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, 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. 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. However, we know much less about the potential spillover effects of children's health shocks on parents' labor market careers.

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

A child's illness is a stressful event that can have major implications for the household's well-being. Families might incur substantial costs when deciding how to best cope with these health shocks. 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 compensate for the additional medical costs. In addition, these shocks can also have significant consequences for gender inequality if women are more likely than men to assume the bulk of caregiving responsibilities or carry the mental health burden in the home. Understanding the multifaceted ways parenthood can disparately affect women in the labor market compared to men 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 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 after the age where the child entered school. 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 in the child's life.

With these data and design, we first show that there is no indication that parents' outcomes follow different trends before the child's health shock. Sharp breaks in the trajectories only become visible after the event. Overall, we find that maternal earnings suffer a substantial and persistent drop after a child's hospitalization or death. Data from two countries allows us to document the strong robustness of our findings: three years after a hospitalization, maternal earnings are 4.7% lower in Finland and 4.6% lower in Norway, compared to two years before the shock. The impact is insignificant for fathers, and the estimated coefficients are much smaller. For mortality shocks, we find that mothers' earnings drop by more than 20% three years after the shock, while there is no significant effect for fathers.

We also analyze a critical question: Are families insured against the impact of these health shocks? We show that although transfers offset part of the negative impact, families are not fully insured: The drop in maternal income after taxes is about one-third smaller than the drop in labor earnings. From a family perspective, the average impact on family earnings in case of hospitalizations is small (1.2% in Finland and 1.3% in Norway). However, a significant part of this impact remains uninsured. For mortality shocks, the drop in family earnings is quite substantial, almost 9%, and the decrease in family income is also significant (4%). Moreover, we observe a decrease in family allowances in this case, which is consistent with the absence of bereavement support.

Importantly, we exploit the richness and complementarities of the data from both countries to explore several mechanisms. We first analyze whether the social insurance attenuates or aggravates the maternal labor supply response. Using spatial and temporal variation in the allowances families receive after a child's health shock, we do not find evidence that the level of social insurance affects mothers' labor supply decisions. Next, we explore whether mothers adjust their labor supply by changing the type of firm they work for. We do not find evidence that mothers move to more family-friendly firms. We also do not observe changes in the risk of marital dissolution. However, we find that children's health shocks have a substantial impact on parents' mental well-being. The results of a mediation analysis suggest that the mental health deterioration could be the primary mechanism behind effects for mortality shocks, while it only explains a relatively small part of the variation for hospitalizations.

We therefore explore whether the increased burden of care drives the effect for hospitalizations. We show that the negative impact on mothers' earnings is larger for recurrent health shocks that require substantial care. We also show that the adverse effects are greater if the grandparents do not live close to the family. Furthermore, 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 partners were (relatively) involved in childcare (as proxied by the take-up of paternity leave). Instead, our results align more with the fact that these shocks increase caregiving demands, and that women primarily shoulder this burden.

Finally, we estimate Conditional Average Treatment Effects using causal forest algorithms (Athey and Imbens, 2016; Wager and Athey, 2018; Athey et al., 2019) to study heterogeneous effects. We show that the level declines in earnings are larger among highly educated mothers with higher earnings. However, in terms of labor force participation and mental health, the sickness of a child places a greater burden on mothers with relatively lower socioeconomic backgrounds. This result is consistent with mothers with lower attachment to the labor force, leaving or losing their jobs after this event. Given that children of mothers from lower socioeconomic backgrounds are almost three times more likely to suffer a hospitalization during childhood,[1] 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. Previous studies find a negative association between childhood disability or illness and maternal employment (e.g. Wasi

[1]We calculate the hospitalization rate for children by mother's education and occupation. See Figure A1 for more details.

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 (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 with children who have poorer health are likely to differ from other families. This makes it difficult to distinguish between the effect of having a child with an illness from 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 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 identified health shocks and to focus on a sample of similar 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 allows us to investigate what type of hospitalization drives the negative impacts on maternal labor earnings. Combining data from Finland and Norway demonstrates the robustness in the magnitude of the effect of this shock on mothers' labor market careers. Finally, we also provide new evidence on three crucial findings 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,[2] 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. There is a large literature on how health shocks impact own labor market outcomes (e.g, Bound et al., 1999; Dobkin et al., 2018; García-Gómez, 2011; García-Gómez et al., 2013; Jones et al., 2019; Lindeboom et al., 2016; Meyer and Mok, 2019; Trevisan and Zantomio,

[2] In subsequent work, Adhvaryu et al. (2023) study whether the safety net plays any role in mitigating the impact of childhood cancer shocks on family labor market outcomes using a policy reform. 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.

2016; Wagstaff, 2007). Other papers have examined the spillover effects, with particular attention paid to how one spouse's health shock affects the other spouse's employment and earnings (García-Gómez et al., 2013; Fadlon and Nielsen, 2021; Jeon and Pohl, 2017; Jiménez-Martín et al., 1999). There is also work on how unexpected health shocks from parents can affect the labor supply of their adult children (Rellstab et al., 2019; Frimmel et al., 0), and on the spillover effects of siblings' health (Black et al., 2020).

This study also contributes to the literature that investigates the impact of parenthood on family labor supply, which shows sizeable effects on mothers' labor supply and earnings.[3] 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 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 to as high as 50%-60% in Germany and Austria (Kleven et al., 2019a). In addition, Gunnsteinsson and Steingrimsdottir (2019) find that the child penalty is larger in families in which a child is born with a disability.

In this paper, we show that health shocks during middle childhood to adolescence still have a disproportionate effect on women's labor market outcomes compared to those of men, even in two countries that rank high in terms of gender equality and with some of the most comprehensive gender and family policies in the OECD (OECD, 2018). Moreover, the impact on women's labor earnings is substantial: it amounts to about 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, 2022). 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 literature on the child penalty 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

[3]These include, among others, papers by Adda et al. (2017); Angrist and Evans (1998); Angelov et al. (2016); Bertrand et al. (2010); Lundborg et al. (2017).

suggest that the disproportionate costs of children for women's careers do not end with childbirth.

The paper is structured as follows. Section 2 presents the empirical strategy. Section 3 provides background information on the institutional context and introduces the data. Section 4 reports the main results. Section 5 presents robustness checks. 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 with a child who suffers a health shock may be different from other families. To illustrate this, Figure A2 plots the coefficients of regressing different family and child characteristics on a dummy equal to one if the child suffered an (overnight) hospitalization.[4] Having a child who is 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 were 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 the child entered school. 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 Fadlon and Nielsen (2021, 2019) employed in a similar setting. Our treatment group consists of families whose child experiences the shock at a given year τ. The control group consists of families from the same age

[4] Figure A3 shows the same comparison for mortality.

cohorts[5] whose child experienced the same shock in $\tau + \Delta$ (4 years later in our main specification).[6] 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 these two groups of families would have followed similar trends in absence of the shock. We provide several pieces of evidence supporting the validity of this assumption. First, Figure 1 compares these two groups of affected families and shows that all differences in observable characteristics disappear, in contrast to the previous comparison between affected and unaffected families (Figure A2).[7] The only exception is gender, which we control for in all our specifications.[8] This exercise provides reassuring evidence that families with children who experience a hospitalization at different ages have similar observable characteristics.

We further provide visually clear results of our estimation and show that there is no evidence that the treatment group followed 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 greater if the child requires substantial and persistent care after the first hospitalization, as measured by the number of specialist visits and subsequent 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 react to a health shock that, in general, is not severe (skin conditions), while there is a substantial drop after a hospitalization due to a more severe condition (cancer).

More formally, the estimated equation is a dynamic (period-by-period) difference-in-differences

[5]Families in 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.

[6]In Table A14 we show that our results are robust to alternative choices of Δ.

[7]Similar results for the mortality sample can be found in Panel (b) of Figure A3.

[8]Boys and girls differ in the average age at which they experience a hospital admission.

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 of 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.[9] CBY_i are child birth year fixed effects, and ω_s calendar-year fixed effects. Finally, we cluster standard errors at the parent level.

3 Institutional Setting and Data

3.1 Institutional Setting

Table A1 shows that Finland and Norway are similar in size, economic development, and inequality indicators. Both countries also have a similar level of health care expenditure and health indicators. Finland and Norway have universal public health coverage. Local authorities provide primary healthcare in health centers, while 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. Hospitals provide emergency medical services. Both countries charge co-payments for some services. However, children under 18 in Finland are exempt from outpatient charges, and only pay co-payments for a maximum of 7 days of inpatient care per year. Outpatient prescription drugs are also free (Keski-

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

maki 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). In addition, there are safety net mechanisms that impose annual caps on out-of-pocket expenditures. 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 private hospitals, but the private provision of outpatient care is much more common (OECD, 2017).

Panel B in Table A1 shows the different subsidies that parents of sick children can receive. First, parents in both countries can receive the Special Care Allowance during hospital treatment and subsequent care at home.[10] 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 allowance 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, Finnish parents can be granted a disability allowance for disabled or chronically ill children (if the need for regular care, attention, or rehabilitation lasts for more than six months). Finally, family members in both countries can also be granted an informal care allowance from their municipality if they take care of a severely disabled or chronically ill child at home.[11] The entitlement, amount, and payment period of the allowances are determined based on the care and rehabilitation the child requires.

If a child dies, in Finland, his/her parents are not entitled to receive any allowance; a survivors' pension only replaces lost income when a family wage earner dies. The payment of child benefits ends with the child's death, and recipients need to return the benefits if they were paid for more than one month after the child's death.[12] 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 received 100% care allowance for more than three years).

[10]Maximum of 60 days in Finland.

[11]Information available here and here, for Finland and Norway respectively.

[12]Information available here.

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

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 1988-2018 with birth-registration data to identify families. The FLEED-FOLK covers the entire population (aged between 16 and 70) with information on year of birth, education level, annual labor earnings, and employment status. We use two different sources for health data. 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. Moreover, it also includes all outpatient visits to hospitals after 1998. The second dataset is the Cause of Death Registry, which includes information on all death dates and causes between 1990 and 2018.

For Norway, data on labor market outcomes come 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. We use the Norwegian Patient Registry (NPR) from 2008 to 2014 for health data. It includes all hospital admissions, both inpatient and outpatient stays. In addition, we also observe primary health care services use from 2006 to 2014 in the Control and Distribution of Health Reimbursement database (KUHR).

We focus on the first child in each family who suffered a health shock. For hospitalizations in Finland, the sample includes families whose child underwent the first hospitalization between ages 7 to 18.[13] For fatal shocks, the sample consists of all families whose child died between ages

[13]We focus on children who are relatively healthy and experience the shock after entering school.

7 and 18. In contrast, we focus on the first hospitalization observable in the data after age 6 in Norway, due to data availability.[14] We further restrict the sample to children who did not have any hospitalization in the year before the health shock. Figure A4 shows that there is substantial variation in terms of the age at which the shock occurs.

Tables A2 and A3 provide 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 7 and 18 during the period from 1995 to 2014 in Finland (Column (1)).[15] We use mortality data from the Finnish administrative register. The final matched sample for the mortality analysis consists of 2,369 children (Column (3) in Table A2). In Norway, the final matched sample includes 25,342 children's hospitalizations (Column (1), Table A3).

3.3 Incidence of health shocks

How common are these health shocks? We first analyze some descriptive statistics for a specific cohort in Finland that can be followed until adulthood: children born in 1990. Figure A5 shows the percentage of children who suffered a hospitalization by age group. Around 50% of children born in 1990 had 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 between 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 A5, we plot which share of these first hospitalizations was followed by at least one other hospital stay, by age. For all ages, at least around 50% of the children who suffered

[14] In Norway, hospitalizations data goes from 2008–2014. We do not have enough cohorts to use the same restriction as in the Finnish data.

[15] Similarly to Fadlon and Nielsen (2019) the same household may appear both in the treatment and in the control group for earlier treated units. A household is never used as a control for itself.

their first hospital stay had to be hospitalized again. In Panel (d), we zoom in on the health shocks that occur the age for entering school, and we calculate the number of future stays after the first hospitalization. Again, around 50% of the sample only suffered a single hospital stay. However, more than 20% of the children suffered a second stay after the first and more than 10% of children had more than five stays.

