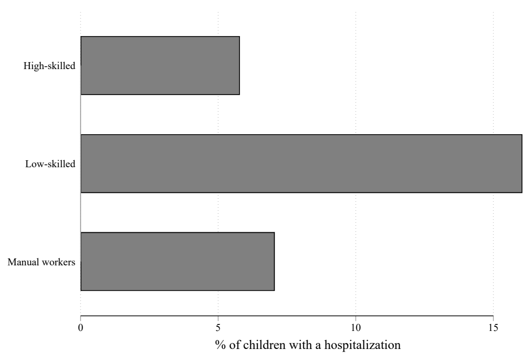
(a) Hospitalizations by educational level



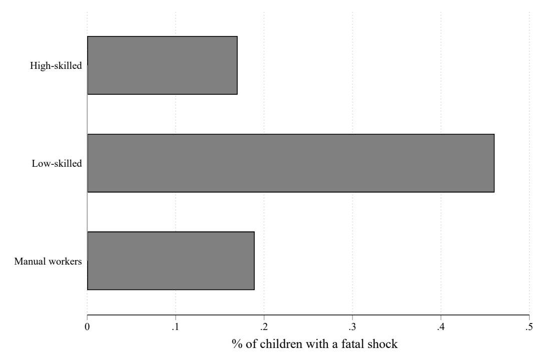
(b) Mortality by educational level



(c) Hospitalizations by occupation

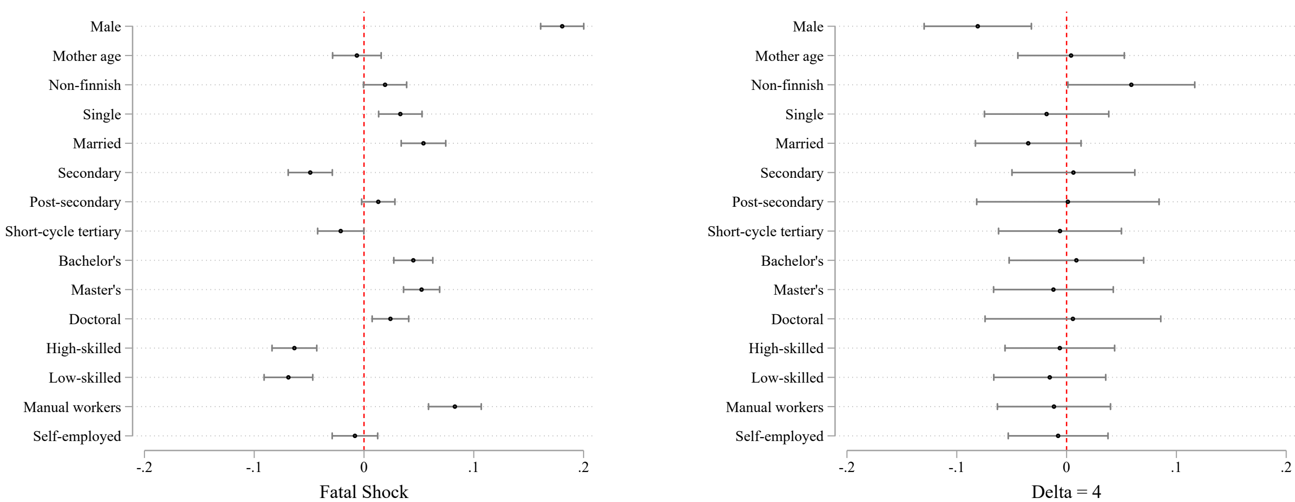


(d) Mortality by occupation



Notes: This figure shows the percentage of children who suffered a hospitalization or a fatal shock by educational level (panel a and b) and for selected occupations (panel c and d) for all children born between 1990 and 2014. We use administrative data from Finland

Figure A2: Mortality: Differences in Characteristics



(a) Across Families

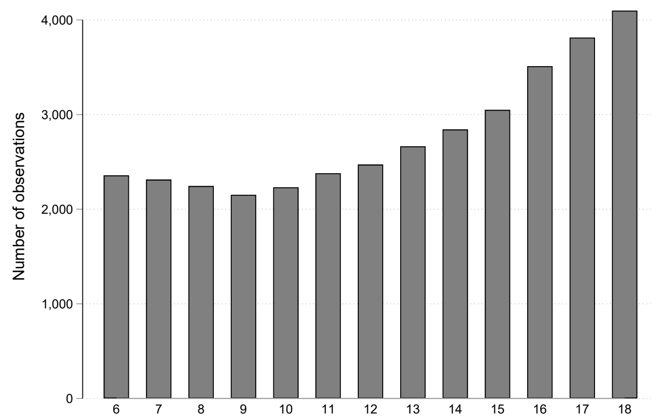
(b) Within Affected Families

Notes: The figure shows the coefficients and 95% CI from separate regressions of each (standardized) variable. In panel (a), we regress the variables on an indicator that takes a value of 1 if the family suffered a fatal shock and 0 if not. In panel (b), we regress the same variables on an indicator that takes a value of 1 if the family is in the treatment group and 0 for the control group (the child experiences the shock 4 years later). To keep the scale of the graphs comparable, we exclude the results for gestational weeks and birth weight (large and significant coefficients in panel (a) and small and non-significant in panel (b)). All specifications include year-of-birth fixed effects. Standard errors are clustered at the mother level.

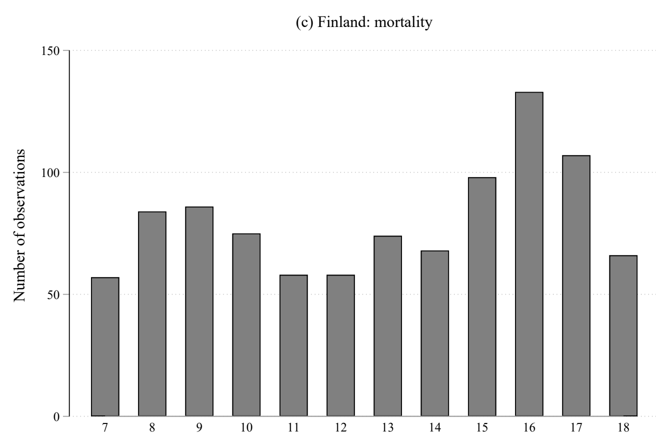
Figure A3: Number of Observations by Child's Age at Event Time

(a) Finland: hospitalizations

(b) Norway: hospitalizations



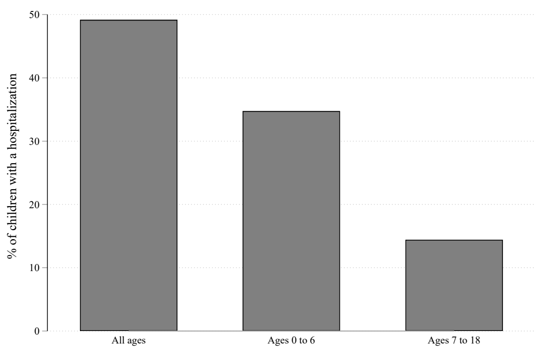
(c) Finland: mortality



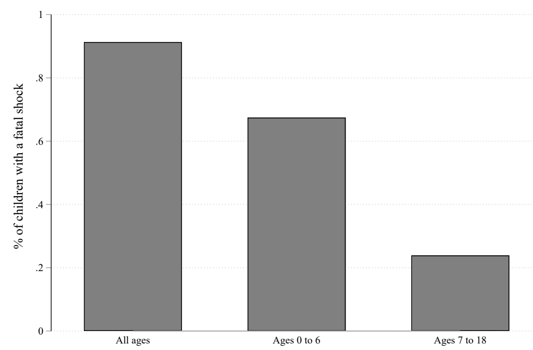
Notes: This figure shows the number of observations by the age of the child at hospital admission for Finland (panel (a)) and Norway (panel (b)). In panel (c), we show the number of observations by age of the child at the time of the fatal shock for Finland. The sample includes all children who suffered their first health shock between ages seven and eighteen in Finland. In Norway, we focus on the first hospitalization observable in the data after age six, restricting the sample to children that did not suffer any hospitalization in the year before the health shock.

