The Caregiving Penalty: Caring for Sick Parents and the Gender Pay Gap

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Abstract

The aging of the population is increasing the demand for adult caregiving. In most of the world, care for the elderly and sick is provided almost exclusively by families and, within families, by women. This paper studies the impact of adult caregiving on gender inequality in the labor market. Using administrative data from Chile, we leverage variation in a parental health shock –the first cancer hospitalization of a parent– to examine who bears the burden of adult caregiving. After a parental health shock, daughters but not sons experience a reduction in employment and earnings. A parental health shock creates a caregiving penalty –the effect of the shock on daughters relative to sons– of 11% on earnings, increasing the overall gender pay gap by 9%. These penalties affect women even if they earn more than their partners or brothers, suggesting that gender norms influence the distribution of adult caregiving. Additionally, penalties are concentrated among women who are mothers, suggesting a correlation across the life cycle between care given to children and then to aging parents.

JEL codes: J16, J22, J31, I14
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In 2019, one in six people provided unpaid care to a relative or friend with a sickness or disability (OECD 2021).[1] The demand for adult caregiving is rising rapidly due to population aging. Today, there are approximately seven working-age people for every person aged 65 years or over. In 2050, this number will fall to only three (UN 2023). In most places, adult caregiving is almost exclusively provided by families. Thus, the burden of balancing paid work against the well-being of an aging or sick loved one will only grow over time. Yet, even within families, the burden of caregiving is not borne equally: over 75% of caregivers are women (ILO 2019). Female caregivers are also more likely to be primary caregivers and to provide more hours of total care than male caregivers (AARP 2009). The impending rise in adult caregiving has the potential to amplify existing gender inequalities.

However, assessing the relationship between adult caregiving and gender inequalities is challenging due to the nature of unpaid care. Unpaid care is often referred to as "invisible work" as it is rarely measured (Heggeness 2023). While survey data has provided valuable information about informal care, these settings usually lack sources of quasi-random variation that can be leveraged to address selection bias.[2][3] In the case of motherhood, it is standard to use the timing of the first birth to assess the impact of children on women's labor market outcomes. However, adult caregiving can arise from various circumstances and can be provided by different people, making it harder to identify abrupt changes in care provision.

This paper studies how adult caregiving affects gender inequalities in the labor market. To overcome the previous challenges, we focus on the most frequent caregiving relationship among adults: adult children caring for a parent (Table 1).[4] For identification, we leverage

[1] Share of informal carers providing daily or weekly care among the population aged 50 and over.

[2] See Carmichael and Charles (1998) and Carmichael and Charles (2003).

[3] For example, unemployment increases the probability of providing care (Fischer et al. 2022), while employment and earnings reduce the willingness to provide care (Carmichael et al. 2010). Thus, not accounting for selection might significantly overstate the impact of caregiving on labor market outcomes (Heitmueller 2007). Additionally, self-reported caregiving might be subject to justification bias. In self-reported health status, justification bias refers to respondents overstating their level of disability or health problems in order to justify non-employment and being a welfare recipient (Black et al. 2017; Dobkin et al. 2018). A similar bias might be present in self-reported caregiving.

[4] Parent care is also the most frequent type of caregiving among mid-life caregivers in European OECD countries (OECD 2021) and in the US (Wagner and Takagi 2010).

variation in the occurrence and timing of an unexpected parental health shock that increases the need for parental care. We define a parental health shock as the first cancer hospitalization experienced by a parent. Using a differences-in-differences event study framework, we assess how the employment and earnings of working-age sons and daughters evolve after a parental health shock.

We study this question in Chile, a country undergoing a rapid process of population aging, where, like most countries, adult caregiving falls almost exclusively on families. Chile spends 0.02% of its GDP on long-term care, and public and private provisions combined cover less than 5% of the target population.[5] Across the globe, countries that broadly provision formal adult care –whether public or private– are the exception rather than the norm (Lloyd-Sherlock 2014; Feng 2019). The Chilean case is representative of how most countries, especially low and middle-income countries, are facing rising adult caregiving demands: by relying almost exclusively on families for care provision.

We focus on cancer for two reasons. First, cancer has become one of the most common health shocks disproportionally affecting older individuals.[6] One in three men and one in four women will develop cancer over their lifetime (Fitzmaurice et al. 2017). Cancer is the major contributor to disease burden worldwide, and projections forecast that the global cancer burden will continue to grow in the next decades (Kocarnik et al. 2022).[7] In Chile, cancer accounts for almost half of the population that requires palliative care (Pérez-Cruz et al. 2023). Second, cancer constitutes an unexpected and severe health event that rapidly increases care demand, which we leverage for identification (Gupta et al. 2018). Cancer sets on motion an ongoing and uncertain treatment, during which patients often require help with medical coordination, emotional support, and daily activities such as bathing and feeding. We use the first cancer hospitalization as a health event severe enough to induce variation in adult care provision.

[5]Other Latin American countries spend similar amounts. (Uruguay: 0.04%, Argentina: 0.05%). Public long-term care services are practically nonexistent in the region (IDB 2020).

[6]People over 65 years old make up 60% of new cancer diagnoses and 70% of cancer deaths (Berger et al. 2006).

[7]The Disability-Adjusted Life Year (DALY) is a metric that captures the total burden of disease –both from years of life lost due to premature death and years lived with the disease.

We use detailed administrative records for the universe of individuals in the Chilean Social Registry of Households. This registry is the information system used by the Chilean State to allocate a wide range of social subsidies and programs among potential beneficiaries. Built from administrative databases from several institutions, it covers approximately 5 million households and 13 million people, equivalent to 75% of the Chilean population. This sample excludes the highest-income households in Chile, in which the burden of caregiving might be mitigated due to their greater capacity to afford formal care.[8] We create a novel data linkage that allows us to (i) identify individuals who experience a health shock from hospitalization records, (ii) identify their working-age children from birth records, and (iii) observe children's labor market trajectories from unemployment insurance records. Our final sample comprises 14,000 working-age children with a parental health shock and 226,000 control children, whom we observe through an 11-year period, from 5 years before to 5 years after the parental health shock.