Figure A6 shows the number of observations by primary diagnosis (for Finland in Panel (a), and Norway in Panel (b)) and by mortality cause (in Panel (c)) for our main sample. In both countries, the main category is injury, poisoning, and other external causes. These are followed by diseases of the respiratory and digestive systems, and symptoms, signs, and abnormal clinical and laboratory findings. Similarly, the largest category for the mortality sample is injuries and other external causes, followed by deaths due to neoplasms.

4 Results

4.1 Hospitalizations

Figure 2 plots 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 prior to the child's hospital admission. A break in the trajectory becomes visible only after the event. The magnitude of the effects is very similar for Finland and Norway: one year after the child's hospitalization, maternal earnings drop by 2.4% and 1.9%, respectively, over the mean in $t-2$. The negative effect is persistent and appears to increase with time.

Table A4 provides further details on the estimates. One year after the shock, mothers' earnings have dropped by €517 and €608 for Finland and Norway, respectively.[16] Three years after the shock, mothers in Finland earn, on average, €1000 less than two years before the event. In Norway,

[16]The estimate for $t-1$ in Norway is marginally significant and negative. This could be driven by the less restrictive definition of health shocks for this country. See Section 3 for details.

the drop in earnings is €1438. This represents a drop of 4.7% and 4.6% for Finland and Norway, respectively (Column (2)).[17] Column (3) shows the results for the probability of employment. For Finland, the drop in employment also becomes visible only after the shock occurs. For Norway, the estimates for one and two years after the shock are negative but not significant for year one and marginally significant for year two.[18] Three years after the shock, the probability of working is significantly lower in both countries: 2 pp lower in Finland and 1.4 pp lower in Norway. This amounts to a 2.2% and 1.6% decrease in the probability of a mother working over the mean in $t-2$. Similar to the results for labor earnings, there is a snowball effect on employment: the probability of not being employed seems to increase over time.[19]

We apply an event study method as a complementary strategy (Table A5) exploiting within individual variation. 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).[20] The results of this exercise are consistent with those obtained using the diff-in-diff approach. Although the coefficients are slightly larger, the magnitude of the effects is similar: we find that three years after a child's hospitalization, maternal labor earnings decreased by 7.4% in Finland and by 5% after two years in Norway.[21]

In contrast, we do not observe any significant negative impact after the shock for fathers in either country (second Panel of Figure 2). However, there is some suggestive evidence that the

[17]Figure A7 shows that a health shock has a wide-ranging impact on the income distribution, with a stronger effect on the probability of falling into the lower percentiles.

[18]For earnings, we can only reject the null that the effects for both countries are equal for $t = 2$ (marginally significant at the 10% level). For employment, we can only reject the null for $t = 0$ and $t = 2$ (again, marginally significant). We cannot reject the null for the rest of the periods. Given the similarities in the institutional setting (see Section 3), we refrain from interpreting the differences in the magnitude of the coefficients.

[19]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, we observe a reduction in employment of 0.020 pp three years post-shock, which translates to a 2.17% decrease. Considering that average earnings in t-2 are €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 less than one-third of the earnings decrease.

[20]We omit two event time dummies to avoid multicollinearity (Sun and Abraham, 2020).

[21]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.

situation deteriorates over time, but the drop is not significant and the magnitude is small (see Column (1) in Table A7). We test if the effect on maternal earnings shown in Figure 2 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 genders for two and three years after the shock. This suggests that children's health shocks have a disproportionate effect on women's labor market outcomes compared to those for men.

4.2 Mortality

Figure 3 presents the results for the impact of a child's fatal health shock on parents' labor earnings. In Panel (a), 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 a deterioration in their health preceding the child's death. This 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. Despite this, we observe a large drop in maternal earnings after the fatal shock occurs. In particular, in the year of the shock, maternal earnings drop by 16%.

To reduce this anticipation effect, we concentrate on fatal shocks due to injuries, poisonings, or other consequences of external causes (hereafter referred to as "injuries") for the remainder of the mortality analysis.[22] The results using this sample of mortality shocks are displayed in Panel (b) of Figure 3. We do not see evidence of an anticipation effect when we focus on this 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 of a hospitalization. In particular, mother's earnings one year after the fatal shock are €3,600 lower compared to her earnings in $t-2$ (Table A6 column (1)). This represents a decrease of 18%. Three years after the death of a child, mothers' earnings follow the same negative trend with a 21% reduction.[23] Moreover, there is also

[22]Codes S00-T88 (ICD-10 Classification).

[23]Comparing these estimates (Figure 3 Panel (b)) in the last periods with the estimates that include all fatal shocks

a drop of 8.2 pp (9.5%) in their working probability (Table A6 column (3)).[24]

We do not observe any effect on fathers' labor earnings (lower panel of Figure 3). The coefficients are insignificant, relatively small in magnitude (except for $t = 0$), and for some periods even positive (Table A8). We can reject the null hypothesis that the coefficients on maternal and 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

How much of this impact do transfers compensate? We have three pieces of information in the data that can help shed some light on this question. First, we have information on total income. This measures disposable income, consisting of earned income, entrepreneurial income, property income, current transfers, and tax-deductible expenses. Second, we also observe total transfers received.[25] Individuals can receive transfers from the employment pension, social security payments, sickness benefits, unemployment benefits, etc. And third, we also have information on the combined child benefits families receive in Finland. This includes parental allowances, child home care allowances, child benefits, child's disability allowance, and special care allowance. To simplify the comparisons, we quantify the average effect over three years after the shock.

Table 1 shows the results for children's hospitalization shocks. In column (1), we show the 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 smaller: over the three years after the hospitalization of a child mothers' disposable income is €374 (1.8%) and €495 (1.3%) lower relative to before the shock, in Finland and Norway, respectively. This reveals that transfers partially offset the impact of a shock on labor earnings. Compared to the decrease in maternal labor earnings, the drop in disposable income is around 37% smaller for Finland and

(Panel (a)), we observe that the effects are larger in the former.

[24]Figure A7c illustrates the impact on mothers' earnings distribution.

[25]For Finland, this data is only available after 2000.

45% smaller in Norway.

In column (3), we observe an increase in the transfers received: a 2.3% increase in Finland and a 2.6% increase in Norway. In column (4), we show that families receive more child allowances after their child suffers a hospitalization. Mothers receive on average 81 additional euros. This means that around 20% of the drop in maternal labor earnings is insured solely through targeted child benefits.

Similar to the analysis on labor earnings, the impact of children's hospitalizations on fathers' disposable income is negligible (see results in Table A9 in the Appendix). Moreover, we do not observe any significant increase in transfers or child allowances fathers receive.

To examine the magnitude of the overall effect, we also explore the impact from the household perspective (Table A10 in the Appendix). The effects on family earnings are relatively smaller, since there is only a negative impact for mothers, and overall family earnings are considerably higher. However, the decline is still significant in both countries, with a 1.2% in each. 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 show an increase in family transfers. Similarly, child allowances show an increase of 1.8%. These findings indicate that, although the overall impact on family earnings is small, around 80% and 70% of the earnings decline in Finland and Norway, respectively, remains uninsured.

Overall, the impacts on family earnings in the case of hospitalizations are small on average, but a significant part of this impact still remains uninsured in the context of Finland and Norway. The effects on family earnings can be substantial in the case of more severe shocks (as we explore in Section 6.1). Importantly, there is an unequal gender distribution of this negative impact within households.

In Table A11, we carry out the same exercise for mortality shocks. Again, we find that the drop in 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, mother's disposable income is approximately €1789 lower than her earnings before the shock. This represents a 8% reduction in maternal total income that is not compensated through transfers. The drop in maternal disposable income is 53% smaller 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 allowances. 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 A12 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 the context of children's health shocks?[26] To answer this question, we follow the approach in Fadlon and Nielsen (2021) and exploit spatial and temporal variation in the allowances the family receives after a child's health shock.[27]

We follow the approach in Fadlon and Nielsen (2021) and 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 the allowances received in the post-period on 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 A8 in the Appendix shows there is substantial heterogeneity: in a given-municipality-

[26]We focus on understanding the role of social insurance as a potential mechanism in explaining the drop in maternal earnings. We refrain from performing a full welfare analysis, as this would require analyzing the impact on children's development, and this is beyond the scope of this paper.

[27]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.

year, the average family allowances provided in our sample amounts to €20100, and the variation 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 A13. 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. 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 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 benefits caused by a policy change.

5 Robustness Checks

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. There is a 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. We explore the robustness of our results to different choices of the control group in Table A14. In particular, we estimate Equation 1 again with the control group defined as families whose children suffered a hospitalization two years after (column (1) of Table A14), and three years after the treated group (column (2)). For comparison, column (3) shows the results of our main specification.

The coefficients are stable and 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. Moreover, each estimate falls within the confidence intervals of the others. The same holds for the mortality sample as shown in Table A15. One year after fatal shock, mothers' earnings fall by €3632 in our main specification ($\Delta = 4$). The corresponding drop is €3538 for $\Delta = 3$, and €3704 for $\Delta = 2$. This shows that our results are 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 A16 shows the results of this exercise for hospitalizations (Table A17 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.

6 Mechanisms

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 caregiving activities from family members.[28]

6.1.1 Recurrent health shocks

We first analyze whether persistent hospitalizations that impose a high burden of care drive the effect. 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 A9 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. On average, the number of visits jumps to more than 4 in the year of the shock. We define high-burden hospitalizations as those that require more visits in the year of the shock than the average (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.

Column (1) of Table 2 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 mothers' labor earnings. We can reject the null hypothesis that the average effects of high- and low-burden hospitalizations are equal to each other after the shock.

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

6.1.2 By diagnosis: Skin conditions vs. Cancer

Another potential approach to exploring conditions with different burdens 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.[29] These two conditions are interesting to study given that the implications in terms of care are very different.[30] While a skin condition is expected to generate a need for timely care, cancer is a condition with a much more complicated prognosis. In addition, 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 2 shows the results for cancer and skin conditions. As expected, mothers' earnings suffer a significant drop after a child's cancer diagnosis. The drop in maternal earnings is more than €2,000. However, we do not observe a similar decrease for 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 and Utilization Project (HCUP) Chronic Condition Indicators (CCI) for the International Classification of Diseases, which categorizes diagnosis codes into chronic and non-chronic conditions.[31] 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 A10. We find that maternal earnings decrease by €792 (equivalent to 3.9%) after the diagnosis of a child's chronic disease. In contrast, the impact is smaller for acute conditions, averaging €399 (or 1.85%).

This evidence further suggests persistent and severe conditions that require substantial care and support from caregivers drive the impact. In addition, the results of this exercise also show that

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

[30]We also estimate the effects for all children's diagnosis groups (Figure A10). It should be noted that there is considerable variability in the severity of the conditions within diagnosis groups.

[31]More information available here.

neither mutual shocks or child hospitalizations caused by a deterioration in maternal earnings are likely to explain our main findings.

6.1.3 Grandparents' support

Grandparents can play an essential role as caregivers for their grandchildren. For example, Frimmel et al. (0) find that the first grandchild's birth increases the grandmother's probability of leaving the labor market, and 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 whether the grandparents lived close to the family or not. The results of this exercise are presented in column 3 in Table 2. We find that the negative impact of the hospitalization of a child is stronger if 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.

6.2 Mental Health

Some studies find that parents of children with poor health or disabilities report higher stress levels and worse sleep quality (Stabile and Allin, 2012). Mental health has also been found to impact labor market outcomes (Biasi et al., 2018; Salokangas, 2021).

We explore this potential mechanism by looking at the number of contacts with the healthcare 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.[32]

Table 3 shows the results of the average impact of a child's hospitalization on parents' medical visits with a mental health diagnosis, and Table A18 shows the impact for each time period. Af-

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

ter the child's health shock, there is a substantial deterioration in the parents' mental well-being. Compared to two years before the shock, mothers visit specialists or hospitals at a higher rate for issues related to mental health conditions. The number of visits increases by more than 55% one year after the shock in Finland, and the effects on visits is 6% in Norway. We also observe an increase in the number of visits by fathers, marginally significant in the year of the shock in Finland (Table A18). The coefficient for Norway is also positive but insignificant.[33] Table A19 shows the results on mental health for families whose child suffers a fatal shock. We observe a large and significant increase in the number of mothers' visits with a mental health diagnosis for all periods after the shock. In contrast, only the coefficient for the year of the shock is large in magnitude and significant for fathers. Overall, our results suggest that this stressful event leaves parents, in particular mothers, in a vulnerable position in terms of mental health.