Figure A4: Descriptive: children born in Finland in 1990

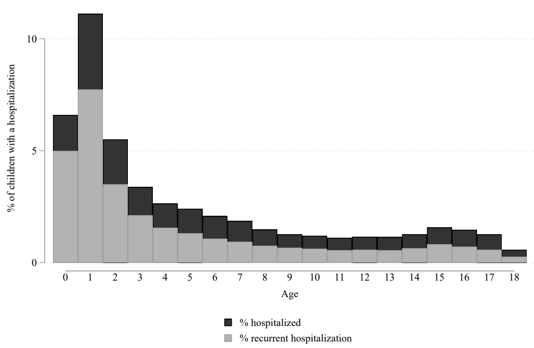
(a) Hospitalizations by age group



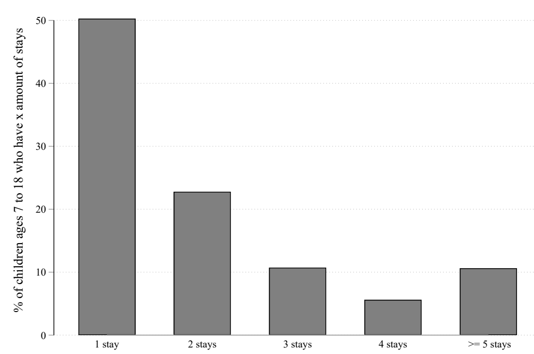
(b) Mortality by age group



(c) Hospitalization recurrence



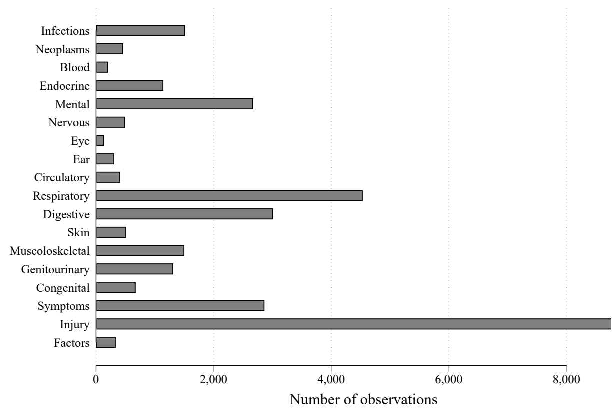
(d) Number of stays



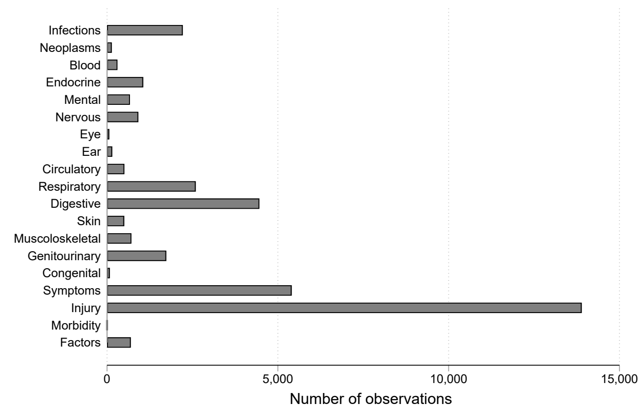
Notes: This figure provides different descriptive graphs for the sample of children born in 1990, in Finland. Panel (a) shows the percentage of children who suffered a hospitalization from ages 0 to 18 and then decomposed into two groups based on school starting age. Panel (b) plots the same information for mortality. Panel (c) shows the percentage of children who suffered a hospitalization by age, and the percentage of children who suffered recurring hospitalizations (defined by at least 2 hospital stays). Panel (d) shows the percentage of children with a given amount of hospital stays for the sample of children who suffered a hospitalization from ages 7 to 18.

Figure A5: Hospitalizations and Mortality Shocks by Main Diagnosis Group

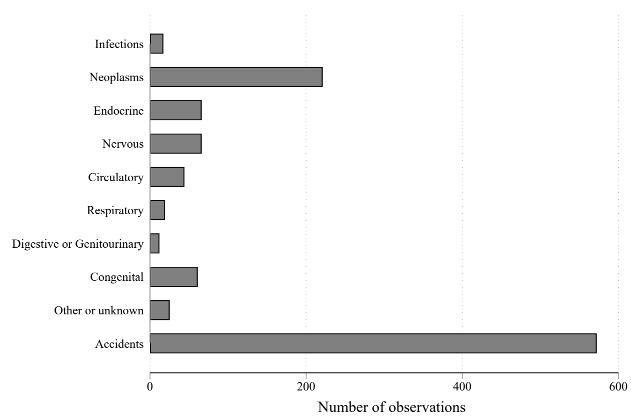
(a) Finland: hospitalizations



(b) Norway: hospitalizations



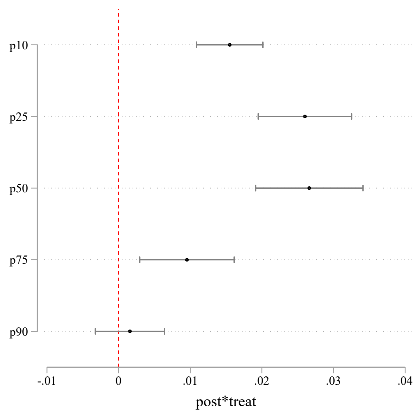
(c) Finland: mortality



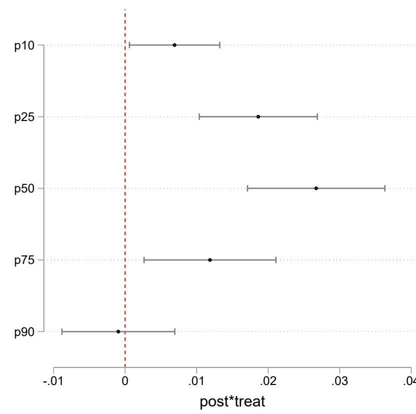
Notes: This figure shows the number of children who suffered a hospitalization by main diagnosis group (ICD-10 Chapters) for Finland (panel (a)) and for Norway (panel (b)). Panel (c) splits fatal shocks by cause of death. Categories include: Certain infectious and parasitic diseases, neoplasms, diseases of the blood and blood-forming organs and certain disorders involving the immune mechanism, endocrine, nutritional and metabolic diseases, mental and behavioural disorders, diseases of the nervous system, diseases of the eye and adnexa, diseases of the ear and mastoid process, diseases of the circulatory system, diseases of the respiratory system, diseases of the digestive system, diseases of the skin and subcutaneous tissue, diseases of the musculoskeletal system and connective tissue, diseases of the genitourinary system, congenital malformations, symptoms, signs and abnormal clinical and laboratory findings not elsewhere classified, injury, poisoning and certain other consequences of external causes, and factors influencing health status and contact with health services. All categories contain at least five observations.

Figure A6: Hospitalizations and Mortality: Impact on Maternal Earnings' Distribution

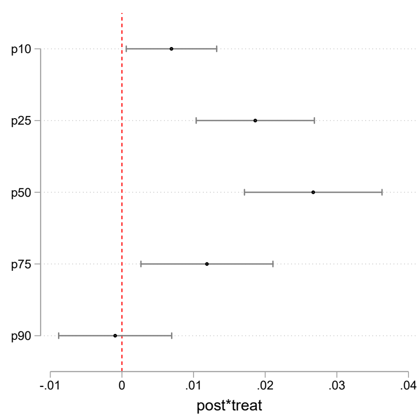
(a) Finland: Hospitalizations



(b) Norway: Hospitalizations

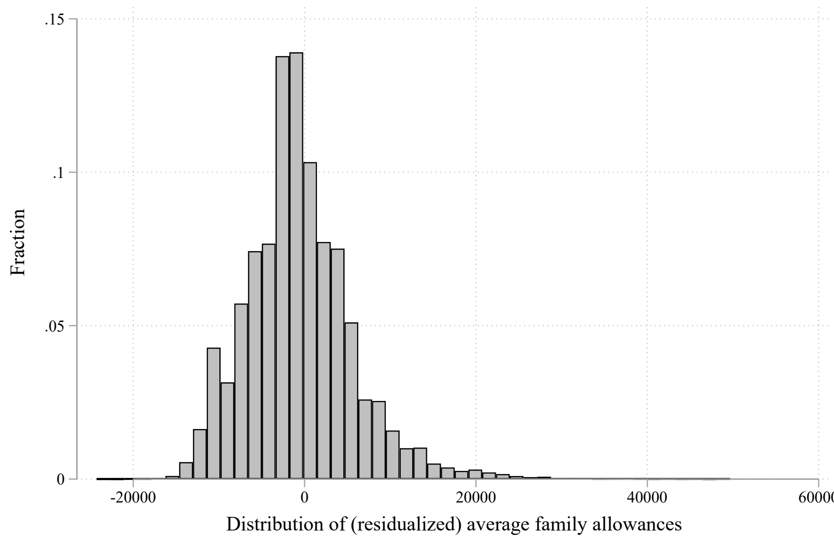


(c) Finland: Mortality



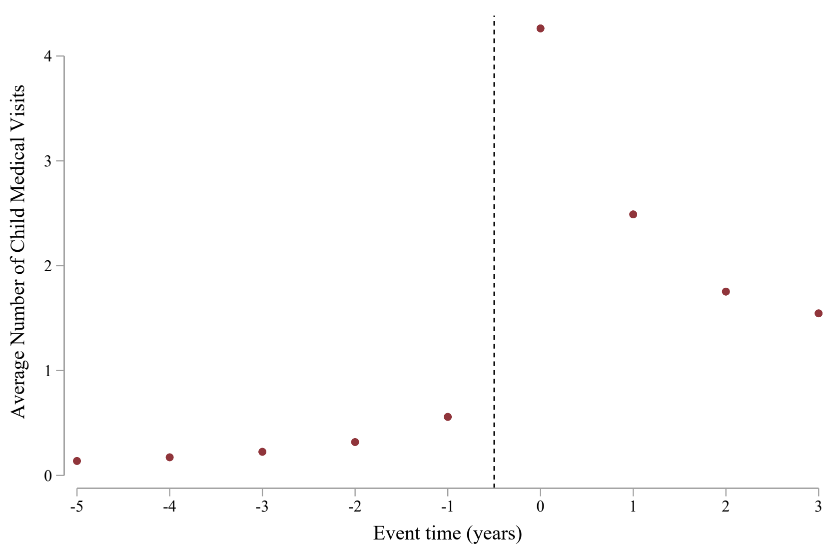
Notes: The figure shows the coefficients and 95% CI from separate regressions for dummy variables that take value equal to one if the mothers' earnings drop below a given percentile of the earnings distribution. In panel (a), results for Finland. In panel (b), results for Norway. In panel (c), results for mortality, for Finland. The figure shows the coefficients for the interaction between a post dummy (after hospitalization) and the treat dummy in Equation 1. All specifications include controls for calendar year, child's year of birth, child's gender, age of the parent, and parent's education level. Clustered standard errors at the mother level.

Figure A7: Distribution of (residualized) Family Allowances by Municipality-Year



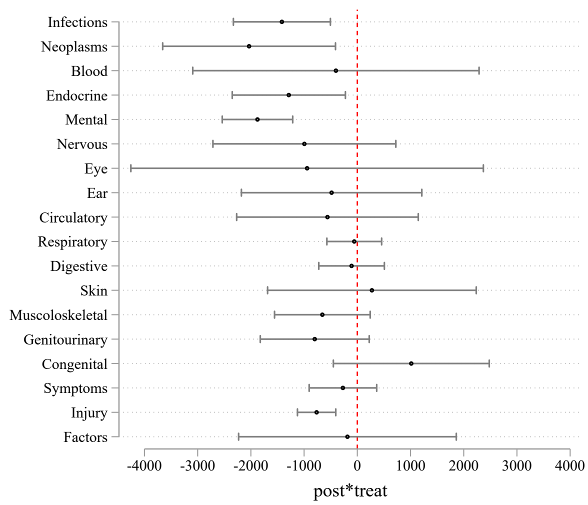
Notes: This figure shows the year-by-municipality ("leave-one-out") mean of (residualized) family allowances. To construct it, we first regress at the individual level, the family allowances received on ICD10 diagnosis code fixed effects and predict the residuals. We then sum all the (adjusted) individual family allowances and divide them by the number of children who suffered a health shock (leaving out a child's own family allowance), in a given municipality-year. We use administrative data from Finland.