We use a difference-in-differences stacked event study to estimate the labor market effects of a parental health shock on children. We estimate effects on employment and earnings separately for sons and daughters. We find that a parental health shock creates a divergence in the labor market outcomes of daughters and sons. Daughters' employment and earnings fall after the shock. On average, daughters experience a 3% and 4% decline in employment and earnings, respectively, in the five years after the shock. These declines are persistent and do not show any sign of recovery within the 5-year post-shock period. We find strong evidence that sons do not experience similar costs. Instead, after a parental health shock, sons' earnings increase by 1.5%, although this effect is less precisely estimated. For treated families, a parental health shock increases the gender gap in earnings by 4 percentage points, equivalent to a 9% increase.

We provide additional evidence that the caregiving shock is uncorrelated with other shocks that might affect female employment. Families that face health shocks that lead to higher and more persistent care needs see a larger reduction in the employment and earnings of daughters. In contrast, parental health shocks that do not increase care needs

[8] 5% of adults over 50 years who required care have a paid caregiver (ENDIDE 2022).

do not affect daughters' labor market outcomes. On the other hand, the increase in sons' earnings is driven by low-income families, where the need to generate additional income to compensate for earning losses or health expenditures is more pressing. As a result, in low-income families, a parental health shock increases the gender gap by 10 percentage points.

Following the literature on child penalties, we define the "caregiving penalty" as the percentage by which daughters fall behind sons due to a parental health shock.[9] We estimate penalties of 5% in employment and 11% in earnings five years after the parental health shock. These penalties are sizeable. They amount to 40% and 58% of the child penalties estimated by Kleven et al. (2019).

Our results show that a parental health shock leads to a gender specialization within families that is consistent with daughters providing unpaid care and sons providing financial resources. The opposing effects that a parental health shock has on sons and daughters can result from two factors. Due to pre-existing gender disparities in earnings, women face lower opportunity costs of providing adult care than men. Additionally, gender norms about care establish that care is primarily a responsibility of women.[10] We find reductions in daughters' outcomes even in cases where they earned more than their brothers and their partners, suggesting that opportunity costs alone cannot explain the different effects by gender and that gender norms matter in the allocation of caregiving. Finally, we find that the costs of parent care are concentrated among women who are mothers, suggesting a correlation between the distribution of child care and parent care.

This study contributes to a growing body of work that studies the role that caregiving plays in explaining gender disparities in the labor market. However, this work to date has focused almost exclusively on child care. There is compelling evidence that women pay large and persistent costs for motherhood (Cristia 2008; Bertrand et al. 2010; Angelov et al.

[9] Kleven et al. (2019) use this definition for child penalties. The penalty is defined as the effect on women relative to the effect on men, scaled by the women's expected outcomes.

[10] We refer to gender norms broadly as the societal expectations, beliefs, and rules regarding how men and women should behave. Regarding care, the concept encompasses situations ranging from explicit obligations or responsibilities to circumstances where women rather than men prefer to provide care, or where women engage more in care work because they believe or are believed to be better caregivers than men.

2016; Lundborg et al. 2017; Kleven et al. 2019; Kleven 2022; Goldin et al. 2022; Cortés and Pan 2023; Kleven et al. 2023) and that motherhood accounts for a significant share of current gender disparities in the labor market (Kleven et al. 2019, 2023). In contrast, men seem to benefit from parenthood (Goldin et al. 2022).

We contribute to this literature by focusing on the role of another type of caregiving in explaining gender disparities. Like child care, adult care can be a lengthy and intense activity that interferes with paid work.[11] However, adult care differs in ways that can influence how its burden is allocated (Mommaerts and Truskinovsky 2023). Adult care begins later in life, it offers less capacity for anticipation, it involves more uncertainty about its tasks and duration, various family and non-family members can provide it, and it can take place at home or in formal care institutions. To our knowledge, this study is the first to demonstrate that adult caregiving widens gender disparities in the labor market and to quantify its contribution to the gender gap. Furthermore, we document that the contribution of adult caregiving to gender gaps works through two channels: daughters reduce their employment and earnings due to unpaid care, while sons increase their employment and earnings to generate additional financial resources.

We also contribute to an emerging literature studying the effects of parental health shocks on adult children. Two recent studies that assess the labor market consequences for children of different parental health events find from null (Rellstab et al. (2020) for the Netherlands) to negative effects (Halla et al. (2023) for Austria). Other recent work shows that in European countries, children's labor market outcomes are responsive to long-term care policies (Massner and Wikström 2023; Halla et al. 2023; Shen 2021; Løken et al. 2017). Interestingly, in these studies, health shocks have similarly moderate impacts on both men and women. There's one main feature that differentiates our setting –and generally that of low and middle-income countries– from high-income European countries. In Chile, adult caregiving is provided almost exclusively by families, whereas high-income countries are more likely to provide public long-term care services and have developed markets for

[11] Half of caregivers have provided care for at least 2 years and 30% provide care for at least 20 hours per week (Pickens et al. 2018).

formal care.[12] Our results suggest that care policies are relevant in determining how the burden of caregiving is allocated and show that gender norms matter for this allocation. The contrast between our findings and those for European countries is in line with recent work showing wide variation in child penalties by region (Kleven et al. 2023) and by GDP per capita (Aaronson et al. 2020).