How much of the effect on maternal labor earnings does mental health deterioration drive? We perform a mediation analysis in the spirit of Gelbach (2016) and Sorrenti et al. (2024). Appendix B describes the methodology. 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 for understanding whether this mechanism can potentially explain the treatment effects.

The results of this exercise are shown in Figure A11. 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 play a more critical role. For mortality shocks, the impact on mental health can explain more than half of the drop in maternal labor earnings in the year of the shock. This result suggests that the mechanisms behind the effects of non-fatal and fatal shocks are very different: While the mental health shock is the primary driver of the negative impact for fatal shocks, it is

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

more plausible that the decrease in earnings for hospitalization shocks stems 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 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 in contrast was the secondary earner. We then estimate our DiD specification by splitting our data into these two subsamples. The results are in Table A20.

Two things are worth noting. First, we observe significant negative effects for both primary and secondary earner mothers in both Finland and Norway. Second, the impacts in both countries are larger for primary earners: the negative impact in Finland is more than four times larger (5.6% compared to 1.2%), and double the size (4.3% vs 2.2%) in Norway. 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 earnings losses are greater among highly educated mothers with higher (pre-event) earnings. Together, this evidence provides suggestive evidence that specialization within the household is unlikely to drive the observed effects.

This result can be interpreted in light of studies in the literature on the child penalty 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, parenthood largely seems to have no effect on men's labor market trajectories, irrespective of their relative earnings potential in the household. 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. 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 these household dynamics, we exploit the share of parental leave the father takes in the child's first year of life, using data from Norway. Figure A12 plots the share of parental leave taken by the father during the first year after birth. The distribution is right-skewed, with most fathers taking a very low share of the total parental leave in the household. In our sample, the average share of fathers' leave is 7.3%. Only 27% of fathers take any leave, and around 4.8% of fathers take at least 10% of all parental leave taken by the household.

The first columns of Table A21 show the results for families where the father took any leave, 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 where the 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 suggest that mothers are the ones who suffer the negative shock even in households where the father was relatively more involved in childcare (as proxied by paternity leave take-up). 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). We have information on marital status for both countries. Table 3 and Figure A13 (in Panel (a) for Finland and Panel (b) for Norway) show the results. We do not find evidence of an increased risk of divorce after the child was hospitalized, 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 A22 that the effects are very similar across these two groups, but somewhat larger for divorced women. Divorced women may still receive significant financial support from their former spouses in Finland and Norway.[34] As a result, both married and divorced women might have a financial cushion to adjust their responses if they have strong preferences or cultural norms that favor in-family care during shocks.

The category of unmarried women in both Finland and Norway consists of both women who are cohabitating with a partner and single women. We observe a similar effect size in Norway but find no significant effect in Finland (see columns (3)). This difference could stem from variations in family structure composition between the two countries, which complicates the interpretation of the results. However, we can directly identify single mothers from our data in Finland. Column (4) in the table presents results for this subgroup, revealing a notably smaller coefficient. This estimate is less precise due to the 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 shown that women prefer jobs that are more "family-friendly" after having children. Pertold-Gebicka et al. (2016) and Kleven et al. (2019b) find that mothers have a higher probability of working in the public sector following parenthood, which is known to have more flexible working conditions. Similarly, mothers may also seek a more family-friendly job after a child's hospitalization. We take advantage of the availability of rich occupational data in Finland to explore this margin of adjustment. In Column (3) in Table 3, and Panel (a) of Figure A14, we show that mothers are not more likely to work in the public sector after their child undergoes a

[34]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)).

health shock. More generally, column (4) in Table 3, and Panel (b) in Figure A14 examine whether mothers have a higher probability of moving to a different company after their child's health shock. Again, we do not find evidence that mothers have a higher probability of switching to a different job (firm) 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? Given the richness of our data, we characterize the 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.

We estimate CATE (Conditional Average Treatment Effects) on a large set of observable characteristics of the child, mother, family, and type of shock (diagnosis).[35] We follow the approach in Britto et al. (2022) and run the causal forest over first-differences.[36] For this analysis, 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 on mothers' labor market outcomes. Figure A15a 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 A23 compares the characteristics of mothers with below- and above-median treatment effects and formally tests for the difference in means.

[35] The algorithm starts by building trees. Each of the trees stratifies the set of characteristics into a number of regions (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. 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.

[36] In this way, the treatment group indicator is orthogonal to the covariates, so the unconfoundness assumption in Wager and Athey (2018) holds. See Britto et al. (2022) for more details. We do not allow the same observation to appear in both the treatment and control group.

Although most of the differences are statistically significant, their magnitude is only large (above 0.2) for four characteristics. In particular, more affected mothers are less likely to have lower education, more likely to have higher education (master's degree), more likely to be among the highest (pre-event) earning group (Q4), and it is more likely that their household earnings gap is small (Q1). To explore this, Figure A16a 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, again suggesting 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 is related to the share of data-driven sample splits over a given characteristic (Athey et al., 2019). Mother's education and 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 splits.

If we only consider the absolute drop in labor earnings after the shock, these patterns suggest that mothers who are hurt the most are those who have more to lose. In particular, a child's sickness 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.

Next, we examine the heterogeneity in the employment probability. Figure A15b shows that there is also substantial variation in the impact of a child's health shock on the probability of being employed. At the extensive margin, mothers who make the largest adjustment in terms of labor supply are those with lower earnings before the shock and larger earnings gap with their partners (Table A24). 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 Figure A16b). This pattern could be explained by mothers with a lower attachment to the labor force (for example, part-time workers) leaving the labor force after this adverse event.

Finally, we examine the heterogeneity in the impact on a mother's mental health. Figure A15c 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 (small) drop of 0.5 pp to an increase of 2.5 pp. We observe here the same income gradient as for employment: Table A25 shows that there are more women with low incomes (Q1, Q2) and large household earnings gaps (Q4) among the most affected mothers. 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 A16c.

Overall, our results indicate that the decreases 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 leaving or losing their jobs after encountering this adverse event. This finding is of particular concern, given that mothers from lower socioeconomic backgrounds are nearly three times more likely to experience a child's hospitalization[37] 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 that suffer the illness or death of a child and those that do not.

In particular, we use long panels of high-quality administrative data from two different coun-

[37]The same socioeconomic gradient is visible for fatal shocks (Panel b and d of Figure A1).

tries, Finland and Norway, on family income and health trajectories. We construct counterfactuals for treated households through families that 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' labor market outcomes. We find that mothers' earnings are 4.7% and 4.6% 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, 2021), 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, 2022). 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.

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. We do not find evidence of any significant impact for fathers.

We study whether 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 part of the variation.

Subsequently, we investigate 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. Using 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 live 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 where a child experiences a health shock, especially by providing mental health support. Moreover, these results also have important implications for 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 show that health shocks that occur during middle childhood to adolescence also disproportionately affect women's labor market outcomes in two countries usually portrayed as exemplars of gender equality, and with very generous family policies.

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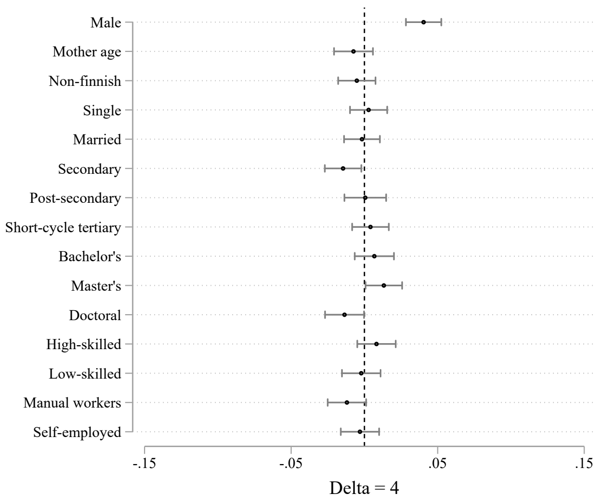
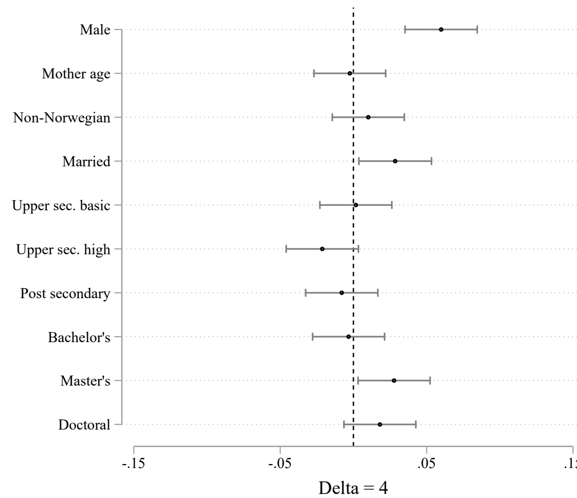
Figures and Tables