Figure A8: Hospitalizations: Children's Number of Visits

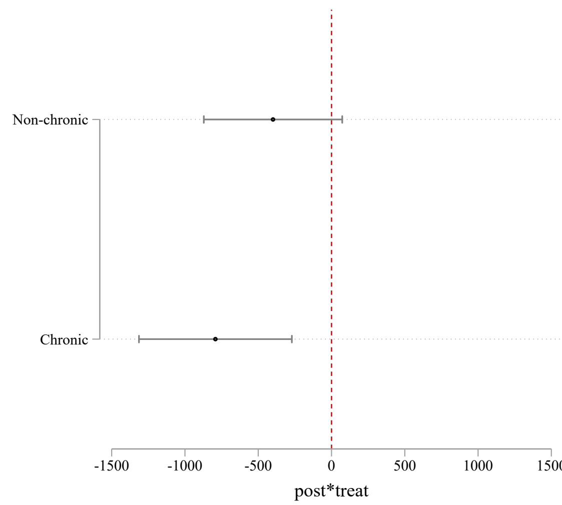


Notes: This figure shows the average number of children's inpatient and outpatient visits by event time (ranging from five years before to three years after their first hospitalization). We use administrative data from Finland.

Figure A9: Hospitalizations: Type of Health Shock



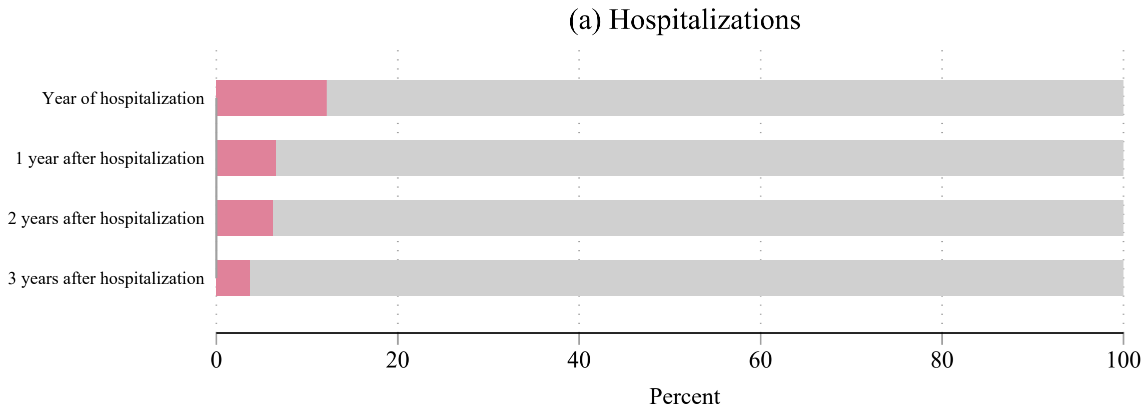
(a) By diagnosis code

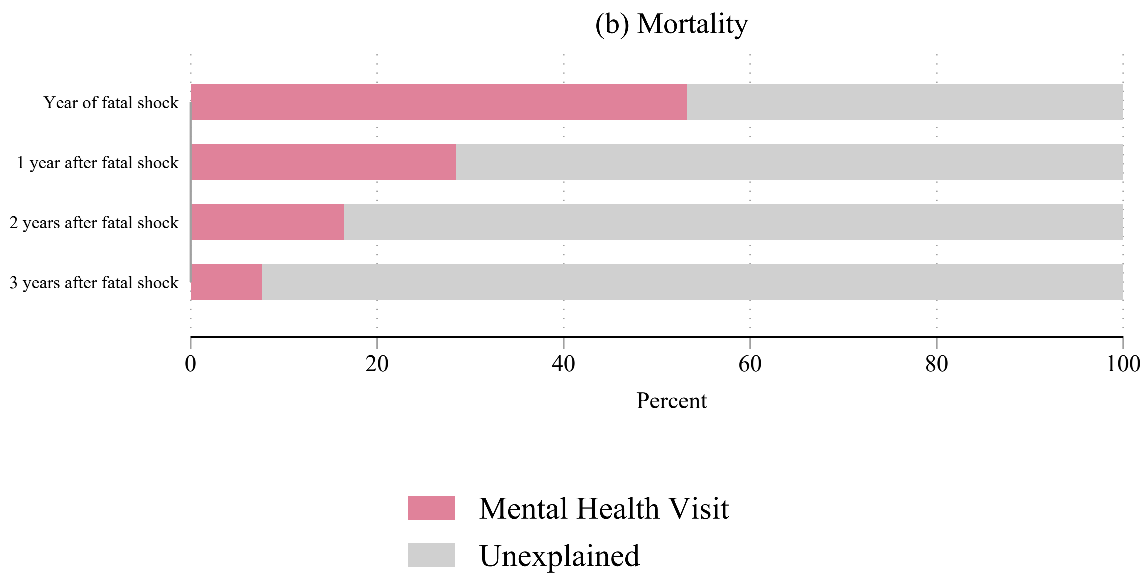


(b) By chronicity of health condition

Notes: The figure shows the coefficients and 95% CI from separate regressions for each subgroup of health shock. In panel (a), we split the shocks by ICD-10 codes. In panel (b), we categorize health shocks in chronic vs non-chronic following the Healthcare Cost and Utilization Project (HCUP) Chronic Condition Indicators (CCI) for the International Classification of Diseases. The figure shows the coefficient for the interaction between a post dummy (after hospitalization) and the treat dummy in Equation 1. All specifications include controls for calendar year, child's year of birth, child's gender, age of the parent, and parent's education level. Clustered standard errors at the parent level

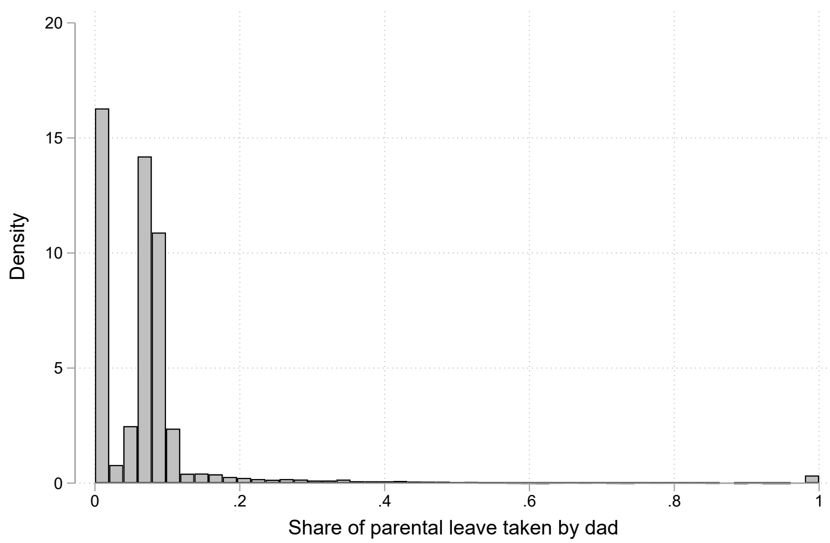
Figure A10: Mental Health: Mediation Analysis





Notes: This figure shows the results of the mediation analysis presented in Equation 3. Panel (a) shows the percentage of the treatment effect of a child's hospitalization shock on maternal labor earnings explained by the deterioration of maternal mental health. Panel (b) shows the same results for mortality shocks. The former specification includes controls for calendar year, child's year of birth, child's gender, and each parent's age and educational level. The latter includes the same controls but considers only the mother's age and does not control for education. Standard errors are clustered at the mother level.

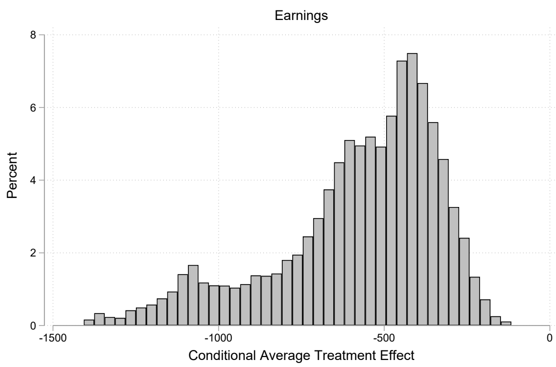
Figure A11: Fathers' Share of Parental Leave



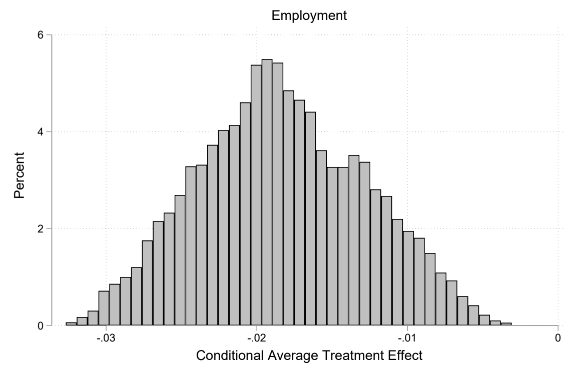
Notes: This figure shows the distribution of fathers' share of parental leave take-up for children in our sample. We use administrative data from Norway.