We provide the first evidence that, in the absence of formal care, a parental health shock leads to a gender specialization within the family, increasing the earnings of men and reducing the earnings of women, thereby widening the existing gender pay gap. The vast majority of developing countries are facing an aging population with no substantive long-term care policies. Our work suggests that adult caregiving will play an important and growing role in maintaining and potentially expanding gender disparities in the labor market in the coming years.

The rest of the paper is organized as follows. Section 1 describes the institutional background of the labor market and adult caregiving. Section 2 describes the data. Section 3 lays out the methodology. Sections 4 and 5 present results for parental health and children's labor market outcomes. Section 6 discusses robustness analysis. Section 7 concludes.

1. Institutional Background

The rise in adult care needs is a global phenomenon (UN 2017). However, the conditions and capabilities employed to address it vary widely across countries and regions. In this section, we describe from a global perspective gender inequalities in the labor market, adult care needs and policies, and the distribution of adult care work in Chile. We further posit that the Chilean context is similar to that of other countries in the region and to overall lower and middle-income countries.

[12]For example, The Netherlands and Austria both spend over 1.5% of their GDP on long-term care services.

1.1. The Labor Market

Gender Disparities in the Labor Market. In Chile, as in other Latin American and lower and middle-income countries (LMICs), the labor market is characterized by wide gender disparities (Kleven et al. 2023). In 2019, the female labor force participation rate was roughly 55%. Latin American countries and LMICs show similar or lower rates, while high-income countries, the European Union, and the United States have rates at least 10 percentage points higher. The gender gap in labor force participation is around 30%, a larger gap than that observed for high-income countries. (Figure A1). The gender gap among employees in earnings is around 20% (IMF 2018).

Informal Employment. While informal employment accounts for half of employment in Latin America, the informal labor market share in Chile is around 27%, the lowest in the region (ILO 2023). Men and women exhibit similar rates of informal employment.

1.2. Adult Care

Care Needs. Worldwide, the share of the population aged 65 years or older has nearly doubled in recent decades (Figure A2). With an aging population, the prevalence of chronic diseases also rises. Chronic diseases tend to be of long duration and result in long-term health consequences and often create a need for long-term treatment and care. Currently, chronic diseases are the leading cause of death and disability in the world, disproportionally affecting low and middle-income countries (PAHO 2023). Chile is in an advanced stage of population aging, and chronic diseases account for over 85% of deaths and for 68% of its disability cases (PUC 2021).

Long-term Care Policies. In most countries, and particularly in low and middle-income countries, population aging is outpacing the development of long-term care policies and services. In most LMICs, public support plays little role in adult caregiving (Feng 2019). In Chile, public expenditure on long-term care amounts to 0.02% of GDP.[13] Public plus

[13] Other Latin American countries have broadly similar expenditures. For example, Uruguay and Argentina spend 0.04% and 0.05% on long-term care, respectively.

private provision of long-term care facilities covers less than 5% of the adult population with some degree of dependency, and there are no policies subsidizing formal home care.[14] This landscape contrasts with high-income countries. On average, OECD countries spend 1.7% of their GDP on long-term care. Countries such as the Netherlands, Sweden, and Norway allocate over 3% of their GDP to long-term care (OECD 2019). Policies in place include domestic help, social assistance, personal care, and nursing care (Rellstab et al. (2020) and Massner and Wikström (2023)).

Informal and Family-based Care. The lack of long-term care policies or markets makes families the main source of adult care (Feng 2019). In Chile, over 95% of adult caregivers are unpaid caregivers, and over 80% are household members. Children comprise half of caregivers caring for an adult in the same household, followed by spouses (30%) (Table 1). Within families, the majority of caregivers are women. Across the world, women carry out three-quarters of unpaid care work. However, the gender distribution of unpaid care varies by region. In Latin America and other LMICs, women comprise over 75% of caregivers (ILO 2019). In OECD countries, caregiving is distributed more equally. On average, 62% of caregivers are women, and the share of women caregivers does not exceed 55% in countries like Austria, The Netherlands, and Sweden (OECD 2021).

In Chile, because caregiving largely falls on adult children and predominantly on women, daughters are the most frequent caregivers for adults with dependency (ENDIDE 2022).[15] The main role of children as adult caregivers aligns with social beliefs about care. 68% of adults consider it the child's obligation to take care of a parent when the parent is unable to take care of themselves, and 60% believe that in these cases parents should live with children (*Bicentenario* Survey 2021). This responsibility is not perceived equally for sons and daughters: 40% of adults believe that daughters have a higher responsibility in parent care than sons, while 30% believe sons have a higher financial responsibility towards parents. This gender division between care support and financial support is more

[14]Caregivers of individuals with severe dependency are entitled to a monthly payment of US$40 only if they are not employed.

[15]Among children, 70% of caregivers are daughters.

pronounced in lower-income households (Herrera and Fernández 2013). In contrast, around 30% of people in European countries believe children should live with their parents when an elderly parent can no longer live without regular help. This figure is less than 10% in Nordic countries (Ruppanner and Bostean 2014).

1.3. Cancer

Incidence. Cancer cases have increased due to demographic changes and progress in other health conditions (Honoré and Lleras-Muney 2006). As age is the most important risk factor for developing cancer, the disease disproportionately affects individuals in the age group of 65 years and older, which comprises 60% of new cancer diagnoses and 70% of cancer deaths (Berger et al. 2006; Yancik 2005). Currently, cancer is the leading cause of death worldwide, accounting for nearly one in six deaths (WHO 2022). In Chile, it has been the leading cause of death since 2019 (INE 2019). Cancer incidence rates are projected to increase by 55% worldwide and by 75% in Chile between 2020 and 2040 (Cancer Research UK 2023; Atun 2023).