Figures

Figure 1: Differences in Characteristics: Within Affected Families



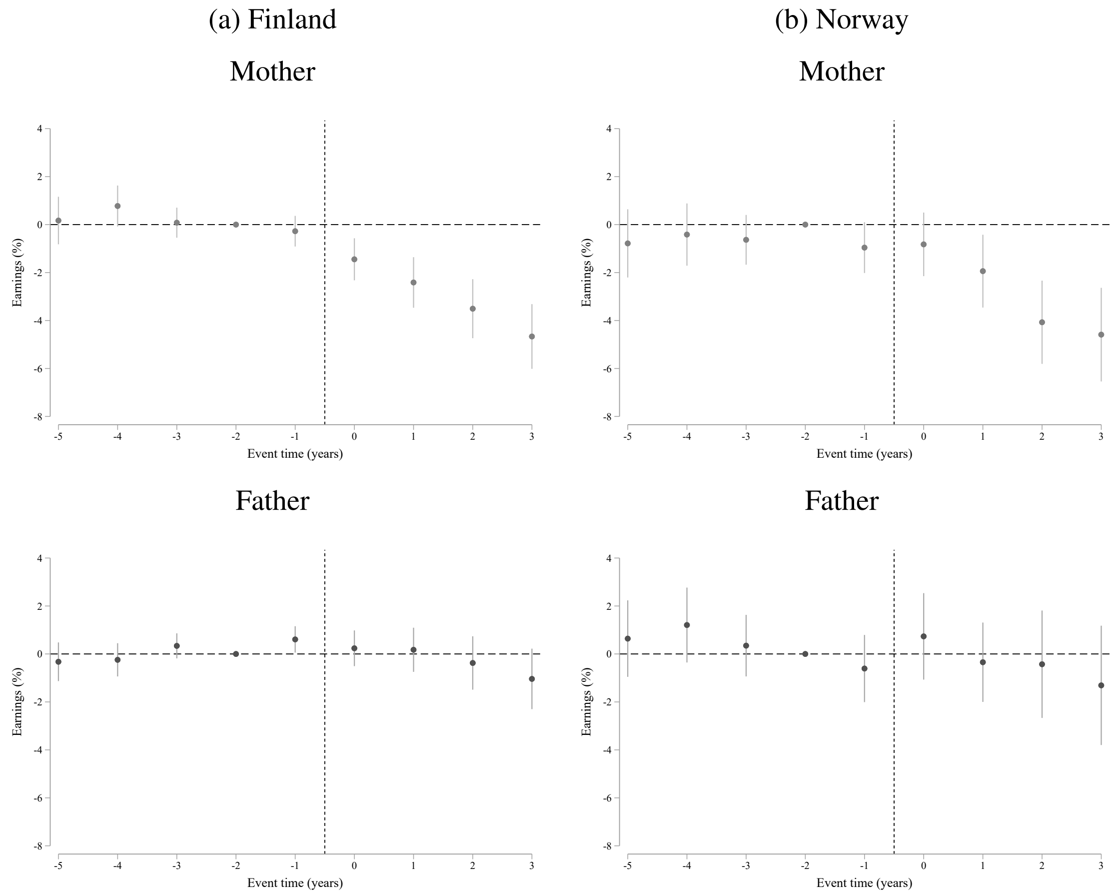
(a) Finland



(b) Norway

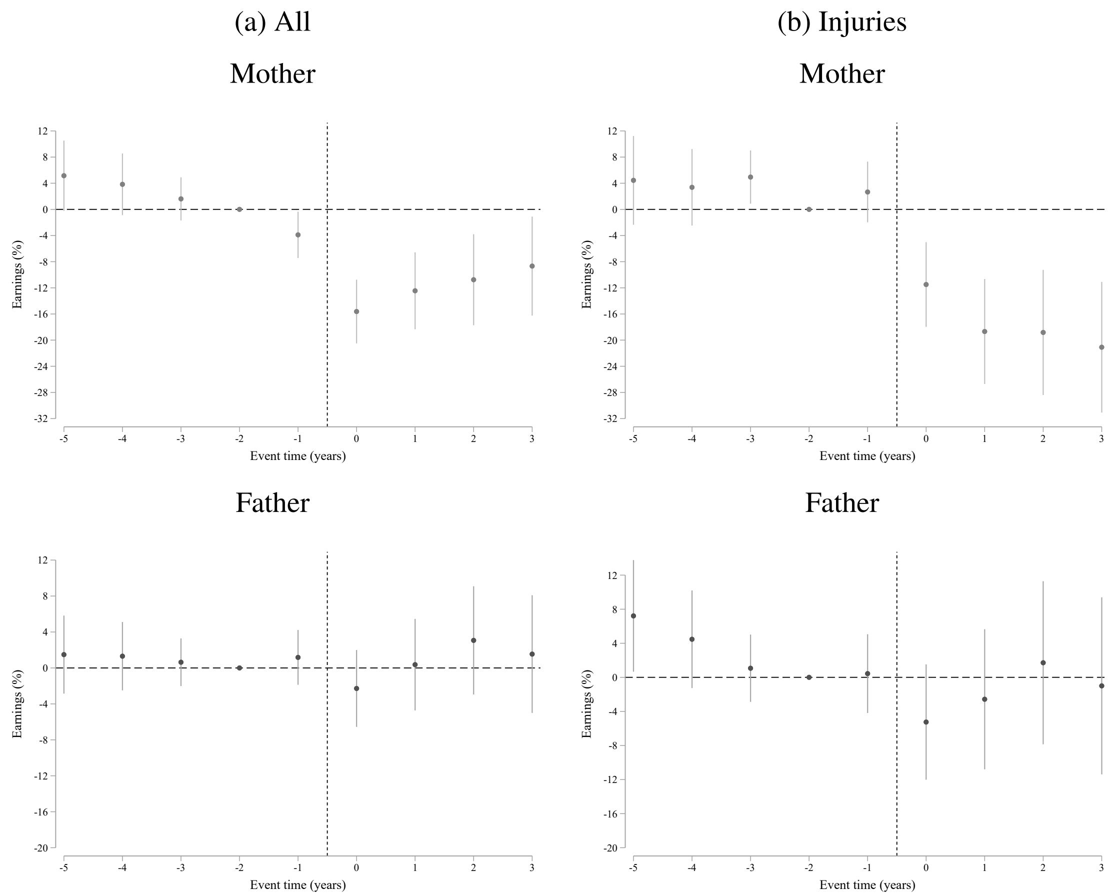
Notes: The figure shows the coefficients and 95% CI from separate regressions of each (standardized) variable on an indicator that takes a value of 1 if the family is in the treatment group, and 0 for the control group (the child experiences the shock 4 years later). Panel (a) shows the results for Finland,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

Figure 2: Hospitalizations: Mothers' and Fathers' Labor Earnings



Notes: This figure shows the impact of a child's hospitalization on 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 3: Impact of a Child's Fatal Shock on Mothers' and Fathers' Labor Earnings



Notes: This figure shows the impact of a child's fatal shock on 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.

Tables

Table 1: Hospitalizations: Mothers' Institutional Support

	(1) Earnings (€)		(2) Total Income (€)		(3) Transfers (€)		(4) Allowance (€)
	Finland	Norway	Finland	Norway	Finland	Norway	Finland
$Post_t * Treat_i$	-621.645***	-724.727***	-374.879***	-495.468***	110.945***	204.125**	81.494***
	(103.908)	(206.108)	(65.381)	(183.633)	(36.287)	(95.006)	(23.280)
Observations	376778	228078	376778	228078	376778	228078	376778
Controls	YES	YES	YES	YES	YES	YES	YES
Mean Y_{t-2}	21959.975	31345.526	21194.327	38804.201	4691.505	7814.071	3484.942

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 2: 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 the event study specification 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 3: Hospitalizations: Mechanisms

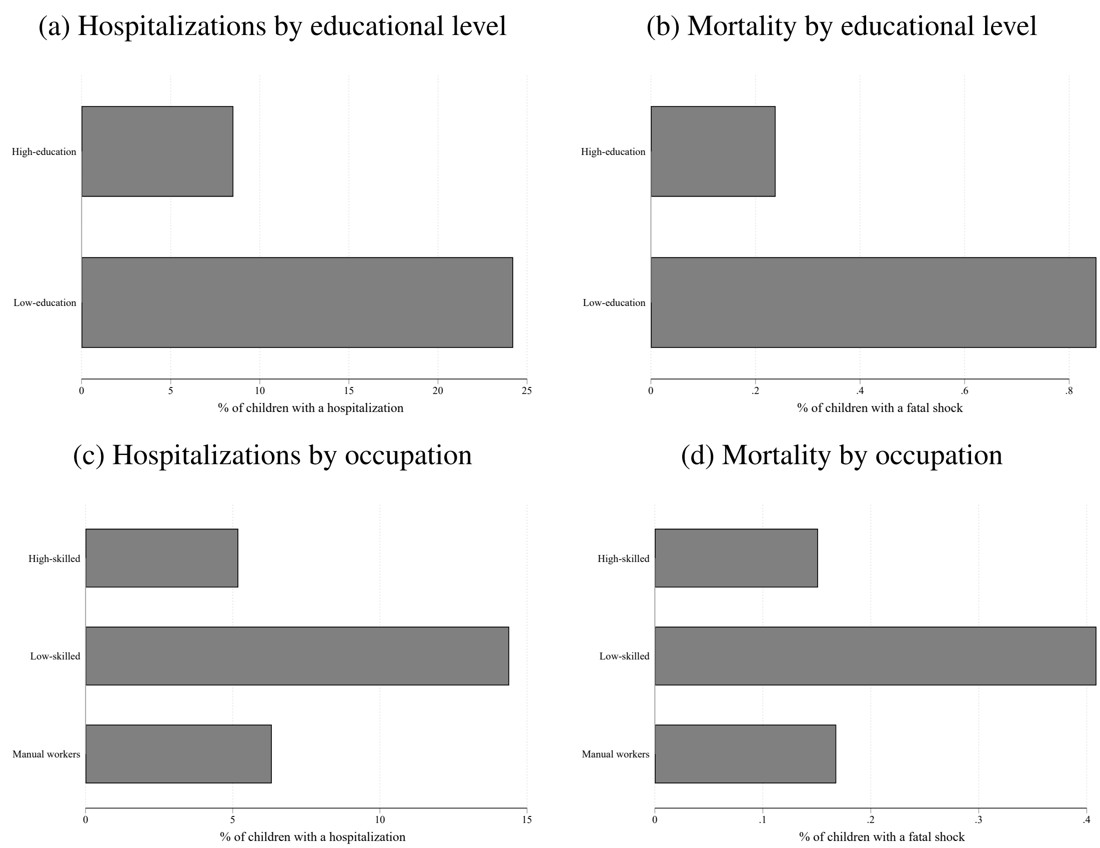
	(1) Mental Health Visits		(2) Divorce		(3) Public sector	(4) Changing jobs
	Finland	Norway	Finland	Norway	Finland	Finland
$Post_t * Treat_i$	0.065***	0.030*	-0.001	-0.002	-0.004	-0.001
	(0.019)	(0.018)	(0.003)	(0.003)	(0.004)	(0.003)
Observations	387856	174783	400315	228078	400315	401787
Controls	YES	YES	YES	YES	YES	YES
Mean Y_{t-2}	0.135	0.489	0.116	0.114	0.428	0.110

Notes: This table shows the impact of a child's hospitalization on number of mother's mental health encounters (in column (1)), probability of divorce (in column (2)), probability of having a public sector job (in column (3)), and probability of changing jobs (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.

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Appendix A: Figures and Tables (For Online Publication)

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



(a) Hospitalizations by educational level

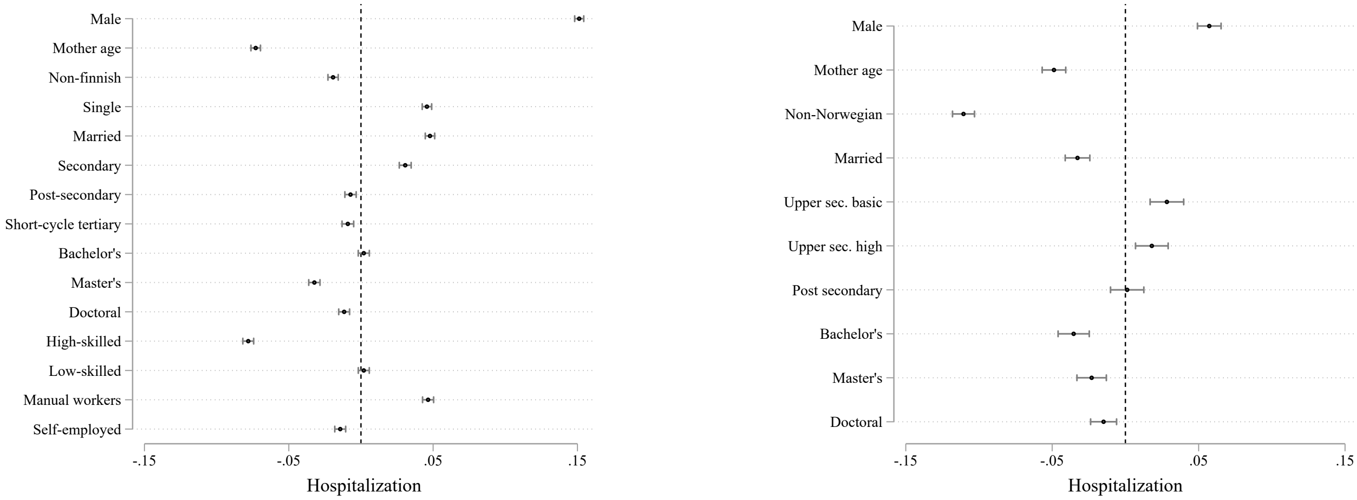
(b) Mortality by educational level

(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: Differences in Characteristics: Across Families

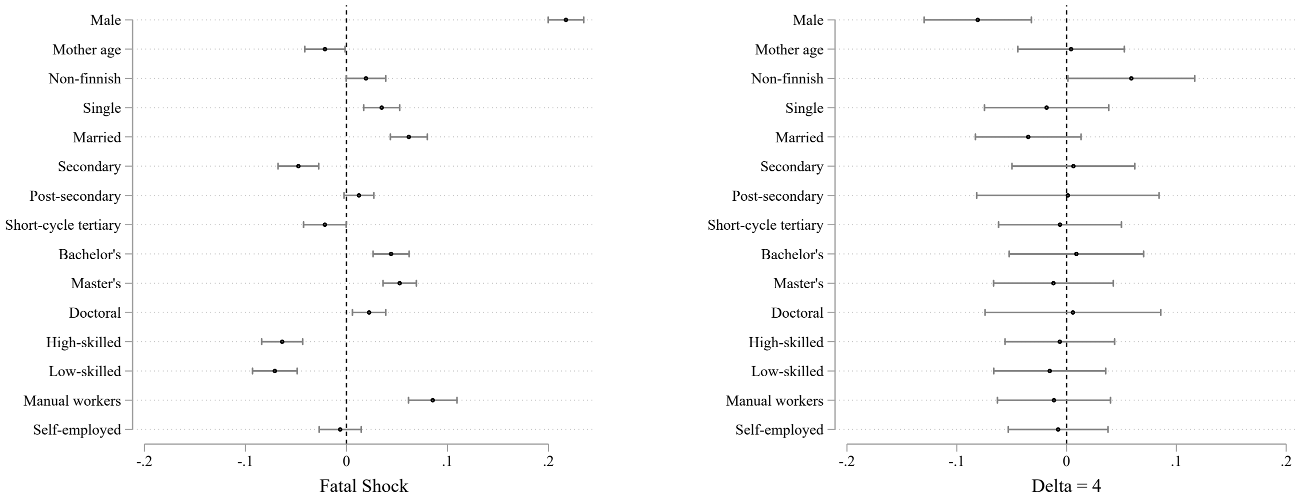


(a) Finland

(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 A3: Mortality: Differences in Characteristics