Figure A12: Hospitalization: Distribution of CATE

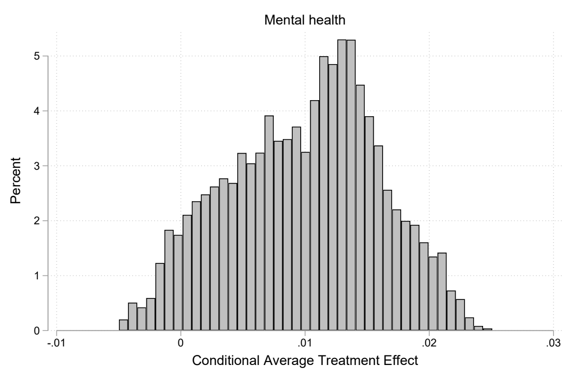
(a) Labor earnings



(b) Employment

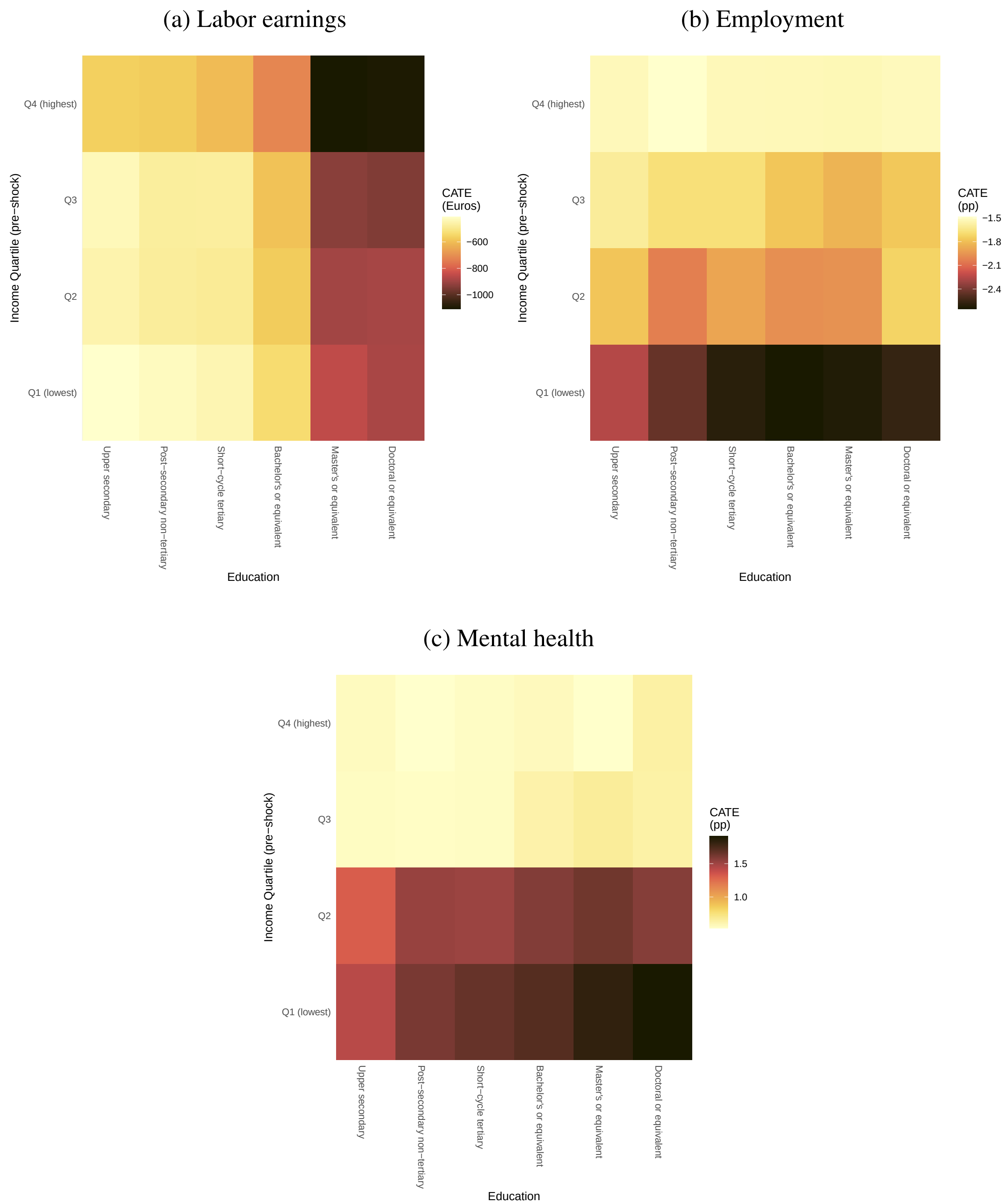


(c) Mental health



Notes: Panel (a) of this figure shows the distribution of estimated conditional average treatment effects for maternal labor earnings, panel (b) for employment, and panel (c) for the probability of being diagnosed with a mental health condition. We estimate CATE (Conditional Average Treatment Effects) on a large set of characteristics of the child, mother, and family, as well as type of shock (using the hospital diagnosis). The full list of variables in Table A19. We use administrative data from Finland

Figure A13: Hospitalization: CATE Partial Dependence on Income and Education



Notes: This figure shows how CATE varies with maternal income and education for maternal labor earnings (panel a), employment (panel b), and mental health (panel c). We estimate CATE (Conditional Average Treatment Effects) on a large set of characteristics of the child, mother, and family, as well as type of shock (using the hospital diagnosis). The full list of variables in Table A19. We use administrative data from Finland

Table A1: Institutional Characteristics

	(1) Finland	(2) Norway
A. Countries Characteristics		
Population	5521606	5347896
GDP per Capita	\$51556.526	\$68345.069
GINI Index	27.3	27.6
Health Care Expenditure (% GDP)	9.037	10.049
Life Expectancy at Birth	81.785	82.907
Physicians (per 1,000 people)	3.812	2.698
Low-birthweight babies (% of births)	4.122	4.488
Mortality rate, under-5 (per 1,000 live births)	2.4	2.4
B. Institutional Support Characteristics		
Universal Public Health	Yes	Yes
Special Care Allowance	Yes	Yes
Disability Allowance	Yes	No
Informal Care Allowance	Yes	Yes
Survivor Pension for Parents	No	No
C. Gender Norms		
Labor force participation rate, female (%)	76.6	75.61
Child Penalty	25	23
"A job is alright but what most women really want is a home and children" (% Agree)	32.1	22.9
"A man's job is to earn money; a woman's job is to look after the home and family" (% Agree)	11.9	9.18
"All in all, family life suffers when the woman has a full-time job" (% Agree)	16.3	15.9

Notes: The statistics in panel (a) come from the World Bank website. All statistics reported correspond to 2019 data or the latest data available. The labor force participation rate, female is calculated as the % of female population ages 15-64. The numbers for the child penalty come from Sieppi and Pehkonen (2019) and Andresen and Nix (2021), respectively. Statistics in panel (c), on gender norms, come from own calculations using the European Value Study 2017. We report the percentage of respondents who agree or strongly agree with a given statement. For comparison, the respective numbers for Germany are 28.1, 13.5, and 44.9 and, for the UK, 32.2, 16.9, and 33.1.

Table A2: Finland- Summary Statistics

	Hospitalizations				Mortality			
	(1) DiD		(2) All		(3) DiD		(4) All	
	mean	sd	mean	sd	mean	sd	mean	sd
Child Characteristics								
Age at event time	13.271	3.802	11.875	3.224	15.331	3.967	12.910	3.439
Male	0.518	0.500	0.526	0.499	0.647	0.478	0.602	0.490
Mother Characteristics								
Mother's age at birth	29.163	4.082	29.377	5.218	28.610	5.135	28.815	5.171
Age mother at admission	42.936	5.655	41.736	6.221	44.463	6.304	42.186	6.140
Finnish	0.985	0.121	0.977	0.149	0.982	0.131	0.975	0.155
Single	0.010	0.101	0.017	0.129	0.008	0.090	0.010	0.097
Married	0.210	0.407	0.270	0.444	0.262	0.440	0.263	0.441
Upper secondary	0.434	0.496	0.472	0.499	0.532	0.499	0.509	0.500
Post-secondary	0.007	0.082	0.008	0.088	0.010	0.098	0.006	0.079
Short-cycle tertiary	0.310	0.463	0.281	0.449	0.264	0.441	0.272	0.445
Bachelor's	0.096	0.295	0.100	0.300	0.088	0.284	0.094	0.291
Master's	0.142	0.349	0.130	0.336	0.099	0.299	0.110	0.313
Doctoral	0.011	0.103	0.010	0.099	0.007	0.081	0.009	0.093
High-skilled white collar	0.184	0.387	0.157	0.364	0.126	0.332	0.137	0.344
Low-skilled white collar	0.508	0.500	0.479	0.500	0.469	0.499	0.460	0.499
Manual workers	0.165	0.371	0.198	0.399	0.237	0.425	0.224	0.417
Self-employed	0.016	0.126	0.013	0.112	0.011	0.107	0.010	0.098
Earnings mother t=-2	21265.922	15020.591	20528.224	15721.872	17845.181	14731.818	18227.234	15868.393
Prob. working mother t=-2	0.919	0.273	0.885	0.319	0.827	0.378	0.812	0.391
Prob. unemployed mother t=-2	0.000	0.005	0.000	0.004	0.000	0.000	0.000	0.000
Total income mother t=-2	20676.556	9726.987	20764.401	10275.266	20323.934	9526.436	21298.852	10490.904
Prob. mental health visit mother t=-2	0.015	0.123	0.022	0.145	0.038	0.190	0.042	0.200
Prob. working in the public sector mother t=-2	0.414	0.492	0.378	0.485	0.390	0.488	0.398	0.490
Prob. changing job mother t=-2	0.110	0.312	0.119	0.323	0.124	0.330	0.138	0.345
Prob. divorced t=-2	0.116	0.320	0.142	0.349	0.168	0.374	0.167	0.373
Father Characteristics								
Age father at admission	43.011	5.541	44.116	6.866	44.823	6.549	44.688	6.667
Upper secondary	0.535	0.499	0.563	0.496	0.638	0.481	0.617	0.487
Post-secondary	0.009	0.092	0.010	0.101	0.011	0.105	0.015	0.121
Short-cycle tertiary	0.196	0.397	0.181	0.385	0.153	0.360	0.154	0.362
Bachelor's	0.107	0.309	0.104	0.305	0.092	0.289	0.096	0.295
Master's	0.136	0.342	0.124	0.330	0.086	0.280	0.095	0.293
Doctoral	0.017	0.130	0.018	0.132	0.021	0.142	0.023	0.150
Earnings father t=-2	33478.007	21834.650	30489.696	22726.303	27289.063	21592.623	28547.097	22255.169
Prob. working father t=-2	0.951	0.215	0.896	0.305	0.861	0.346	0.866	0.340
Prob. unemployed father t=-2	0.000	0.006	0.001	0.030	0.002	0.041	0.001	0.032
Total income father t=-2	26401.338	15282.171	25323.212	15753.136	23786.602	15066.965	25135.177	16148.476
Prob. mental health visit father t=-2	0.013	0.115	0.020	0.141	0.022	0.145	0.019	0.136
Prob. working in the public sector father t=-2	0.202	0.401	0.175	0.380	0.158	0.365	0.157	0.364
Prob. changing job father t=-2	0.137	0.344	0.136	0.343	0.128	0.334	0.126	0.332
Observations	48274		50172		2369		958	

Notes: This table reports the mean and the standard deviation for the variables exploited in the analysis using the Finnish administrative data. The first two columns are for hospitalization shocks: the sample used in the diff-in-diff analysis is shown in column (1) and the full sample of observations in column (2). The last two columns provide the same information for mortality shocks: for the diff-in-diff sample in column (3) and the full sample in column (4). Mothers and fathers' education and occupation variables are measured the year of childbirth.