Care Needs. The economic and social costs of cancer arise not only from expenditures on treatment and the negative impact on the patients' employment and earnings (Gupta et al. 2015), but also from its impact on the patient's family and caregivers. Cancer patients often need assistance with daily task activities, medical care, and social and emotional support. Cancer increases dependency, disability, and the difficulty of daily activities (Table 2). If the illness worsens, care also intensifies. Time devoted to caregiving is particularly high during the last year of life (Berry et al. 2017).[16] In Chile, cancer patients account for almost half of all patients requiring palliative care (Pérez-Cruz et al. 2023). The characteristics of cancer caregivers are very similar to the characteristics of adult caregivers in general, as previously described.

[16] Hospital admissions, especially low-intensity admissions, also increase during the end of life (Zeltzer et al. 2023).

2. Data

We use comprehensive administrative data for the universe of individuals in the Social Household Registry (*Registro Social de Hogares*) of the Ministry of Social Development and Family in Chile. The Social Household Registry is the information system used by the Ministry to gather information about the country's residents with the aim of allocating social services, welfare programs, and other forms of public assistance. The registry is composed of several administrative databases from different sources plus self-reported information from households. It contains information for approximately 5 million households and 13 million people, representing 75% of the national population. Households excluded from the registry correspond to higher-income households. We rely primarily on three sources of information:

Hospital discharge records. Hospital discharge records from 2007-2019 contain data on hospitalization date, primary diagnosis, and length of stay for all hospitalizations in the country.

Vital statistics. Birth and death records up to 2022 include the date of birth, and the date and cause of death. Additionally, they contain parents' identification, allowing us to link parents to children.

Unemployment insurance records. Unemployment insurance records from 2006-2019 contain information on monthly employment and earnings for workers employed in the formal private sector.

Data construction. We build our treatment sample by identifying from hospital discharge records individuals hospitalized due to cancer. We define a health shock as the first cancer hospitalization a person experiences. We restrict our sample to individuals who had at least one child between 30 and 60 years old at the time of the first cancer hospitalization. Additionally, we restrict our sample to families in which we can identify both parents and in which all siblings share the same parents.[17] These restrictions allow us to identify treatment at the family level. We build a pure control sample by matching "treated" families –those with a parental health shock– to families similar in composition, educational level, and age where neither parent has had a cancer hospitalization. Using a coarsened exact matching, we match on family composition (number of children and number of daughters), parents' and children's educational levels, and on 5-year groups for parents' age and age at the birth of the first child. Finally, using unemployment insurance records, we build an individual panel of annual frequency that contains the employment and earnings of adult children in both treated and control families.

Our final sample consists of 8,162 treated families and 146,131 control families, with 14,045 treated adult children aged 30-60 years at the time of the parental health shock and 226,566 control children. The average family has 2.6 children, and fathers and mothers are on average 64 and 61 years old at the time of their first cancer hospitalization (Table A2). Adult children are on average 35 years old at the time of the parental health shock.[18] Our sample has low education: less than 30% of children have a college degree. The employment rate was 58% for sons and 37% for daughters one year before the parental health shock. Men and women had annual earnings of around US$7,200 and US$3,500 respectively. Control and treated children displayed similar employment rates and earnings before the parental health shock (Table A3).

3. Research Design

Treatment. In an experimental setting, to identify the causal impact of adult caregiving on labor market outcomes, we would randomly increase the care burden for treated families and compare their outcomes to control families where care needs haven't changed. In practice, we can identify the causal impact of adult caregiving by leveraging quasi-random variation in the need for care arising from severe health shocks. We define a health shock

[17] The share of births with data on both parents significantly drops for cohorts born before 1970. As a result, our sample primarily consists of children aged 30-45 at the time of the first parental cancer hospitalization (Figure A3).

[18] Figure A3 shows the distribution of age at the parental health shock for both children and parents.

as the first cancer hospitalization a person experiences.[19] We focus on cancer because it is a highly prevalent disease that substantially increases the need for care (Table 2). Unlike other chronic health conditions, cancer is an unanticipated event mostly unrelated to patients' behavior (Tomasetti and Vogelstein 2015; Tomasetti et al. 2017).[20] Age is the most important risk factor for cancer (National Cancer Institute 2023). Medical studies suggest that only between 30% and 50% of cancer cases are related to environmental factors (Tomasetti and Vogelstein 2015; Tomasetti et al. 2017; World Health Organization 2023). Among cancers primarily induced by environmental factors –such as smoking, alcohol consumption, diet, physical activity, infections, pollution, and occupational hazards–, cancer risk is highly correlated with socioeconomic status (Singh and Jemal 2017). Conditional on age and socioeconomic status, cancer can be thought of as a quasi-random event.[21]

Additionally, we focus on cancer hospitalizations to utilize health shocks that are severe enough to cause substantial variation in care needs.[22] According to this definition, cancer diagnoses that do not lead to hospitalization are not considered treatment in our setting. This excludes, for example, cancer cases that require only observation and no treatment or intervention, and thus do not modify care needs. However, this also excludes cases where the patient requires care but is never admitted to the hospital. We partially address this issue by removing cancer deaths from our control sample.[23] Parents with a cancer diagnosis who are never hospitalized and who survive the disease for at least 8 years are potentially included in our control sample. If cancer diagnoses increase care needs for this

[19]A similar approach with various definitions of health shocks has been used in recent studies to assess the effect of one's own health on labor market outcomes (Datta Gupta et al. 2015; Dobkin et al. 2018) and the effect of relative's health shocks on labor market outcomes –for example, to assess the impact of children's health shocks on parents' labor market outcomes (Breivik and Costa-Ramón 2022; Eriksen et al. 2021; Adhvaryu et al. 2023; Vaalavuo et al. 2023) and the impact of spouses' health shocks on the other spouse's labor market outcomes (Fadlon and Nielsen 2021; Jeon and Pohl 2017).

[20]For example, Fadlon and Nielsen (2021) show that households that eventually experience a stroke or a heart attack follow different employment trajectories than households that never experience these health events.