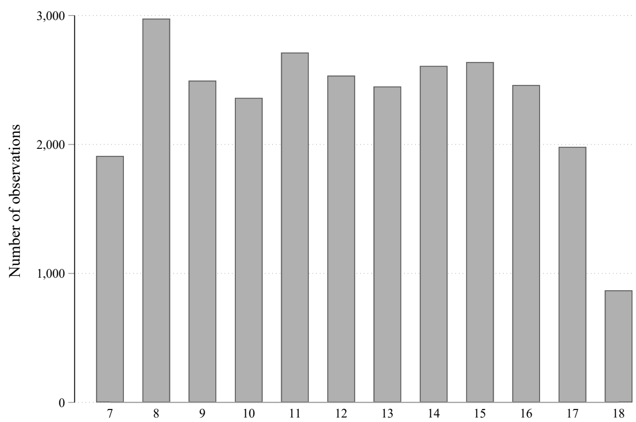
(a) Across Families

(b) Within Affected Families

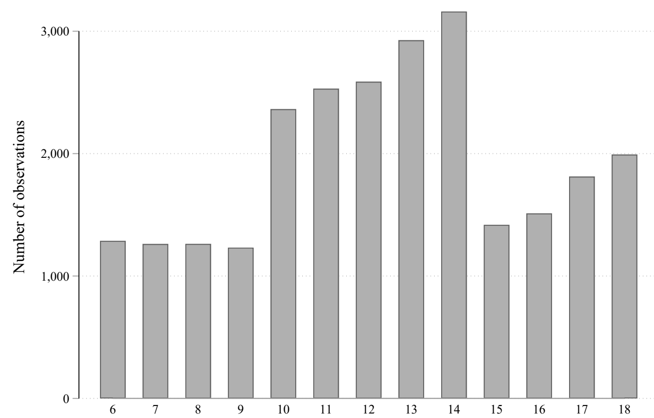
Notes: The figure shows the coefficients and 95% CI from separate regressions of each (standardized) variable. In panel (a), we regress the variables on an indicator that takes a value of 1 if the family suffered a fatal shock and 0 if not. In panel (b), we regress the same variables on an indicator 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 A4: Number of Observations by Child's Age at Event Time

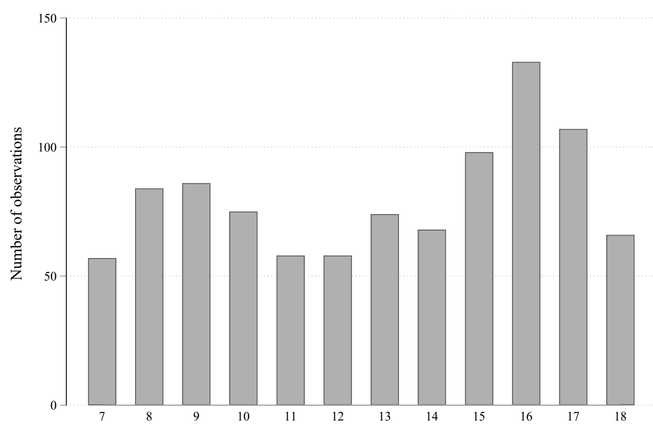
(a) Finland: hospitalizations



(b) Norway: hospitalizations



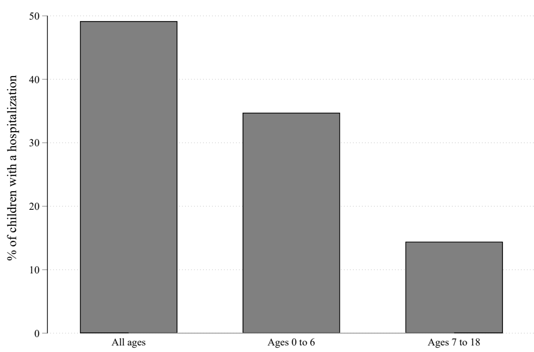
(c) Finland: mortality



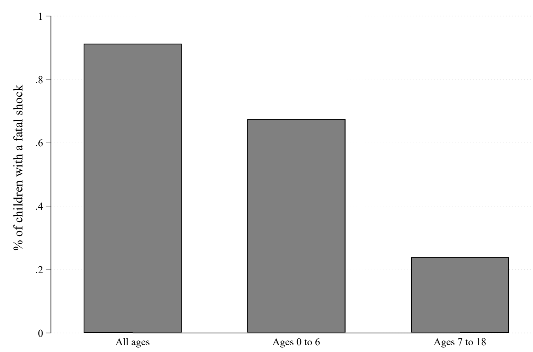
Notes: This figure shows the number of observations by the age of the child at hospital admission for Finland (panel (a)) and Norway (panel (b)). In panel (c), we show the number of observations by age of the child at the time of the fatal shock for Finland. The sample includes all children who suffered 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 A5: Descriptive: children born in Finland in 1990

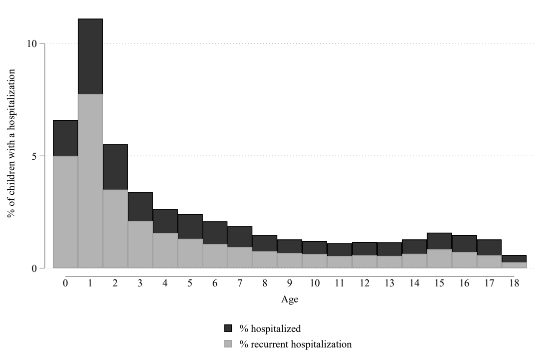
(a) Hospitalizations by age group



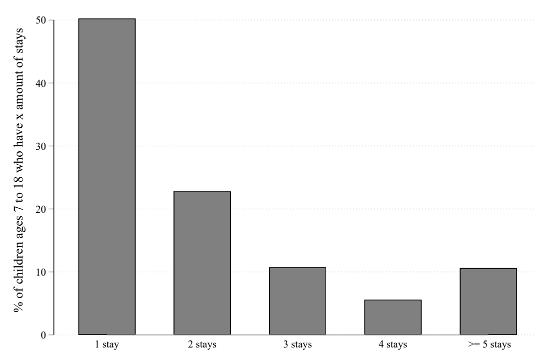
(b) Mortality by age group



(c) Hospitalization recurrence



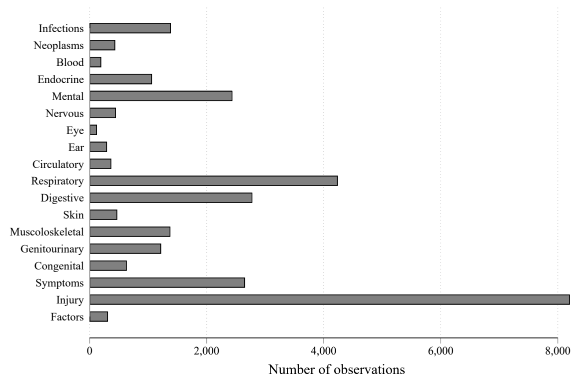
(d) Number of stays



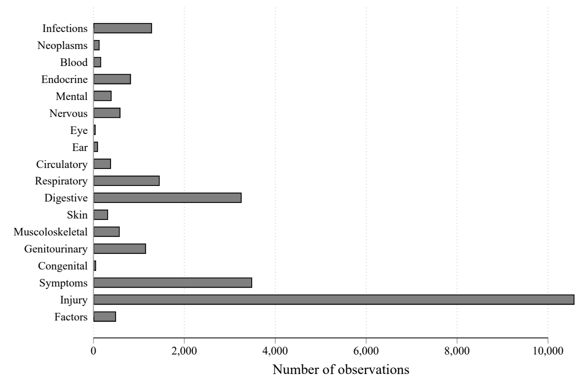
Notes: This figure provides different descriptive graphs for the sample of children born in 1990, in Finland. Panel (a) shows the percentage of children who suffered a hospitalization from ages 0 to 18 and then decomposed into two groups based on school starting age. Panel (b) plots the same information 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 number of hospital stays for the sample of children who suffered a hospitalization from ages 7 to 18.

Figure A6: Hospitalizations and Mortality Shocks by Main Diagnosis Group

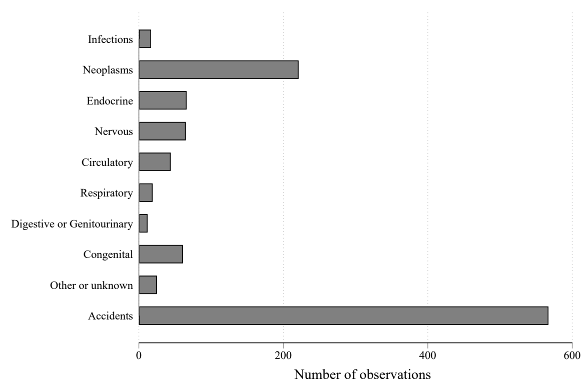
(a) Finland: hospitalizations



(b) Norway: hospitalizations

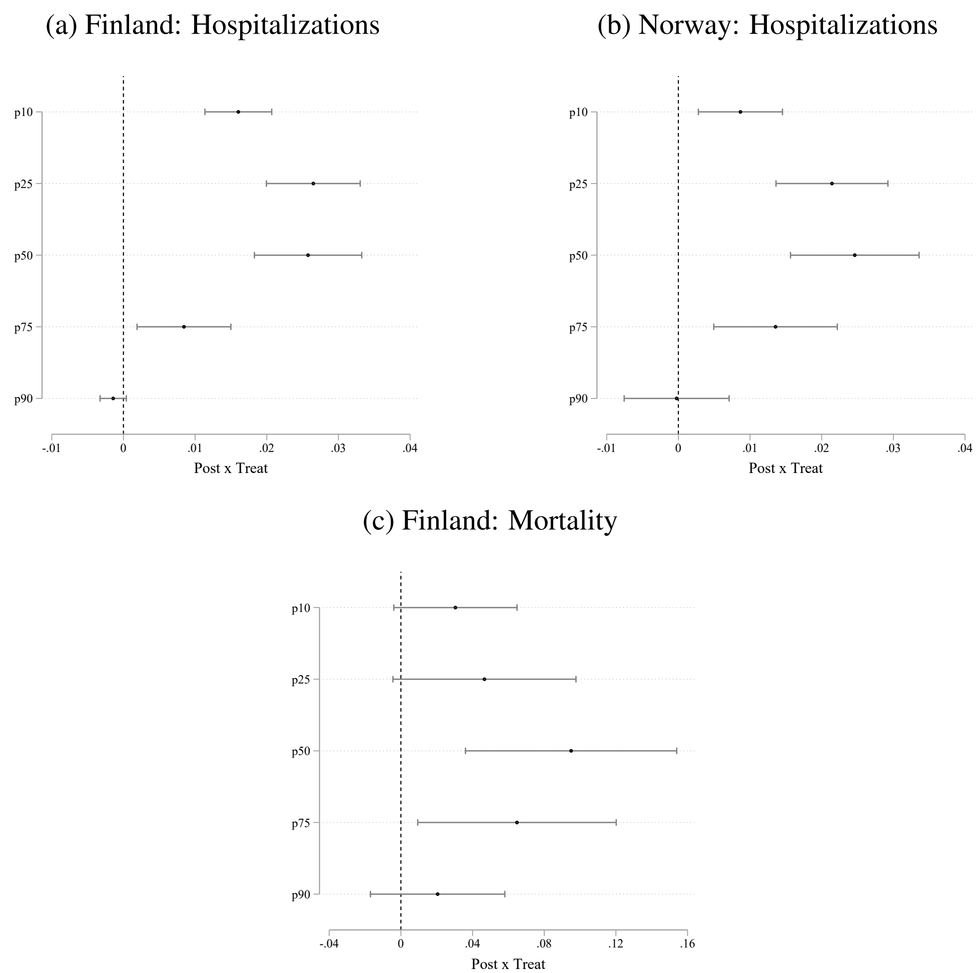


(c) Finland: mortality



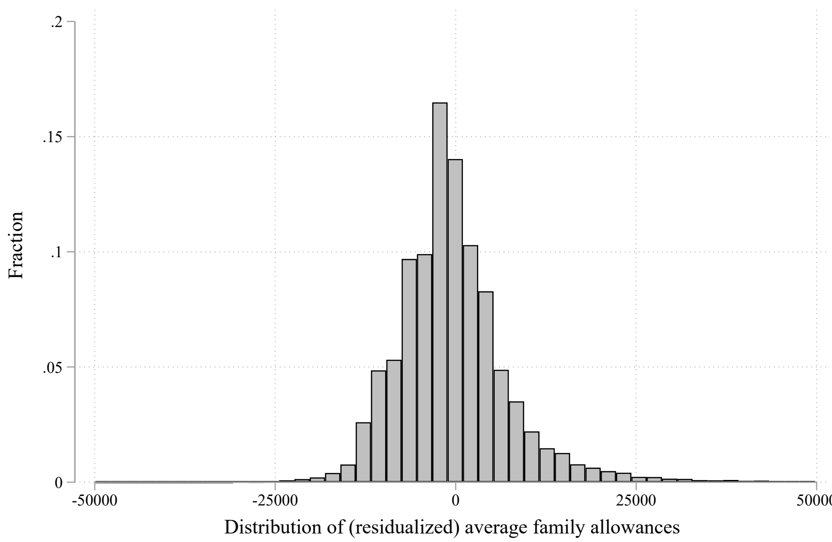
Notes: This figure shows the number of children who suffered a hospitalization by main diagnosis group (ICD-10 Chapters) for Finland (panel (a)) and for Norway (panel (b)). Panel (c) splits fatal shocks by cause of death. Categories include: Certain infectious and parasitic diseases, neoplasms, diseases 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.