Table A3: Norway– Summary Statistics

	(1) DiD		(2) All	
	mean	sd	mean	sd
Child Characteristics				
Age at event time	12.414	3.374	12.754	3.828
Male	0.548	0.498	0.541	0.498
Mother Characteristics				
Mother's age at birth	28.810	4.437	28.690	5.260
Age mother at admission	41.224	5.320	41.444	6.079
Norwegian	0.849	0.358	0.830	0.375
Married	0.632	0.482	0.610	0.488
No education mother	0.003	0.051	0.005	0.072
Primary school mother	0.004	0.066	0.008	0.086
Lower secondary mother	0.172	0.377	0.208	0.406
Upper secondary, basic educ. level mother	0.077	0.266	0.089	0.285
Upper secondary, final year mother	0.294	0.456	0.278	0.448
Post-secondary non-tertiary mother	0.023	0.149	0.024	0.154
Bachelor's or equivalent level mother	0.344	0.475	0.307	0.461
Master's or equivalent level mother	0.062	0.241	0.056	0.231
Doctoral or equivalent level mother	0.005	0.074	0.005	0.069
Earnings mother t=-2	30722.236	24692.319	30599.858	24568.802
Prob. working mother t=-2	0.803	0.397	0.788	0.409
Total income mother t=-2	38228.001	22934.563	40085.750	21440.789
Total transfers mother t=-2	7884.261	8860.316	8437.732	9723.704
Prob. mental health visit mother t=-2	0.153	0.360	0.170	0.376
Prob. temporary DI mother t=-2	0.060	0.238	0.071	0.256
Prob. permanent DI mother t=-2	0.001	0.036	0.002	0.043
Prob. divorce mother t=-2	0.012	0.111	0.014	0.116
Father Characteristics				
Age father at admission	43.708	5.642	44.465	6.830
No education father	0.001	0.038	0.003	0.050
Primary school father	0.004	0.064	0.005	0.070
Lower secondary father	0.181	0.385	0.199	0.399
Upper secondary, basic educ. level father	0.070	0.255	0.086	0.281
Upper secondary, final year father	0.361	0.480	0.332	0.471
Post-secondary non-tertiary father	0.055	0.227	0.054	0.226
Bachelor's or equivalent level father	0.214	0.410	0.192	0.394
Master's or equivalent level father	0.087	0.282	0.078	0.268
Doctoral or equivalent level father	0.012	0.107	0.010	0.099
Earnings father t=-2	56370.670	47831.542	54576.941	46669.518
Prob. working father t=-2	0.897	0.304	0.872	0.334
Total income father t=-2	58315.070	46728.648	60295.908	44909.814
Total transfers father t=-2	2513.083	7618.839	3370.206	8917.984
Prob. mental health visit father t=-2	0.090	0.286	0.098	0.297
Prob. temporary DI father t=-2	0.032	0.176	0.038	0.191
Prob. permanent DI father t=-2	0.002	0.041	0.003	0.055
Prob. divorce father t=-2	0.012	0.109	0.013	0.113
Observations	24316		36125	

Notes: This table reports the mean and the standard deviation for the variables exploited in the analysis using the Norwegian administrative data. These descriptive statistics are for hospitalization shocks: the sample used in the diff-in-diff analysis is shown in column (1) and the full sample in column (2). Mothers and fathers' education and occupation variables are measured the year of childbirth.

Table A4: Hospitalizations: DiD vs. Event Study with Individual Fixed Effects

	(1) Earnings DiD (€)		(2) Earnings FE (€)	
	Finland	Norway	Finland	Norway
-5	36.260	-199.724		
	(108.398)	(237.686)		
-4	166.305*	-123.308	86.674***	64.428
	(93.366)	(216.523)	(28.220)	(85.817)
-3	17.047	-229.748	70.398**	-42.251
	(68.632)	(172.738)	(28.424)	(107.914)
-1	-59.126	-307.845*	-187.423**	-278.010***
	(69.882)	(177.189)	(40.576)	(95.734)
0	-310.543***	-283.370	-563.200***	-404.276***
	(95.867)	(221.354)	(63.619)	(148.208)
1	-517.681***	-620.884**	-844.078***	-777.707***
	(115.358)	(252.637)	(83.566)	(214.373)
2	-752.394***	-1279.759***	-1166.970***	-1602.635***
	(134.557)	(287.903)	(101.488)	(274.580)
3	-1000.763***	-1450.364***	–1523.420***	
	(147.714)	(327.171)	(120.315)	
Observations	401787	212688	393366	241780
Controls	YES	YES	YES	YES
Mean Y_{t-2}	21450.555	30722.236	20649.215	30599.858

Notes: This table shows the impact of a child's hospitalization on maternal earnings (Euro) using the difference-in-differences specification in Equation 1 (in column (1)) and the event study approach with individual fixed effects laid out in Equation (2) (in column (2)), for both Finland and Norway, respectively. For the event study, we implement the IW estimator proposed by Sun and Abraham (2020). In the DiD specification, we include the usual controls for calendar year, child's year of birth, child's gender, and each parent's age and educational level. In the event study, we include controls for calendar year and individual fixed effects. Standard errors are clustered at the parent level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Hospitalizations: Fathers' Labor Outcomes

	(1) Earnings (€)		(2) Earnings (%)		(3) Employment	
	Finland	Norway	Finland	Norway	Finland	Norway
-5	-109.915	377.702	-0.326	0.700	-0.002	0.007^{**}
	(138.768)	(481.219)	(0.411)	(0.900)	(0.002)	(0.003)
-4	-82.649	621.514	-0.245	1.100	-0.000	0.004
	(119.201)	(477.208)	(0.353)	(0.800)	(0.002)	(0.003)
-3	113.819	85.978	0.337	0.200	-0.001	0.003
	(89.802)	(389.012)	(0.266)	(0.700)	(0.002)	(0.002)
-1	204.808^{**}	-333.297	0.607^{**}	-0.600	-0.004^{**}	-0.000
	(94.586)	(426.918)	(0.280)	(0.800)	(0.002)	(0.002)
0	79.929	471.037	0.237	0.800	-0.005^{**}	-0.001
	(128.229)	(548.662)	(0.380)	(1.000)	(0.002)	(0.003)
1	58.752	-197.917	0.174	-0.400	-0.005^{*}	-0.005
	(158.391)	(497.685)	(0.469)	(0.900)	(0.002)	(0.003)
2	-126.972	-237.545	-0.376	-0.400	-0.006^{**}	-0.007^{**}
	(191.686)	(681.629)	(0.568)	(1.200)	(0.003)	(0.003)
3	-350.942	-944.994	-1.040	-1.700	-0.009^{***}	-0.015^{***}
	(217.156)	(759.326)	(0.643)	(1.300)	(0.003)	(0.004)
Observations	401787	212688	401787	212688	401787	212688
Controls	YES	YES	YES	YES	YES	YES
Mean Y_{t-2}	33750.607	56384.200	100.000	100.000	0.953	0.924

Notes: This table shows the impact of a child's hospitalization on the father's earnings (Euro) (in column (1)), earnings as a % of mean earnings in $t-2$ (in column (2)), and working probability (in column (3)). The table shows the estimated coefficients for the interaction between the event time dummies and the treat dummy in Equation 1. All specifications include controls for calendar year, child's year of birth, child's gender, and each parent's age and educational level. Standard errors are clustered at the parent level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Mortality: Fathers' Labor Outcomes

	(1) Earnings (€)	(2) Earnings (%)	(3) Employment
-5	1904.739**	7.214**	0.018
	(882.862)	(3.344)	(0.019)
-4	1180.717	4.472	0.016
	(772.168)	(2.925)	(0.018)
-3	282.384	1.070	-0.004
	(532.206)	(2.016)	(0.015)
-1	115.981	0.439	-0.000
	(622.708)	(2.359)	(0.015)
0	-1385.598	-5.248	-0.038**
	(912.172)	(3.455)	(0.018)
1	-678.874	-2.571	-0.032
	(1107.780)	(4.196)	(0.022)
2	452.526	1.714	-0.040
	(1289.359)	(4.883)	(0.027)
3	-264.102	-1.000	-0.035
	(1400.067)	(5.303)	(0.028)
Observations	10562	10562	10562
Controls	YES	YES	YES
Mean Y_{t-2}	26402.652	100.000	0.845

Notes: This table shows the impact of a child's fatal shock on the father's earnings (Euro) (in column (1)), earnings as a % of mean earnings in $t-2$ (in column (2)), and working probability (in column (3)). We use administrative data from Finland, and the sample includes all fatal shocks due to injuries, poisonings, or other consequences of external causes. The table shows the estimated coefficients for the interaction between the event time dummies and the treat dummy in Equation 1. All specifications include controls for calendar year, child's year of birth, child's gender, and the father's age. Standard errors are clustered at the parent level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Hospitalizations: Fathers' Institutional Support