[21]This is, in fact, a stronger assumption than the conditional parallel trends assumption we need for identification.

[22]Dobkin et al. (2018) use non-pregnancy hospital admissions as "adverse health shocks" to study the economic consequences of hospital admissions for the person who endured the shock.

[23]We drop 2% of our control sample due to this decision as most individuals who die from cancer without a prior cancer hospitalization are older than our treatment sample.

group, our control sample can be partially treated, biasing our results downward towards a null effect.

Specification. We use a difference-in-differences event study approach to estimate the dynamic effect of a parental health shock on adult children's labor market outcomes. Because health shocks are staggered over time, we employ an estimator that is robust to heterogeneity across cohorts.[24] We use a stacked event study similar to that discussed by Gardner (2022) and applied by Cengiz et al. (2019). We organize our data in groups or stacks. Stacking serves two purposes in our setting. First, each stack is composed of treated and control units that are similar in family composition, educational level, and age Second, all treated units in the same stack received treatment in the same year. Leveraging only within-stack variation, we estimate effects only from "clean" comparisons between similar units.[25]

We set the year of the first cancer hospitalization as $t = 0$. Our baseline specification considers a balanced panel of adult children whom we observe every year for 5 years before the shock through 5 years after the shock. We study the evolution of employment and earnings as a function of event time. We exclude $t = -1$ from the regression, so all effects in $t \neq -1$ are measured relative to the year before the parental health shock. Specifically, we denote as Y_{ics} the outcome of interest for individual i in stack c in calendar year s. We estimate the following equation separately for men and women.

$$Y_{ics} = \sum_{t}^{T} \beta_t \cdot D_{ics}^t + \mu_i \times \eta_c + \delta_s \times \eta_c + \epsilon_{ics} \tag{1}$$

D_{ics}^t is equal to 1 if s is t years since i's health shock, $\mu_i \times \eta_c$, and $\delta_s \times \eta_c$ represent unit-by-stack and year-by-stack fixed effects, respectively. We cluster standard errors at

[24] With staggered treatment, the standard dynamic difference-in-differences specification only delivers a sensible causal estimand under strong assumptions. If there are heterogeneous effects across cohorts, then the standard specification is subject to issues of negative weights and cross-lag contamination (Roth et al. 2023).

[25] A "forbidden", as opposed to a "clean" comparison, uses units already treated as controls (Borusyak et al. 2023).

the family level as this is the level at which treatment is assigned.[26] Moreover, clustering at the family level accounts for the fact that a control family can act as control for multiple treated families if these share the same characteristics but are treated in different years. We weight control units to match the number of treated units in each stack. Additionally, our preferred specification includes a full set of age dummies to control non-parametrically for life-cycle trends. We show in Section 6 that the results are robust to alternative specifications.

We estimate equation 1 separately for men and women, obtaining $\hat{\beta}^g$ with $g = \{\mathrm{m}, \mathrm{w}\}$, where m and w stand for men and women respectively. A relevant share of our sample –especially women– has zeros in the main outcomes due to non-participation in formal employment. To include this information, we estimate equation 1 in levels and rescale $\hat{\beta}^g$ to present results in percentages. Following Kleven et al. (2019), we compute:

$$P_t^g \equiv \frac{\hat{\beta}_t^g}{E[\tilde{Y}_{ics}^g | t]}$$

where $\tilde{Y}_{ics}^g \equiv \hat{Y}_{ics}^g - \hat{\beta}_t^g$. D_{ics}^t represents the change in the outcome relative to the counterfactual, which is the estimated outcome in the absence of a parental health shock. Additionally, we compute adult care penalties as:

$$P_t \equiv \frac{\hat{\beta}_t^m - \hat{\beta}_t^w}{E[\tilde{Y}_{ics}^w | t]} \tag{2}$$

P_t represents how much daughters are impacted by a parental health shock relative to sons. In addition to 1, we present results for a standard difference-in-difference specification (equation 3) that estimates average effects for our full period of analysis. In this equation, D_{ics} is equal to 0 for pre-treatment periods (–5 to –1) and to 1 for post-treatment (0 to

[26]This follows from the design-based approach that recommends clustering standard errors at the level at which treatment is independently assigned (Roth et al. 2023).

+5). We use this specification to summarize our main results or to show results for specific samples.

$$Y_{ics} = \beta \cdot D_{ics} + \mu_i \times \eta_c + \delta_s \times \eta_c + \epsilon_{ics} \tag{3}$$

The validity of our specification relies on a conditional parallel trends assumption. In this setting, this means that, conditional on family composition and socioeconomic status, the labor market outcomes of working-age children exposed to a parental health shock would have evolved similarly to the labor market outcomes of control children in the absence of the shock. If the occurrence of a parental health shock were correlated with changes in children's labor market outcomes, for instance, if cancer occurs in families with more unhealthy behaviors that in turn affect the evolution of children's labor market performance, the parallel trends assumption would not be valid.

In Section 5, we show visual and statistical evidence for the plausibility of the parallel trends assumption in our setting. Additionally, in Section 6 we show that our results are robust to restricting the analysis to a sub-sample of treated units for which the identifying assumption is more likely to hold. Furthermore, we show that our results are also robust to a weaker version of the parallel trends assumption: that only cancer timing and not cancer occurrence is uncorrelated with the evolution of outcomes.

A second assumption needed for identification is the no-anticipation assumption. This means that a parental health shock does not affect children's labor market outcomes prior to $t = 0$. In our setting, if a parental cancer diagnosis increases care needs before the year of the first cancer hospitalization, this would constitute a violation of the no-anticipation assumption and would lead to an underestimation of the causal effect of the parental health shock, under the assumption that anticipation effects have the same sign as post-shock effects (Malani and Reif 2015). While it is certainly possible that care needs increase before the first parental cancer hospitalization, we show in Section 5 that there's no evidence of relevant anticipation effects in our setting. Additionally, in Section 6, we show that our results are robust to using a different reference period and restricting the analysis to a subset of cancer cases for which anticipation is less likely to occur.