Figure A7: Hospitalizations and Mortality: Impact on Maternal Earnings' Distribution



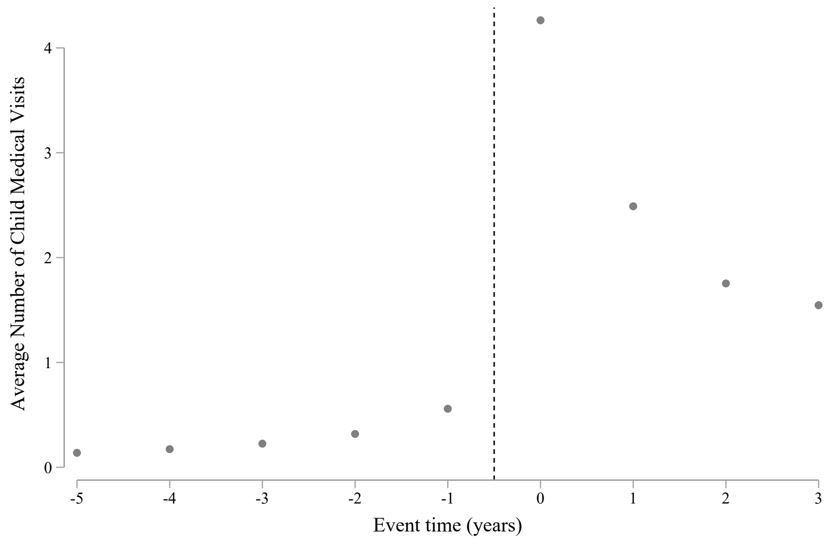
Notes: The figure shows the coefficients and 95% CI from separate regressions for dummy variables that take value equal to one if the mothers' earnings drop below a given percentile of the earnings distribution. In panel (a), results for Finland. In panel (b), results for Norway. In panel (c), results 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 A8: Distribution of (residualized) Family Allowances by Municipality-Year



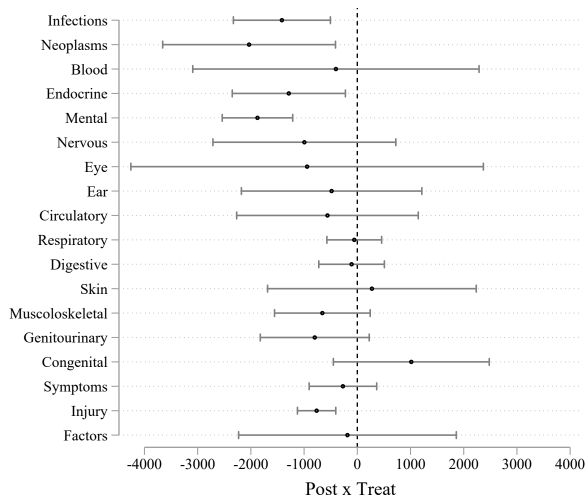
Notes: This figure shows the year-by-municipality ("leave-one-out") mean of (residualized) family allowances. To construct it, we first regress at the individual level, the family allowances received on ICD10 diagnosis code fixed effects and predict the residuals. We then sum all the (adjusted) individual 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 A9: Hospitalizations: Children's Number of Visits

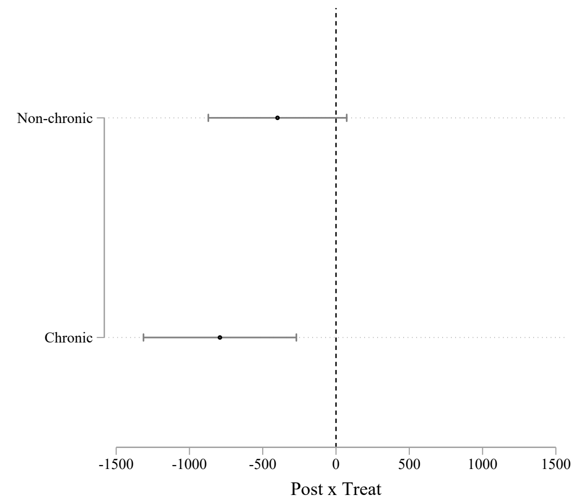


Notes: This figure shows the average number of children's inpatient and outpatient visits by event time (ranging from five years before to three years after their first hospitalization). We use administrative data from Finland.

Figure A10: Hospitalizations: Type of Health Shock



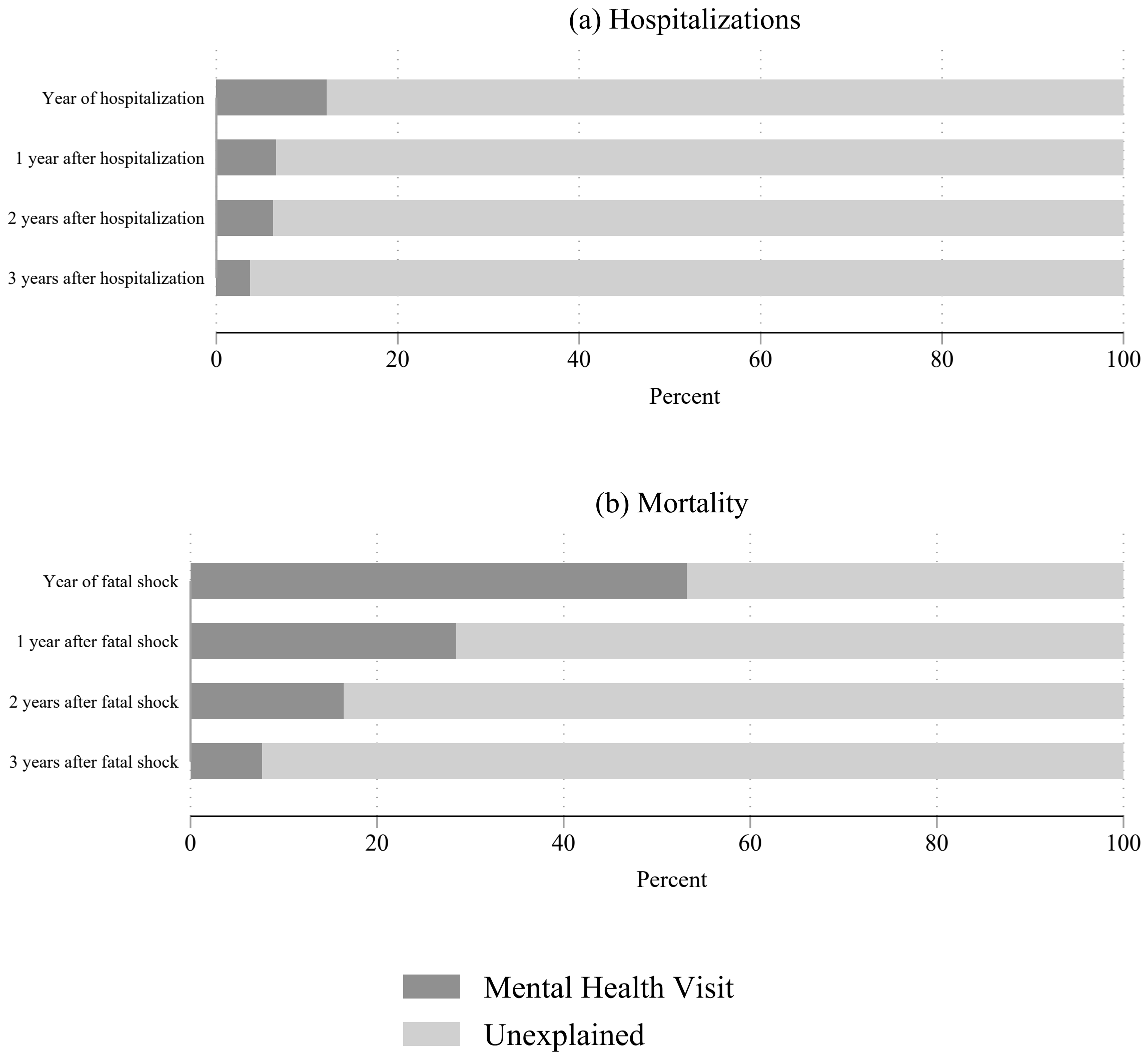
(a) By diagnosis code



(b) By chronicity of health condition

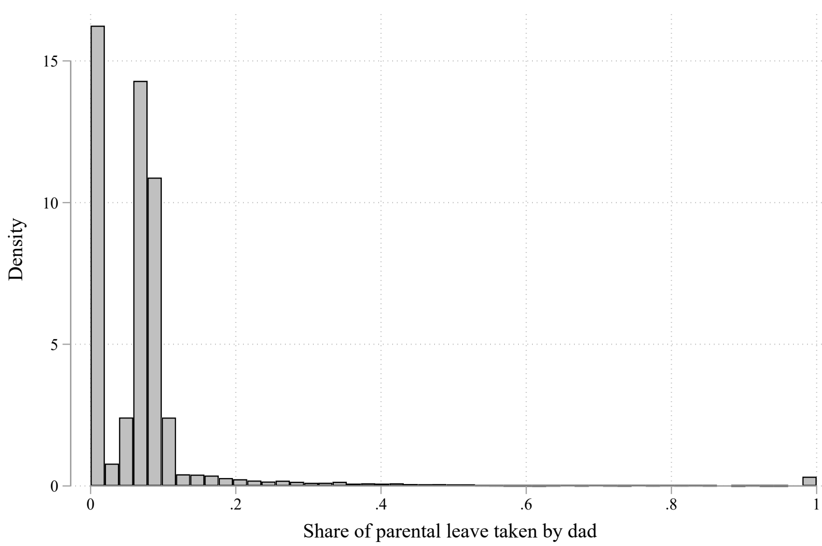
Notes: The figure shows the coefficients and 95% CI from separate regressions for each subgroup of health shock. In panel (a), we split the shocks by ICD-10 codes. In panel (b), we categorize health shocks in chronic vs non-chronic following the Healthcare Cost and Utilization Project (HCUP) Chronic 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 A11: Mental Health: Mediation Analysis



Notes: This figure shows the results of the mediation analysis presented in Equation 2. 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.

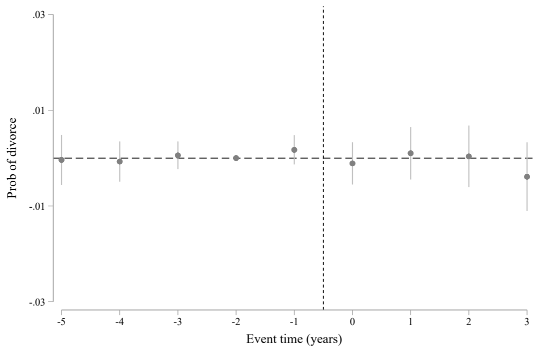
Figure A12: Fathers' Share of Parental Leave



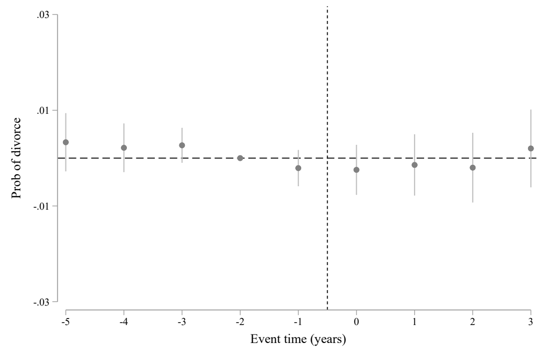
Notes: This figure shows the distribution of fathers' share of parental leave take-up for children in our sample. We use administrative data from Norway.