	(1) Earnings (€)		(2) Total Income (€)		(3) Transfers (€)		(4) Allowance (€)
	Finland	Norway	Finland	Norway	Finland	Norway	Finland
$Post_t * Treat_i$	-57.036	-365.588	-107.299	-251.263	32.930	54.149	38.312
	(147.756)	(545.581)	(100.534)	(534.337)	(37.387)	(89.293)	(25.103)
Observations	376778	212688	376778	212688	376778	212688	376778
Controls	YES	YES	YES	YES	YES	YES	YES
Mean Y_{t-2}	34460.921	56381.801	27198.223	58327.587	1312.107	2512.578	3151.977

Notes: This table shows the impact of a child's hospitalization on the father's earnings (in column (1)) total income (in column (2)), transfers (in column (3)), and child allowances received (in column (4)), for both Finland and Norway, respectively. The table shows the estimated coefficients for the interaction between the post dummy and the treat dummy in Equation 1. All specifications include controls for calendar year, child's year of birth, child's gender, and each parent's age and educational level. Standard errors are clustered at the parent level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Hospitalizations: Family Income and Institutional Support

	(1) Family Earnings (€)		(2) Family Total Income (€)		(3) Family Transfers (€)		(4) Allowance (€)
	Finland	Norway	Finland	Norway	Finland	Norway	Finland
$Post_t * Treat_i$	-678.680***	-1017.044*	-482.178***	-775.332	143.936***	168.679	119.806***
	(188.260)	(618.270)	(124.648)	(594.608)	(53.294)	(141.299)	(44.429)
Observations	376778	200214	376778	200214	376778	200214	376778
Controls	YES	YES	YES	YES	YES	YES	YES
Mean Y_{t-2}	56420.896	87273.605	48392.550	96665.681	6005.715	10339.198	6636.919

This table shows the impact of a child's hospitalization on family earnings (in column (1)) family total income (in column (2)), family transfers received (in column (3)),for both Finland and Norway, respectively, and total family allowance for Finland (in column (4)). The table shows the coefficient for the interaction between a post dummy (after hospitalization) and the treat dummy in equation 1. All specifications include controls for calendar year, child's year of birth, child's gender, age of the parent, and parent's education level. Clustered standard errors at the parent level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Mortality: Both Parents Institutional Support

	(1) Earnings(€)		(2) Total Income(€)		(3) Transfers(€)		(4) Allowance(€)	
	Mother	Father	Mother	Father	Mother	Father	Mother	Father
$Post_t * Treat_i$	-3088.118***	-349.005	-1789.044***	371.978	549.265*	495.338*	-609.270***	-445.643***
	(752.571)	(1007.544)	(408.013)	(610.541)	(326.419)	(285.551)	(184.245)	(154.681)
Observations	9529	9529	9529	9529	9529	9529	9529	9529
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Mean Y_{t-2}	19995.660	27849.954	21411.819	24607.387	5957.317	2647.354	3782.243	2968.623

Notes: This table shows the impact of a child's fatal shock on earnings (in column (1)), total income (in column (2)), transfers (in column (3)), and child allowances received (in column (4)), for both mothers and fathers, respectively. The table shows the estimated coefficients for the interaction between the event time dummies and the treat dummy in Equation 1. We use administrative data from Finland, and the sample includes all fatal shocks due to injuries, poisonings, or other consequences of external causes. All specifications include controls for calendar year, child's year of birth, child's gender, and one parent's age depending on the outcome variable. Standard errors are clustered at the parent level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Mortality: Family Income and Institutional Support

	(1) Family Earnings (€)	(2) Family Total Income (€)	(3) Family Transfers (€)	(4) Allowance (€)
$Post_t * Treat_i$	-4283.423***	-1888.508**	1283.066***	-1173.194***
	(1424.892)	(820.969)	(463.750)	(314.813)
Observations	9529	9529	9529	9529
Controls	YES	YES	YES	YES
Mean Y_{t-2}	47845.614	46019.206	8614.839	6751.087

This table shows the impact of a child's fatal shock on family earnings (in column (1)) family total income (in column (2)), family transfers received (in column (3)), and family allowance (in column (4)). The table shows the coefficient for the interaction between a post dummy and the treat dummy in equation 1. We use administrative data from Finland and the sample includes all fatal shocks due to accidents. All specifications include controls for calendar year, child's year of birth, child's gender, and age of the parent. Clustered standard errors at the parent level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A11: Variation in Social Insurance

	(1) Reduced Form	(2) IV
$Post_t * Treat_i$	-890.562***	-1122.639
	(117.772)	(1572.614)
$Post_t * Treat_i * SI_i$		0.011
		(0.070)
$Post_t * Treat_i * Z_{msi}$	0.003	
	(0.022)	
First stage F		87.79
Observations	259380	259380
Controls	YES	YES
Mean $Y\_t - 2$	20487.248	20487.248

This table shows in column (1) the reduced form, and column (2) the IV estimates for the interaction of the impact of a child's hospitalization with the generosity of the social insurance system in terms of family allowances. The instrument is a leave-out residualized measure based on all children's health shocks that occurred in a municipality in a given year. To construct it, we first regress at the individual level, the family allowances received on ICD10 diagnosis code fixed effects and predict the residuals. We then sum all the (adjusted) individual family allowances and divide them by the number of children who suffered a health shock, in a given municipality-year. We use administrative data for Finland. All specifications include controls for municipality, calendar year, and child's year of birth. Clustered standard errors at the parent level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A12: Hospitalizations: Different Control Groups

	(1) Delta = 2		(2) Delta = 3		(3) Delta = 4	
	Finland	Norway	Finland	Norway	Finland	Norway
-5	37.307	123.874	203.204*	210.56	36.260	-199.724
	(94.962)	(186.282)	(108.809)	(196.043)	(108.398)	(237.686)
-4	30.208	96.413	121.699	75.014	166.305*	-123.308
	(92.753)	(163.416)	(92.803)	(174.754)	(93.366)	(216.523)
-3	-17.188	12.901	2.054	79.000	17.047	-229.748
	(67.789)	(127.862)	(67.893)	(141.799)	(68.632)	(172.738)
-1	-50.592	-311.909**	-50.669	-278.272*	-59.126	-307.845*
	(70.318)	(128.051)	(69.396)	(147.504)	(69.882)	(177.189)
0	-370.240***	-317.334*	-282.300***	-375.721**	-310.543***	-283.37
	(96.892)	(171.04)	(97.142)	(184.823)	(95.867)	(221.354)
1	-516.395***	-583.371***	-516.768***	-829.064***	-517.681***	-620.884**
	(103.744)	(204.921)	(116.974)	(216.215)	(115.358)	(252.637)
2			-568.880***	-1157.167***	-752.394***	-1279.759***
			(125.884)	(248.281)	(134.557)	(287.903)
3					-1000.763***	-1450.364***
					(147.714)	(327.171)
Observations	349963	266679	383113	257816	401787	212688
Controls	YES	YES	YES	YES	YES	YES
Mean Y_{t-2}	22144.850	32867.623	21973.765	31580.188	21450.555	30722.236

Notes: This table shows the impact of a child's hospitalization on maternal labor earnings for different choices of control group. We show the estimation results when the control group consists of families who experienced a child's hospitalization two years later in column (1), three years later in column (2), and four years later in column (3) (our main specification). The table shows the estimated coefficients for the interaction between the event time dummies and the treat dummy in Equation 1. All specifications include controls for calendar year, child's year of birth, child's gender, and each parent's age and educational level. Standard errors are clustered at the parent level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A13: Robustness: Mutual Shocks

	(1) $+/-$ One Week		(2) $+/-$ One Month	
	Finland	Norway	Finland	Norway
-5	22.692	-135.496	9.321	68.472
	(109.017)	(253.912)	(110.482)	(279.975)
-4	163.122*	-73.681	164.186*	85.144
	(93.856)	(229.186)	(95.130)	(254.027)
-3	17.345	-188.744	23.847	-42.156
	(69.107)	(186.834)	(69.963)	(207.989)
-1	-62.913	-342.518*	-53.478	-395.901*
	(70.266)	(191.927)	(71.267)	(214.007)
0	-320.750***	-229.829	-293.342***	-279.612
	(96.331)	(238.694)	(97.583)	(261.920)
1	-522.900***	-488.859*	-471.567***	-501.815*
	(115.956)	(270.702)	(117.412)	(293.500)
2	-748.929***	-1061.256***	-679.122***	-1027.623***
	(135.318)	(307.118)	(136.903)	(337.627)
3	-998.453***	-1106.534***	-930.772***	-1167.537***
	(148.558)	(346.15)	(150.421)	(379.817)
Observations	397321	190467	387718	163215
Controls	YES	YES	YES	YES
Mean Y_{t-2}	21453.994	31033.661	21486.049	31432.983

Notes: This table shows the impact of a child's hospitalization on maternal earnings (Euro) for both Finland and Norway. In column (1), we exclude child hospitalizations where parents were hospitalized or visited a specialist one week before or after the child's shock. In column (2), we do the same but for mutual shocks one month before or after the child's shock. The table shows the estimated coefficients for the interaction between the event time dummies and the treat dummy in Equation 1. All specifications include controls for calendar year, child's year of birth, child's gender, and each parent's age educational level. Standard errors are clustered at the parent level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A14: Mortality: Choice of Delta

	(1) Delta = 2	(2) Delta = 3	(3) Delta = 4
-5	980.588	981.180	863.707
	(616.542)	(667.822)	(673.499)
-4	-37.273	244.293	656.534
	(596.068)	(582.270)	(580.610)
-3	388.984	227.063	961.383**
	(434.429)	(394.335)	(403.634)
-1	-104.126	358.997	518.002
	(502.405)	(454.528)	(460.415)
0	-2160.274***	-2549.356***	-2234.341***
	(680.797)	(649.081)	(642.672)
1	-3704.958***	-3538.926***	-3632.357***
	(696.063)	(783.019)	(796.163)
2		-4007.194***	-3659.945***
		(832.569)	(949.352)
3			-4099.865***
			(991.618)
Observations	7549	9351	10562
Controls	YES	YES	YES
Mean Y_{t-2}	20016.450	19598.187	19443.969