4. Impacts on Parental Health

We estimate the impact of a health shock on two measures of parental health: hospitalizations and mortality, separately for men and women.

Hospitalizations. Days hospitalized spike the year of the first cancer hospitalization (Figure 1, panel (a)). Fathers and mothers spent, on average, 14 and 10 more days in the hospital than control parents during this year, respectively. Hospitalizations decrease after $t = 0$ and return to pre-treatment levels two years later. Treated and control parents exhibit similar trends in hospitalization before the health shock, with a slight increase from $t = -2$ to $t = -1$ for treated parents, suggesting that some health issues related to cancer might appear a few months before the first cancer hospitalization. However, this difference represents only 2.7-6.3% of the change between $t = -1$ and $t = 0$. Control and treated parents display similar trends from $t = -5$ to -2.[27]

Mortality. Upon a parental health shock, mortality rates jump by 18 percentage points for fathers and by 12 percentage points for mothers (Figure 1, panel (b)). Parental mortality keeps increasing in the following years at a decreasing rate. Five years after the health shock, mortality rates are higher for treated parents by 35 and 25 percentage points for fathers and mothers respectively.

A cancer hospitalization is a severe health event that significantly deteriorates an individual's health and substantially increases the likelihood of death. In the case of cancer, death is usually preceded by a period of deterioration, where care needs intensify.

5. Impacts on Children's Labor Market Outcomes

Figure 2 plots the average employment rate and earnings of treated and control children, separately for men and women, during an 11-year period centered on the year of the parental health shock. Treated and control children have similar labor market outcomes

[27] In Section 6 we provide evidence showing that any potential anticipation doesn't affect our results.

–both in levels and trends– prior to the shock. The parental health shock does not seem to modify labor trajectories for sons. However, the case is different for daughters. Upon a parental health shock, daughters' employment and earnings fall immediately. A gap between treated and control daughters emerges and remains quite stable during the following five years. Building on this comparison, we estimate equation 1, which allows us to obtain estimates from within-stack variation and control non-parametrically for age. Treated and control children display similar trends in employment and earnings before the parental health shock.[28] Daughters' employment and earnings immediately fall by 2.5% upon the shock, with no sign of recovery. Five years after the shock, daughters' employment and earnings are 2.5% and 5% lower, respectively. Sons do not face any reduction in employment or earnings after a health shock. Instead, sons' earnings increase post-shock, although the increase is not statistically significant for most years (Figure 3).[29] The average reduction in daughters' employment and earnings during the 5 years following the parental health shock are 3.3% and 3.8%, respectively. Sons' employment and earnings increase, on average, by 0.4% and 1.5% (Table 3).[30]

Five years post-health shock, P_5 –the percentage by which daughters fall behind sons after a parental health shock– is 5% for employment and 11% for earnings (Table 4). These penalties are sizeable. They amount to 40% and 58%, respectively, of the child penalties estimated for Denmark (Kleven et al. 2019). In our sample, a parental health shock increases the gender gap in earnings by 4 percentage points, equivalent to a 9% increase.

5.1. Daughters as Providers of Care

Our results are consistent with daughters undertaking most of the care caused by a parental health shock and facing a penalty in the labor market as a result of adult caregiving. In this section, we provide evidence that indicates that unpaid caregiving is the main driver

[28] Table 3 jointly tests for pre-trends, separately for men and women.

[29] Figure A4 shows results in levels instead of percentages.

[30] For sons, the impact on employment is not statistically different from zero. The impact on earnings is statistically significant at the 10% level. Table A7 shows the same results in levels instead of percent changes.

of our results. In particular, we show that the labor market impact on daughters is larger when the care burden is higher.

By Care Burden. The amount of care that cancer patients need can vary widely. Cancer –even within the same diagnosis– can have different impacts on patients' levels of dependency due to differences in symptoms and the evolution of the illness. We present results separately by a measure of shock intensity or persistence: cancer re-hospitalization. In our sample, 40% of parents with a cancer hospitalization faced multiple hospitalizations due to the disease. Treated families with sick a parent who experienced one or multiple cancer hospitalizations share similar characteristics (Table A4). The health shock affects both groups at a similar age, and children in each group had broadly similar employment and earnings prior to the shock. However, parents with one cancer hospitalization faced a very different evolution of their health status than parents who experienced multiple hospitalizations. Parents with multiple cancer hospitalizations had lower mortality rates at time t_0 but their mortality increased continuously from t_1 onward (Figure 4).[31] Five years post-health shock, mortality rates were more than 10 percentage points higher for parents with multiple cancer hospitalizations relative to parents with a single cancer hospitalization.[32]

These differences imply different care burdens. For the group with a single cancer hospitalization, whether because the disease worsens rapidly, leading to death, or because the patient recovers or stabilizes, the total demand for adult care is lower. For the group with multiple hospitalizations, there is a more gradual decline in health status, consistent with a situation in which the demand for care is present and increased for a longer time.

The average results for children's labor market outcomes mask substantial heterogeneity by the number of parental cancer hospitalizations (N_h). For cases with $N_h = 1$, although daughters' employment falls, the reduction is smaller and there are no statistically significant differences between sons and daughters (Figure 5, panels (a) and (c)). On the other hand, for cases with $N_h > 1$, daughters experience larger and long-lasting impacts both on

[31] Parents who were re-hospitalized also spent more time in the hospital, considering both cancer and non-cancer hospitalizations (Figure 4).