Figure A13: Hospitalizations: Probability of Divorce

(a) Finland



(b) Norway

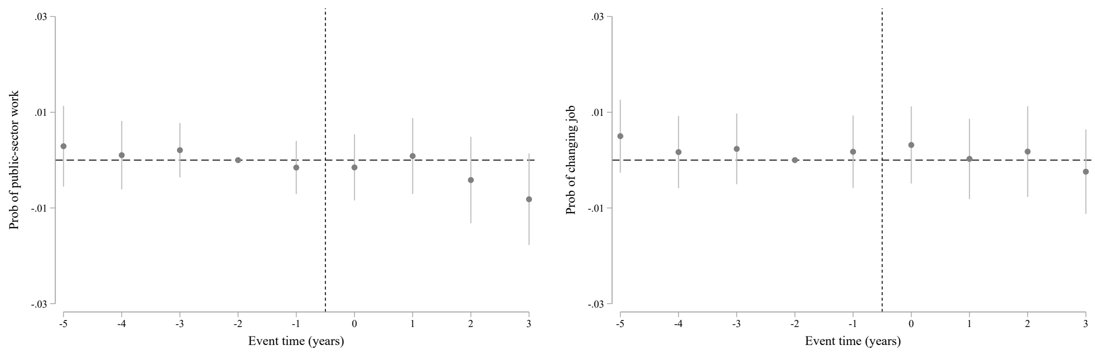


Notes: This figure shows the impact of a child's hospitalization on the probability of relationship dissolution. We plot the coefficients for the interaction between the event time dummies and the treat dummy in Equation 1, with the corresponding 95 percent confidence intervals. Panel (a) plots the results 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 A14: Hospitalizations: Choice of Work Environment

(a) Public-sector work

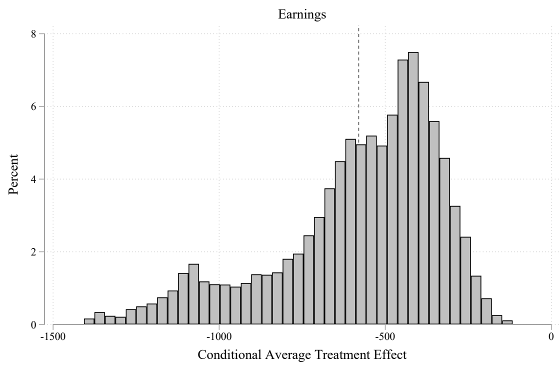
(b) Changing jobs



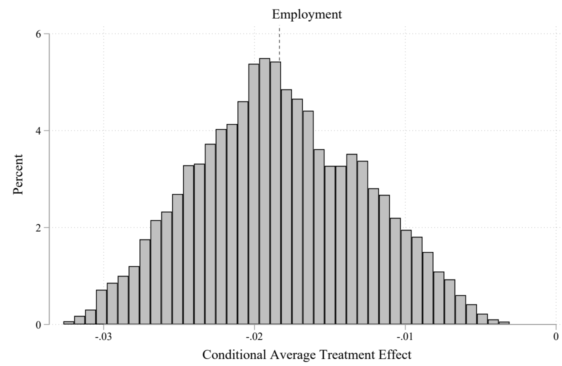
Notes: This figure shows the impact of a child's hospitalization on the probability of working in the public sector (panel (a)) and the probability of switching jobs (panel (b)). We plot the coefficients for the interaction between the event time dummies and the treat dummy in Equation 1, with the corresponding 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.

Figure A15: Hospitalization: Distribution of CATE

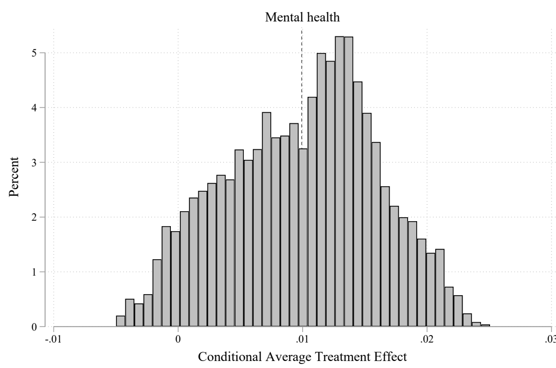
(a) Labor earnings



(b) Employment



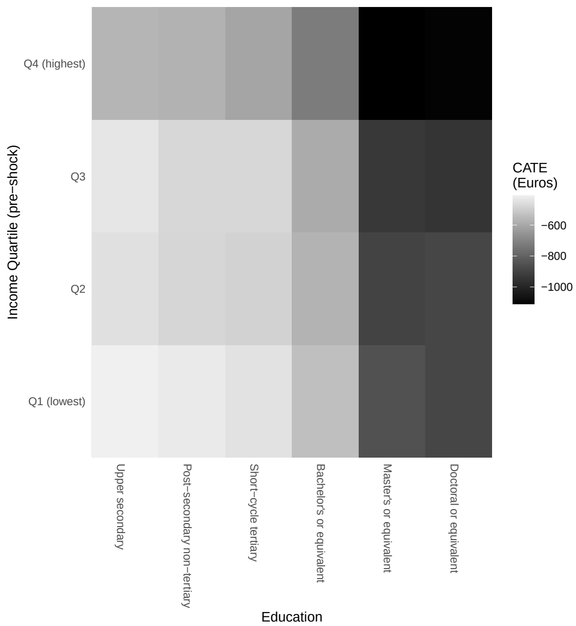
(c) Mental health



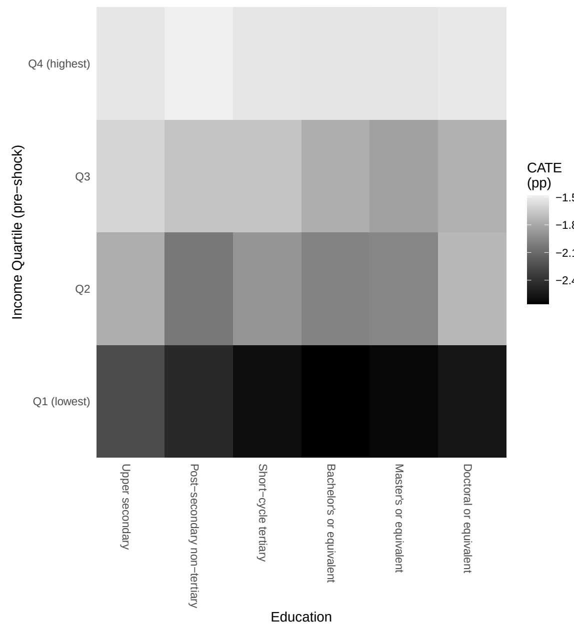
Notes: Panel (a) of this figure shows the distribution of estimated conditional average treatment effects for maternal labor earnings, panel (b) for employment, and panel (c) for the probability of being diagnosed with a mental health condition. We estimate CATE (Conditional Average Treatment Effects) 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 A23. We use administrative data from Finland.

Figure A16: Hospitalization: CATE Partial Dependence on Income and Education

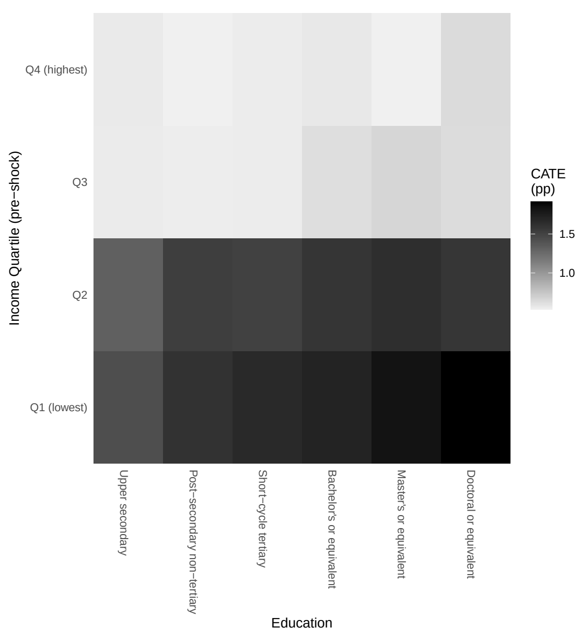
(a) Labor earnings



(b) Employment



(c) Mental health



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 A23. 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. 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 (2022), 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								
Age at birth	29.163	4.082	29.377	5.218	28.610	5.135	28.815	5.171
Age 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 t=-2	21265.922	15020.591	20528.224	15721.872	17845.181	14731.818	18227.234	15868.393
Prob. working t=-2	0.919	0.273	0.885	0.319	0.827	0.378	0.812	0.391
Prob. unemployed t=-2	0.000	0.005	0.000	0.004	0.000	0.000	0.000	0.000
Total income t=-2	20676.556	9726.987	20764.401	10275.266	20323.934	9526.436	21298.852	10490.904
N visits mental health t-2	0.133	1.860	0.187	2.738	0.298	2.813	0.223	1.946
Prob. working in the public sector t=-2	0.414	0.492	0.378	0.485	0.390	0.488	0.398	0.490
Prob. changing job 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 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 t=-2	33478.007	21834.650	30489.696	22726.303	27289.063	21592.623	28547.097	22255.169
Prob. working t=-2	0.951	0.215	0.896	0.305	0.861	0.346	0.866	0.340
Prob. unemployed t=-2	0.000	0.006	0.001	0.030	0.002	0.041	0.001	0.032
Total income t=-2	26401.338	15282.171	25323.212	15753.136	23786.602	15066.965	25135.177	16148.476
N visits mental health	0.081	1.463	0.152	3.398	0.160	1.840	0.140	1.736
Prob. working in the public sector t=-2	0.202	0.401	0.175	0.380	0.158	0.365	0.157	0.364
Prob. changing job 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	12.416	3.361	12.717	3.831
Male	0.550	0.498	0.544	0.498
Mother Characteristics				
Age at birth	28.869	4.441	28.772	5.213
Age at admission	41.285	5.318	41.489	6.056
Norwegian	0.863	0.343	0.841	0.366
Married	0.632	0.482	0.616	0.486
Upper secondary, basic educ. level	0.079	0.269	0.091	0.288
Upper secondary, final year	0.300	0.458	0.280	0.449
Post secondary non-tertiary	0.024	0.152	0.024	0.154
Bachelor's or equivalent level	0.348	0.476	0.309	0.462
Master's or equivalent level	0.065	0.246	0.058	0.234
Doctoral or equivalent level	0.006	0.076	0.005	0.070
Earnings t=-2	31345.526	24833.292	30970.726	24487.482
Prob. working t=-2	0.889	0.314	0.871	0.336
Total earnings t=-2	38804.201	22981.968	38985.678	22222.752
Transfers t=-2	7814.071	8758.957	8352.717	9661.108
N visits mental health t-2	0.489	1.786	0.565	2.019
Prob. divorced t-2	0.114	0.317	0.150	0.357
Father Characteristics				
Age at admission	43.751	5.652	44.451	6.817
Upper secondary, basic educ. level	0.070	0.256	0.089	0.284
Upper secondary, final year	0.368	0.482	0.340	0.474
Post secondary non-tertiary	0.056	0.229	0.054	0.226
Bachelor's or equivalent level	0.220	0.414	0.198	0.398
Master's or equivalent level	0.088	0.284	0.080	0.272
Doctoral or equivalent level	0.012	0.107	0.010	0.100
Earnings t=-2	57267.217	47706.672	54452.395	46161.637
Prob. working t=-2	0.934	0.248	0.906	0.291
Total earnings t=-2	59168.406	46642.523	57245.757	44462.376
Transfers t=-2	2425.208	7512.864	3368.406	8901.197
N visits mental health t-2	0.282	1.649	0.321	1.801
Prob. divorced t-2	0.113	0.317	0.148	0.355
Observations	25342		37031	