Notes: This table shows the impact of a child's fatal shock on maternal labor earnings for different choices of control group. We show the estimation results when the control group consists of families whose child experienced a fatal shock two years later in column (1), three years later in column (2), and four years later in column (3) (our main specification). The table shows the estimated coefficients for the interaction between the event time dummies and the treat dummy in Equation 1. We use administrative data from Finland, and the sample includes all fatal shocks due to injuries, poisonings, or other consequences of external causes. All specifications include controls for calendar year, child's year of birth, child's gender, and the mother's age. Standard errors are clustered at the parent level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A15: Mortality: Mutual Shocks

	(1) +/− One Week	(2) +/− One Month
-5	425.749	270.705
	(696.151)	(731.373)
-4	457.553	565.984
	(606.320)	(638.150)
-3	849.114**	827.841*
	(421.921)	(446.064)
-1	500.835	430.467
	(479.298)	(482.776)
0	-1234.465**	-1422.215**
	(628.412)	(633.732)
1	-2611.367***	-2855.469***
	(790.615)	(807.632)
2	-2512.267***	-2665.291***
	(954.427)	(970.222)
3	-2705.384***	-2756.299***
	(998.594)	(1026.938)
Observations	9863	9234
Controls	YES	YES
Mean Y_{t-2}	19437.122	19468.168

Notes: This table shows the impact of a child's fatal shock on maternal labor earnings. In column (1), we exclude fatal shocks where parents were hospitalized or visited a specialist one week before or after the child's shock. In column (2), we do the same but for mutual shocks one month before or after the child's shock. The table shows the estimated coefficients for the interaction between the event time dummies and the treat dummy in Equation 1. We use administrative data from Finland, and the sample includes all fatal shocks due to injuries, poisonings, or other consequences of external causes. All specifications include controls for calendar year, child's year of birth, child's gender, and the mother's age. Standard errors are clustered at the parent level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A16: Mortality: Parents' Number of Visits Mental Health

	(1) Mother Visits	(2) Father Visits
-5	0.648**	0.189
	(0.251)	(0.142)
-4	0.271*	0.233
	(0.158)	(0.144)
-3	0.181	0.152
	(0.140)	(0.097)
-1	0.237	0.101
	(0.160)	(0.121)
0	1.113***	0.479*
	(0.221)	(0.263)
1	1.564***	0.201
	(0.364)	(0.604)
2	1.004***	0.017
	(0.339)	(0.570)
3	0.739**	-0.043
	(0.340)	(0.557)
Observations	9472	9472
Controls	YES	YES
Mean Y_{t-2}	0.333	0.204

Notes: This table shows the impact of a child's fatal shock on the mother's (column (1)) and the father's mental health (column (2)). The table shows the estimated coefficients for the interaction between the event time dummies and the treat dummy in Equation 1. We use administrative data from Finland, and the sample includes all fatal shocks due to injuries, poisonings, or other consequences of external causes. All specifications include controls for calendar year, child's year of birth, child's gender, and one parent's age depending on the outcome variable. Standard errors are clustered at the parent level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A17: By Fathers' Share of Parental Leave

	(1) Father involved		(2) Father not involved	
	Father leave	Father share $> 10\%$	Father no leave	Father share $< 10\%$
$Post_t * Treat_i$	-466.478	-589.237**	-723.215	-599.591
	(316.334)	(266.240)	(449.105)	(953.862)
Observations	99882	129312	45855	16425
Controls	YES	YES	YES	YES
Mean Y_{t-2}	36764.647	34343.050	31806.504	41923.328

This table shows the impact of a child's hospitalization on maternal labor earnings by whether the father was involved during parental leave (in columns (1)) or not involved (in columns (2)). In particular, we use two definitions of father involvement: the father took a positive amount of leave (fathers' share of parental leave > 0), or was relatively involved (fathers' share of parental leave $> 10\%$). The table shows the coefficient for the interaction between a post dummy (after hospitalization) and the treat dummy in equation 1. We use administrative data from Norway. All specifications include controls for calendar year, child's year of birth, child's gender, age of the parent, and parent's education level. Clustered standard errors at the mother level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A18: Hospitalizations: By Marital Status

	(1) Married		(2) Divorced		(3) Unmarried		(4) Single
	Finland	Norway	Finland	Norway	Finland	Norway	Finland
$Post_t * Treat_i$	-733.994***	-739.551**	-978.437***	-1493.614**	217.125	-969.254**	-265.012
	(113.049)	(287.509)	(281.845)	(620.978)	(262.706)	(408.576)	(329.943)
Observations	311264	125244	53667	26640	47280	44946	49328
Controls	YES	YES	YES	YES	YES	YES	YES
Mean Y_{t-2}	21768.604	32266.866	22378.348	30094.691	18785.673	29259.645	21489.899

Notes: This table shows the impact of a child's hospitalization on maternal earnings for married women (in column (1)) divorced women (in column (2)), unmarried women (in column (3)), for both Finland and Norway, respectively, and single women (in column (4)), for Finland only. The table shows the coefficient for the interaction between a post dummy (after hospitalization) and the treat dummy in Equation 1. All specifications include controls for calendar year, child's year of birth, child's gender, age of the parent, and parent's education level. Clustered standard errors at the parent level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A19: Heterogeneous Treatment Effects: Mothers' Labor Earnings

	Treatment effect			
	Below median	Above median	Diff.	p-value
Male child	0.520	0.519	0.001	0.865
Siblings	0.819	0.807	0.012	0.056
Child 7, 8, 9 yo	0.416	0.356	0.060	0.000
Child 10, 11, 12 yo	0.249	0.259	-0.010	0.174
Child 13, 14, 15 yo	0.189	0.225	-0.036	0.000
Child 16, 17, 18 yo	0.146	0.161	-0.015	0.011
Mother below 30	0.012	0.008	0.004	0.007
Mother 30-35	0.134	0.086	0.047	0.000
Mother 35-40	0.306	0.278	0.028	0.000
Mother 40-45	0.300	0.341	-0.040	0.000
Mother 45-50	0.183	0.211	-0.028	0.000
Mother 50-55	0.058	0.068	-0.010	0.008
Mother 55-60	0.007	0.008	-0.001	0.576
Mother above 60	0.000	0.000	-0.000	0.564
Mother: Upper secondary education	0.580	0.262	0.318	0.000
Mother: Post-secondary non-tertiary education	0.007	0.006	0.001	0.360
Mother: Short-cycle tertiary education	0.354	0.263	0.091	0.000
Mother: Bachelor's or equivalent level	0.059	0.145	-0.086	0.000
Mother: Master's or equivalent level	0.000	0.302	-0.302	0.000
Mother: Doctoral or equivalent level	0.000	0.022	-0.022	0.000
Finnish mother	0.989	0.983	0.006	0.001
Single mother	0.012	0.010	0.002	0.220
Married mother	0.226	0.178	0.048	0.000
Mother: Income Q1 (bottom)	0.292	0.134	0.158	0.000
Mother: Income Q2	0.306	0.207	0.098	0.000
Mother: Income Q3	0.319	0.201	0.117	0.000
Mother: Income Q4 (top)	0.084	0.458	-0.374	0.000
Father below 30	0.018	0.009	0.009	0.000
Father 30-35	0.127	0.090	0.037	0.000
Father 35-40	0.292	0.278	0.014	0.051
Father 40-45	0.290	0.341	-0.050	0.000
Father 45-50	0.193	0.187	0.005	0.412
Father 50-55	0.065	0.078	-0.013	0.001
Father 55-60	0.015	0.015	-0.001	0.740
Father above 60	0.001	0.002	-0.001	0.297
Father: Upper secondary education	0.571	0.465	0.106	0.000
Father: Post-secondary non-tertiary education	0.011	0.007	0.003	0.027
Father: Short-cycle tertiary education	0.234	0.155	0.079	0.000
Father: Bachelor's or equivalent level	0.102	0.121	-0.019	0.000
Father: Master's or equivalent level	0.075	0.219	-0.144	0.000
Father: Doctoral or equivalent level	0.007	0.033	-0.026	0.000
Father: Income Q1 (bottom)	0.162	0.191	-0.030	0.000
Father: Income Q2	0.304	0.202	0.102	0.000
Father: Income Q3	0.310	0.239	0.071	0.000
Father: Income Q4 (top)	0.224	0.367	-0.143	0.000
Household Earnings gap Q1 (bottom)	0.107	0.344	-0.237	0.000
Household Earnings gap Q2	0.280	0.201	0.079	0.000
Household Earnings gap Q3	0.323	0.192	0.131	0.000
Household Earnings gap Q4 (top)	0.290	0.263	0.028	0.000
ICD10 Infections	0.004	0.098	-0.094	0.000
ICD10 Neoplasms	0.001	0.027	-0.026	0.000
ICD10 Blood	0.001	0.013	-0.013	0.000
ICD10 Endocrine	0.004	0.065	-0.061	0.000
ICD10 Mental	0.011	0.164	-0.153	0.000
ICD10 Nervous	0.004	0.029	-0.025	0.000
ICD10 Eye	0.001	0.006	-0.005	0.000
ICD10 Ear	0.004	0.016	-0.012	0.000
ICD10 Circulatory	0.010	0.021	-0.012	0.000
ICD10 Respiratory	0.184	0.108	0.075	0.000
ICD10 Digestive	0.139	0.060	0.080	0.000
ICD10 Skin	0.026	0.008	0.018	0.000
ICD10 Muscoloskele	0.073	0.023	0.050	0.000
ICD10 Genitourinar	0.067	0.026	0.041	0.000
ICD10 Congenital	0.030	0.009	0.020	0.000
ICD10 Symptoms	0.101	0.077	0.024	0.000
ICD10 Injury	0.327	0.240	0.088	0.000
ICD10 Factors	0.014	0.010	0.004	0.024
Observations	7651	7650	15301	

Notes: This table compares a rich set of background characteristics between two groups: relatively less affected mothers (treatment effect close to zero, referred to as the below-median group) and more severely affected mothers (with numerically higher treatment effects, referred to as above-median group). Note, that despite treatment effects being negative for mothers' labor earnings, the groups are defined according to their numerical magnitude, with above-median meaning more affected throughout. All time varying variables are measured in $t-2$. We use administrative data from Finland.