[32] These patterns are in line with evidence showing that predicting mortality within diagnosis is difficult, and that hospitalizations increase during the end of life (Zeltzer et al. 2023).

employment and earnings (Figure 5, panels (b) panel (d)). For those with multiple cancer hospitalizations, employment is persistently 5% lower after a health shock and earnings decrease between 5% and 15%. The penalty P_5 for this group reaches 11% for employment and 17% for earnings.

A health shock that leads to multiple hospitalizations can be understood as a more persistent or severe health shock. However, since re-hospitalizations are, by definition, a result of treatment, conditioning our analysis on re-hospitalization might introduce bias if there are any confounders that affect both re-hospitalization and children's labor market outcomes (Roth et al. 2023). To address this concern, we complement the previous analysis by examining results separately for diagnoses with high and low re-hospitalization rates.[33] We find the same pattern: the fall in daughters' employment and earnings after a parental health shock is driven entirely by cancer diagnoses with a high re-hospitalization rate (Figure A5).[34] Similarly, diagnoses with a high re-hospitalization rate also lead to higher hospitalizations and cumulative mortality (Figure A6).

As effects are larger for cases with a higher care burden, we expect results to be smaller or non-existent for cases with a lower or no care burden. When the parent dies within a month from the first cancer hospitalization, there's no decline in daughters' labor market outcomes (Figure A10, panels (a) and (c)).[35] Similarly, the sudden death of a parent by a stroke or a heart attack does not decrease daughters' employment or earnings (Figure A9).[36]

Finally, we compare cancer to other health shocks that create a lower demand for adult caregiving. We estimate the effect of parental strokes and heart attacks on children's labor market outcomes, excluding sudden deaths from these events.[37] We find no evidence that

[33] We compare the top 40% and bottom 40% of diagnoses by re-hospitalization rate using 4-digit ICD-10 codes. Table A6 shows the types of cancer with high and low re-hospitalization rates and the actual rate of re-hospitalization for each group.

[34] The difference between diagnoses groups is less pronounced than the differences by re-hospitalization as diagnoses do not predict re-hospitalization perfectly (Table A6).

[35] As cases where the parent dies within a month from the first hospitalization are infrequent, the effects are not precisely estimated.

[36] We define a sudden death as one caused by a heart attack or a stroke for a person who had no hospitalizations during the previous year.

[37] We drop from the sample used for these estimations the cases in which a parent died one month or less after their first hospitalization due to a stroke or a heart attack.

reductions in children's employment or earnings arise from these health shocks (Figure A8). The absence of costs for children –and especially daughters– in these cases is consistent with the smaller impact these shocks have on parental health relative to cancer and, thus, the smaller impact on care needs. Non-fatal strokes and heart attacks have smaller effects on subsequent mortality than cancer cases with a single cancer hospitalization (Figure A7).[38]

Taken together, these results show that daughters pay a cost in employment and earnings after a parental health shock that increases the demand for adult caregiving. Given that only health shocks that increase the demand for adult caregiving negatively impact daughters' labor market outcomes, these results are consistent with unpaid caregiving being the mechanism that drives our results. Health shocks that create an ongoing need for care, particularly end-of-life care, seem to be particularly costly for daughters.

5.2. Sons as Providers of Financial Resources

Our results rule out the possibility that sons, on average, bear any labor market costs associated with a parental health shock, as is the case for daughters. However, the results extend further, indicating that sons experience an increase in their earnings after a parental health shock. Sons' earnings increase on average by 1.5% between 0-5 years after the health shock.[39] This effect is driven mostly by men with low employment and earnings. We divide our sample into terciles defined by the pre-shock employment rate of men and women separately. Men with high employment before the parental health shock do not experience any effects on employment or earnings (Figure 6, panels (b) and (d) on the right). On the other hand, men with low employment experience a sizable increase in employment and particularly in earnings (Figure 6, panels (a) and (c) on the left). Earnings are 20% to 40% higher 3 to 5 years after the shock.[40] Among low-employment men and women, a

[38]Additionally, even in a context of family-based adult care, adults with nervous or circulatory system conditions are more likely than cancer patients to be institutionalized (Table A5).

[39]This coefficient is statistically significant at the 10% level.

[40]Women face negative effects in both groups (high and low previous employment). However, the relative impact is larger for lower-employment women, although it is less precisely estimated due to higher rates of non-participation. For the same reason, the effects for men are also less precisely estimated in the low-employment group.

parental health shock increases the gender gap in earnings by 10 percentage points.

Cancer is a costly health shock that generates direct and indirect costs and can be financially destabilizing for poor families. Direct costs include treatment and indirect costs include loss of earnings by either patients, caregivers, or both (Gupta et al. 2018). The behavior of sons is consistent with the need to cover costs related to cancer, which is more pressing in families facing tighter financial constraints.[41]

A parental health shock contributes to gender inequality through two different channels, especially in the lower-income population. First, the rise in care needs reduces daughters' employment and earnings due to adult caregiving. Second, the need for extra financial resources increases sons' employment and earnings. A health shock forces a gender specialization in which women are the main care providers and men are the main financial providers.

5.3. What Explains the Disproportionate Impact on Women?

There are two possible explanations for the disproportionate burden of adult caregiving borne by women. The first is that women have, on average, a lower opportunity cost of informal care than men due to their lower earnings. According to Becker-style models, women should thus allocate more time than men to informal care (Becker 1973, 1974). The second relates to gender norms. Norms can be understood as collective definitions of socially approved conduct, stating rules or ideals; and gender norms are such definitions applied to distinctions between women and men (Pearse and Connell 2016). Regarding caregiving, traditional gender norms dictate that women should provide care, even conditional on opportunity costs (González et al. 2022).[42] In economic literature, gender norms matter for behavior if adherence to norms or stereotypes of one own's group enters the utility function (Akerlof and Kranton 2000; Bertrand 2020). To evaluate the importance of these

[41] Schaller and Eck (2023) find an increase in children-to-parent financial transfers when parental health worsens for the United States.