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: Mothers' Labor Outcomes

	(1) Earnings (€)		(2) Earnings (%)		(3) Employment	
	Finland	Norway	Finland	Norway	Finland	Norway
-5	36.260	-245.771	0.169	-0.784	0.005	0.003
	(108.398)	(227.382)	(0.505)	(0.725)	(0.003)	(0.004)
-4	166.305*	-130.306	0.775*	-0.416	0.008***	0.003
	(93.366)	(207.402)	(0.435)	(0.662)	(0.003)	(0.004)
-3	17.047	-198.994	0.079	-0.635	-0.000	0.003
	(68.632)	(165.717)	(0.320)	(0.529)	(0.002)	(0.003)
-1	-59.126	-301.089*	-0.276	-0.961*	-0.002	0.005*
	(69.882)	(169.293)	(0.326)	(0.540)	(0.002)	(0.003)
0	-310.543***	-258.434	-1.448***	-0.824	-0.007**	0.002
	(95.867)	(211.958)	(0.447)	(0.676)	(0.003)	(0.003)
1	-517.681***	-608.454**	-2.413***	-1.941**	-0.011***	-0.004
	(115.358)	(242.880)	(0.538)	(0.775)	(0.003)	(0.004)
2	-752.394***	-1276.521***	-3.508***	-4.072***	-0.015***	-0.008*
	(134.557)	(277.529)	(0.627)	(0.885)	(0.003)	(0.004)
3	-1000.763***	-1438.267***	-4.665***	-4.588***	-0.020***	-0.014***
	(147.714)	(312.152)	(0.689)	(0.996)	(0.003)	(0.004)
Observations	401787	228078	401787	228078	401787	228078
Controls	YES	YES	YES	YES	YES	YES
Mean Y_{t-2}	21450.555	31345.526	100	100	0.920	0.889

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 A5: Hospitalizations: DiD vs. Event Study with Individual Fixed Effects

	(1) Earnings DiD (€)		(2) Earnings FE (€)	
	Finland	Norway	Finland	Norway
-5	36.260	-245.771		
	(108.398)	(227.382)		
-4	166.305*	-130.306	86.674***	95.563
	(93.366)	(207.402)	(28.220)	(84.189)
-3	17.047	-198.994	70.398**	-3.493
	(68.632)	(165.717)	(28.424)	(105.829)
-1	-59.126	-301.089*	-187.423**	-260.857***
	(69.882)	(169.293)	(40.576)	(94.025)
0	-310.543***	-258.434	-563.200***	-377.690***
	(95.867)	(211.958)	(63.619)	(145.091)
1	-517.681***	-608.454**	-844.078***	-758.149***
	(115.358)	(242.880)	(83.566)	(210.199)
2	-752.394***	-1276.521***	-1166.970***	-1553.388***
	(134.557)	(277.529)	(101.488)	(269.391)
3	-1000.763***	-1438.267***	-1523.420***	
	(147.714)	(312.152)	(120.315)	
Observations	401787	228078	393366	247739
Controls	YES	YES	YES	YES
Mean Y_{t-2}	21450.555	31345.526	20649.215	30970.726

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, 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 A6: 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 A7: Hospitalizations: Fathers' Labor Outcomes

	(1) Earnings (€)		(2) Earnings (%)		(3) Employment	
	Finland	Norway	Finland	Norway	Finland	Norway
-5	-109.915	366.423	-0.326	0.640	-0.002	0.006*
	(138.768)	(465.908)	(0.411)	(0.814)	(0.002)	(0.003)
-4	-82.649	690.705	-0.245	1.206	-0.000	0.003
	(119.201)	(456.063)	(0.353)	(0.796)	(0.002)	(0.003)
-3	113.819	198.427	0.337	0.346	-0.001	0.002
	(89.802)	(374.823)	(0.266)	(0.655)	(0.002)	(0.002)
-1	204.808**	-348.129	0.607**	-0.608	-0.004**	-0.001
	(94.586)	(409.242)	(0.280)	(0.715)	(0.002)	(0.002)
0	79.929	420.130	0.237	0.734	-0.005**	-0.002
	(128.229)	(526.575)	(0.380)	(0.920)	(0.002)	(0.003)
1	58.752	-197.390	0.174	-0.345	-0.005*	-0.006**
	(158.391)	(483.252)	(0.469)	(0.844)	(0.002)	(0.003)
2	-126.972	-245.393	-0.376	-0.429	-0.006**	-0.008***
	(191.686)	(654.340)	(0.568)	(1.143)	(0.003)	(0.003)
3	-350.942	-750.074	-1.040	-1.310	-0.009***	-0.016***
	(217.156)	(726.932)	(0.643)	(1.269)	(0.003)	(0.003)
Observations	401787	228078	401787	228078	401787	228078
Controls	YES	YES	YES	YES	YES	YES
Mean Y_{t-2}	33750.607	57267.217	100.000	100.000	0.953	0.934

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 A8: 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 A9: 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	-383.263	-107.299	-294.068	32.930	64.115	38.312
	(147.756)	(518.704)	(100.534)	(507.944)	(37.387)	(86.285)	(25.103)
Observations	376778	228078	376778	228078	376778	228078	376778
Controls	YES	YES	YES	YES	YES	YES	YES
Mean Y_{t-2}	34460.921	57267.217	27198.223	59168.406	1312.107	2425.208	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 A10: 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***	-1107.990*	-482.178***	-789.536	143.936***	268.240**	119.806***
	(188.260)	(566.107)	(124.648)	(544.211)	(53.294)	(132.209)	(44.429)
Observations	376778	228078	376778	228078	376778	228078	376778
Controls	YES	YES	YES	YES	YES	YES	YES
Mean Y_{t-2}	56420.896	88612.744	48392.550	97972.607	6005.715	10239.279	6636.919

Notes: 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 A11: Mortality: Both Parents Institutional Support

	(1)		(2)		(3)		(4)	
	Earnings(€)		Total Income(€)		Transfers(€)		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 A12: 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

Notes: 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 injuries, poisonings, or other consequences of external causes. 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 A13: 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

Notes: 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 A14: Hospitalizations: Different Control Groups

	(1) Delta = 2		(2) Delta = 3		(3) Delta = 4	
	Finland	Norway	Finland	Norway	Finland	Norway
-5	37.307	199.923	203.204*	297.611*	36.260	-245.771
	(94.962)	(148.023)	(108.809)	(179.351)	(108.398)	(227.382)
-4	30.208	130.435	121.699	206.127	166.305*	-130.306
	(92.753)	(139.816)	(92.803)	(162.661)	(93.366)	(207.402)
-3	-17.188	-52.652	2.054	100.409	17.047	-198.994
	(67.789)	(114.173)	(67.893)	(128.354)	(68.632)	(165.717)
-1	-50.592	-201.766*	-50.669	-148.491	-59.126	-301.089*
	(70.318)	(108.046)	(69.396)	(132.194)	(69.882)	(169.293)
0	-370.240***	-313.389**	-282.300***	-260.402	-310.543***	-258.434
	(96.892)	(146.226)	(97.142)	(170.285)	(95.867)	(211.958)
1	-516.395***	-620.496***	-516.768***	-687.632***	-517.681***	-608.454**
	(103.744)	(162.469)	(116.974)	(200.174)	(115.358)	(242.880)
2			-568.880***	-1047.076***	-752.394***	-1276.521***
			(125.884)	(224.379)	(134.557)	(277.529)
3					-1000.763***	-1438.267***
					(147.714)	(312.152)
Observations	349963	356629	383113	296400	401787	228078
Controls	YES	YES	YES	YES	YES	YES
Mean Y_{t-2}	22144.850	33420.733	21973.765	32167.557	21450.555	31345.526

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 A15: Mortality: Different Control Groups

	(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 A16: Robustness: Mutual Shocks

	(1) +/− One Week		(2) +/− One Month	
	Finland	Norway	Finland	Norway
-5	22.692	-304.034	9.321	-100.182
	(109.017)	(259.766)	(110.482)	(287.490)
-4	163.122*	-150.540	164.186*	12.365
	(93.856)	(235.280)	(95.130)	(261.495)
-3	17.345	-147.025	23.847	15.609
	(69.107)	(191.738)	(69.963)	(214.085)
-1	-62.913	-370.069*	-53.478	-447.489**
	(70.266)	(197.498)	(71.267)	(220.985)
0	-320.750***	-234.509	-293.342***	-325.906
	(96.331)	(244.173)	(97.583)	(268.380)
1	-522.900***	-430.118*	-471.567***	-444.832
	(115.956)	(276.777)	(117.412)	(300.553)
2	-748.929***	-1000.369***	-679.122***	-908.765***
	(135.318)	(312.331)	(136.903)	(344.606)
3	-998.453***	-971.219***	-930.772***	-935.540***
	(148.558)	(349.618)	(150.421)	(385.550)
Observations	397321	183707	387718	157217
Controls	YES	YES	YES	YES
Mean Y_{t-2}	21453.994	31515.831	21486.049	31878.102

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 A17: Mortality: Mutual Shocks

	(1)	(2)
	$+/-$ One Week	$+/-$ 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 A18: 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*	-0.019	-0.031*	-0.027
	(0.021)	(0.039)	(0.017)	(0.055)
-3	-0.019	0.016	-0.019	-0.024
	(0.016)	(0.027)	(0.014)	(0.026)
-1	0.014	-0.009	0.004	0.006
	(0.019)	(0.022)	(0.011)	(0.018)
0	0.059***	0.074***	0.026*	0.025
	(0.023)	(0.025)	(0.015)	(0.023)
1	0.075***	0.054**	0.016	0.016
	(0.026)	(0.026)	(0.018)	(0.024)
2	0.043	-0.018	0.022	0.021
	(0.029)	(0.027)	(0.019)	(0.026)
3	0.031	0.004	0.018	0.027
	(0.029)	(0.028)	(0.020)	(0.025)
Observations	387856	174783	387856	174783
Controls	YES	YES	YES	YES
Mean Y_{t-2}	0.135	0.489	0.079	0.282

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 A19: 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 A20: Hospitalizations: By Mothers' Specialization within the Household

	(1)		(2)	
	Primary Earner		Secondary Earner	
	Finland	Norway	Finland	Norway
$Post_t * Treat_i$	-1669.608***	-2029.866***	-228.938**	-607.808**
	(234.045)	(616.805)	(106.436)	(212.032)
Observations	88175	40014	306512	188064
Controls	YES	YES	YES	YES
Mean Y_{t-2}	29501.611	46828.110	19098.422	28051.328

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

Table A21: By Fathers' Share of Parental Leave

	(1) Father involved		(2) Father not involved	
	Father leave	Father share $> 10\%$	Father no leave	Father share $< 10\%$
$Post_t * Treat_i$	-571.026*	-664.061***	-812.216*	-910.048
	(305.901)	(256.755)	(430.183)	(920.774)
Observations	106722	138555	49374	17541
Controls	YES	YES	YES	YES
Mean $Y\_t - 2$	36911.117	34495.622	31981.333	42114.682

Notes: 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 A22: 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***	-835.429***	-978.437***	-1232.723*	217.125	-763.254**	-265.012
	(113.049)	(269.425)	(281.845)	(645.765)	(262.706)	(359.109)	(329.943)
Observations	311264	141858	53667	25920	47280	55773	49328
Controls	YES	YES	YES	YES	YES	YES	YES
Mean Y_{t-2}	21768.604	33187.978	22378.348	30159.509	18785.673	29277.965	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 A23: 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 A24: 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 A25: 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.

Appendix B: Mediation Analysis (For Online Publication)

We perform a mediation analysis following the approach of Gelbach (2016) and Sorrenti et al. (2024). 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:

$$\frac{dY}{d(I_t \times treat)} = \frac{\partial Y}{\partial M}\frac{\partial M}{\partial(I_t \times treat)} + R_t, \tag{2}$$

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

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

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:

$$M_{is} = \alpha + \beta treat_i + \sum_{t \neq -2, t=-5}^{t=3} \gamma_t \times I_t + \sum_{t \neq -2, t=-5}^{t=3} \delta_t^{m_2} \times I_t \times treat_i + \lambda A_{is} + \phi CBY_i + \omega_s + \epsilon_{is}. \tag{4}$$

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 $R_t = 1 - \frac{\eta \times \delta_t^{m_2}}{\delta_t}$.