Table A20: Heterogeneous Treatment Effects: Mothers' Employment Status

	Treatment effect			
	Below median	Above median	Diff.	p-value
Male child	0.516	0.518	-0.002	0.809
Siblings	0.899	0.720	0.179	0.000
Child 7, 8, 9 yo	0.293	0.481	-0.188	0.000
Child 10, 11, 12 yo	0.253	0.258	-0.005	0.494
Child 13, 14, 15 yo	0.258	0.153	0.106	0.000
Child 16, 17, 18 yo	0.195	0.108	0.087	0.000
Mother below 30	0.004	0.020	-0.016	0.000
Mother 30-35	0.054	0.161	-0.107	0.000
Mother 35-40	0.227	0.356	-0.129	0.000
Mother 40-45	0.329	0.317	0.011	0.134
Mother 45-50	0.298	0.100	0.198	0.000
Mother 50-55	0.080	0.040	0.041	0.000
Mother 55-60	0.009	0.006	0.002	0.073
Mother above 60	0.000	0.000	-0.000	0.317
Mother: Upper secondary education	0.405	0.435	-0.030	0.000
Mother: Post-secondary non-tertiary education	0.007	0.005	0.002	0.148
Mother: Short-cycle tertiary education	0.318	0.305	0.013	0.082
Mother: Bachelor's or equivalent level	0.093	0.110	-0.017	0.000
Mother: Master's or equivalent level	0.162	0.137	0.025	0.000
Mother: Doctoral or equivalent level	0.015	0.009	0.007	0.000
Finnish mother	0.989	0.980	0.009	0.000
Single mother	0.009	0.013	-0.003	0.044
Married mother	0.172	0.247	-0.075	0.000
Mother: Income Q1 (bottom)	0.045	0.381	-0.336	0.000
Mother: Income Q2	0.250	0.266	-0.016	0.026
Mother: Income Q3	0.321	0.199	0.123	0.000
Mother: Income Q4 (top)	0.383	0.154	0.229	0.000
Father below 30	0.005	0.024	-0.020	0.000
Father 30-35	0.062	0.159	-0.097	0.000
Father 35-40	0.198	0.359	-0.161	0.000
Father 40-45	0.345	0.292	0.053	0.000
Father 45-50	0.273	0.111	0.162	0.000
Father 50-55	0.097	0.043	0.054	0.000
Father 55-60	0.019	0.011	0.008	0.000
Father above 60	0.002	0.002	0.000	0.705
Father: Upper secondary education	0.527	0.509	0.018	0.025
Father: Post-secondary non-tertiary education	0.008	0.010	-0.002	0.308
Father: Short-cycle tertiary education	0.225	0.168	0.057	0.000
Father: Bachelor's or equivalent level	0.098	0.125	-0.027	0.000
Father: Master's or equivalent level	0.125	0.167	-0.042	0.000
Father: Doctoral or equivalent level	0.017	0.021	-0.004	0.045
Father: Income Q1 (bottom)	0.186	0.166	0.020	0.001
Father: Income Q2	0.294	0.230	0.064	0.000
Father: Income Q3	0.273	0.271	0.002	0.814
Father: Income Q4 (top)	0.247	0.333	-0.086	0.000
Household Earnings gap Q1 (bottom)	0.334	0.124	0.211	0.000
Household Earnings gap Q2	0.297	0.188	0.109	0.000
Household Earnings gap Q3	0.231	0.289	-0.058	0.000
Household Earnings gap Q4 (top)	0.138	0.400	-0.261	0.000
ICD10 Infections	0.038	0.065	-0.027	0.000
ICD10 Neoplasms	0.013	0.021	-0.008	0.000
ICD10 Blood	0.004	0.009	-0.005	0.000
ICD10 Endocrine	0.026	0.047	-0.021	0.000
ICD10 Mental	0.073	0.100	-0.027	0.000
ICD10 Nervous	0.013	0.017	-0.003	0.083
ICD10 Eye	0.004	0.004	0.000	0.802
ICD10 Ear	0.009	0.008	0.001	0.389
ICD10 Circulatory	0.018	0.013	0.004	0.027
ICD10 Respiratory	0.185	0.107	0.078	0.000
ICD10 Digestive	0.152	0.049	0.103	0.000
ICD10 Skin	0.023	0.009	0.014	0.000
ICD10 Muscoloskele	0.064	0.030	0.034	0.000
ICD10 Genitourinar	0.059	0.032	0.027	0.000
ICD10 Congenital	0.020	0.018	0.002	0.346
ICD10 Symptoms	0.078	0.104	-0.026	0.000
ICD10 Injury	0.215	0.351	-0.136	0.000
ICD10 Factors	0.006	0.016	-0.010	0.000
Observations	7687	7687	15374	

Notes: This table compares a rich set of background characteristics between two groups: relatively less affected mothers (treatment effect close to zero, referred to as the below-median group) and more severely affected mothers (with numerically higher treatment effects, referred to as above-median group). Note, that despite treatment effects being negative for mothers' employment status, the groups are defined according to their numerical magnitude, with above-median meaning more affected throughout. All time varying variables are measured in $t-2$. We use administrative data from Finland.

Table A21: Heterogeneous Treatment Effects: Mothers' Mental Health

	Treatment effect			
	Below median	Above median	Diff.	p-value
Male child	0.500	0.535	-0.034	0.000
Siblings	0.773	0.847	-0.074	0.000
Child 7, 8, 9 yo	0.316	0.459	-0.143	0.000
Child 10, 11, 12 yo	0.269	0.242	0.026	0.000
Child 13, 14, 15 yo	0.226	0.185	0.041	0.000
Child 16, 17, 18 yo	0.190	0.114	0.076	0.000
Mother below 30	0.006	0.018	-0.011	0.000
Mother 30-35	0.061	0.155	-0.094	0.000
Mother 35-40	0.255	0.327	-0.072	0.000
Mother 40-45	0.350	0.297	0.053	0.000
Mother 45-50	0.242	0.155	0.087	0.000
Mother 50-55	0.076	0.044	0.032	0.000
Mother 55-60	0.010	0.005	0.005	0.000
Mother above 60	0.000	0.000	0.000	1.000
Mother: Upper secondary education	0.370	0.470	-0.099	0.000
Mother: Post-secondary non-tertiary education	0.009	0.004	0.005	0.000
Mother: Short-cycle tertiary education	0.323	0.300	0.023	0.002
Mother: Bachelor's or equivalent level	0.099	0.103	-0.004	0.378
Mother: Master's or equivalent level	0.184	0.114	0.070	0.000
Mother: Doctoral or equivalent level	0.015	0.009	0.005	0.002
Finnish mother	0.987	0.982	0.005	0.013
Single mother	0.009	0.012	-0.003	0.063
Married mother	0.197	0.222	-0.024	0.000
Mother: Income Q1 (bottom)	0.030	0.397	-0.367	0.000
Mother: Income Q2	0.074	0.443	-0.369	0.000
Mother: Income Q3	0.442	0.078	0.363	0.000
Mother: Income Q4 (top)	0.455	0.082	0.373	0.000
Father below 30	0.008	0.021	-0.014	0.000
Father 30-35	0.076	0.144	-0.069	0.000
Father 35-40	0.251	0.306	-0.055	0.000
Father 40-45	0.327	0.310	0.017	0.028
Father 45-50	0.231	0.154	0.077	0.000
Father 50-55	0.088	0.051	0.036	0.000
Father 55-60	0.018	0.012	0.007	0.001
Father above 60	0.002	0.002	0.001	0.449
Father: Upper secondary education	0.530	0.506	0.024	0.003
Father: Post-secondary non-tertiary education	0.010	0.009	0.001	0.497
Father: Short-cycle tertiary education	0.217	0.175	0.042	0.000
Father: Bachelor's or equivalent level	0.104	0.119	-0.014	0.005
Father: Master's or equivalent level	0.124	0.168	-0.044	0.000
Father: Doctoral or equivalent level	0.014	0.024	-0.009	0.000
Father: Income Q1 (bottom)	0.183	0.169	0.014	0.025
Father: Income Q2	0.275	0.250	0.025	0.000
Father: Income Q3	0.305	0.238	0.067	0.000
Father: Income Q4 (top)	0.237	0.343	-0.106	0.000
Household Earnings gap Q1 (bottom)	0.380	0.078	0.302	0.000
Household Earnings gap Q2	0.318	0.167	0.151	0.000
Household Earnings gap Q3	0.259	0.260	-0.001	0.912
Household Earnings gap Q4 (top)	0.043	0.495	-0.453	0.000
ICD10 Infections	0.045	0.057	-0.012	0.000
ICD10 Neoplasms	0.018	0.016	0.002	0.421
ICD10 Blood	0.005	0.008	-0.002	0.087
ICD10 Endocrine	0.032	0.041	-0.008	0.005
ICD10 Mental	0.084	0.089	-0.005	0.251
ICD10 Nervous	0.013	0.016	-0.003	0.109
ICD10 Eye	0.005	0.004	0.001	0.210
ICD10 Ear	0.008	0.010	-0.002	0.168
ICD10 Circulatory	0.018	0.014	0.004	0.037
ICD10 Respiratory	0.158	0.134	0.024	0.000
ICD10 Digestive	0.111	0.090	0.020	0.000
ICD10 Skin	0.014	0.018	-0.004	0.082
ICD10 Muscoloskele	0.046	0.048	-0.002	0.517
ICD10 Genitourinar	0.046	0.046	0.000	1.000
ICD10 Congenital	0.016	0.022	-0.006	0.007
ICD10 Symptoms	0.087	0.095	-0.008	0.068
ICD10 Injury	0.286	0.279	0.006	0.380
ICD10 Factors	0.009	0.013	-0.004	0.013
Observations	7687	7687	15374	

Notes: This table compares a rich set of background characteristics between two groups: relatively less affected mothers (treatment effect close to zero, referred to as the below-median group) and more severely affected mothers (with numerically higher treatment effects, referred to as above-median group). All time varying variables are measured in $t-2$. We use administrative data from Finland.