[42] This concept refers to a broad phenomenon that includes expectations, preferences, responsibilities, and perceptions. It encompasses situations ranging from explicit obligations or responsibilities to cases where women prefer to provide care over men, or where they engage more in care work because they are believed to be better caregivers.

factors, we assess whether women experience penalties after a parental health shock even in cases where they do not have lower opportunity costs, which would suggest a role for traditional gender norms in allocating adult caregiving.

We show the results from equation 3 separately for four groups: individuals who earned more than their partners; individuals who earned less than their partners; individuals who earned more than their siblings; and individuals who earned less than their siblings (Figure 7).[43] Women in all groups are negatively affected by a parental health shock, even in cases where there is a lower-earning partner or sibling. In contrast, in none of these groups did men face reductions in employment or earnings. When men are the lower-earner within a family –either relative to a partner or to siblings– they respond to a parental health shock by increasing their employment and earnings.[44]

These results rule out a model in which opportunity costs entirely define the allocation of adult caregiving to women as women bear the costs of caregiving even in cases where they have higher opportunity costs. This suggests that gender norms play a role in determining who provides adult care within families. These results are in line with what has been found for child penalties (Andresen and Nix 2022) and for the overall division of domestic work among couples (Akerlof and Kranton 2000; Bertrand et al. 2015).

The overall pattern of gender specialization coming from adult care resembles the impact that children have on new parents' labor market outcomes. As a last step, we investigate whether the costs of parent care are distributed differently between children who are and are not parents themselves. The negative (positive) effects of a parental health shock for women (men) are concentrated in the subsample of children who are parents (Figure 8). For the subsample of children who do not have kids, the effects are smaller, not statistically significant, and similar between men and women. The concentration of the effects of adult caregiving on children who have kids suggests a correlation between caregiving across the life course. When families are faced with adult care needs, it is more likely that adult care will fall on women who already have cared for children.

[43] We identify partners through marriage data. 22% and 26% of the sons and daughters in our sample are married, respectively. Table A9 compares the main results from equation 3 for the sample of adult children with partner information to the full sample.

[44] As cases with men as the lower-earner are infrequent, most of these results are not precisely estimated.

6. Robustness and Sensitivity Analysis

Validity of Identifying Assumptions. For $\hat{\beta}_t^g$ to identify the causal dynamic impact of a parental health shock on children's labor market outcomes, we need two identifying assumptions: the parallel trends assumption and the no-anticipation assumption.

We rely on a conditional parallel trends assumption: among working-age children of similar socioeconomic status, the occurrence of a parental health shock is uncorrelated with the evolution of labor market outcomes. This assumption seems plausible as treated and control children display very similar employment rates and earnings –both in levels and trends– during the five years we observe prior to the parental health shock (Figure 2). We test for differences in pre-treatment periods and find that all pre-treatment coefficients are insignificant (Figure 3). Moreover, we can't reject the null hypothesis of no pre-trends in a joint test considering all pre-treatment coefficients (Table 3).

However, recent literature has highlighted the limitations of the standard pre-trends analysis. The absence of pre-trends does not guarantee post-treatment parallel trends, and pre-tests usually suffer from low power and thus may not be able to detect existing pre-trends (Roth 2022). In our setting, the parallel trends assumption would be violated if there are confounding factors correlated with both the incidence of parental health shocks and the evolution of children's labor market outcomes. For example, if children from families affected by cancer have poorer health habits or are more exposed to environmental pollution compared to children from unaffected families, these disparities could independently affect their labor market outcomes.[45] In these scenarios, our estimates would be biased as they would also reflect differences in these confounding factors.

We present two pieces of evidence to show that our results are not driven by differential trends between treated and control units. First, we estimate equation 1 using only the subset of cancer types that are mostly unrelated to lifestyle and environmental factors.[46] Our

[45] For example, Graff Zivin and Neidell (2012) and He et al. (2019) show that pollution affects workers' productivity, and Stephens and Toohey (2022) and Schilbach (2019) show that health and alcohol consumption can affect economic outcomes, respectively.

[46] This analysis excludes cervical, esophagus, head and neck, lung, melanoma, and stomach cancer, as defined by Tomasetti et al. (2017).

results are robust to excluding cancer types that are more related to behavior and factors potentially related to labor market outcomes (Figure A11). Second, we estimate equation 1 using only families affected by cancer as both treated and control units. In this case, instead of using pure controls as control sample, we use not-yet-treated individuals as controls and exploit variation in the timing of the parental health shock for identification. For individuals treated in year t, individuals treated in $t+6$ act as controls.[47] Deriving our estimates from comparisons within families affected by cancer yields the same results (Figure A12). These analyses suggest that differential trends between treated and control individuals are not driving our results and support the validity of our identifying assumption.

Regarding no-anticipation, we present two analyses to argue that anticipation is not an issue in our setting. We show that our results are robust to excluding cases with a parental hospitalization in $t = -1$ (Figure A13) and treated units for which the first parental cancer hospitalization takes place between January - March (Figure A14). These two cases are most likely to be potentially affected by anticipation. Additionally, the average effect of a parental health shock is similar if we use $t = -2$ instead of $t = -1$ as the reference period (Table A10).

Alternative Mechanisms. Even if the identifying assumptions are valid, the causal impact of a parental health shock on children's labor market outcomes could not reflect the effect of caregiving if the shock affects labor market outcomes through other channels. Parenthood is the main factor behind gender disparities in the labor market (Kleven et al. 2019). If a parental health shock affects parenthood or child penalties, then our estimates would not represent a causal effect of adult caregiving. We present evidence supporting that adult caregiving is the main driver behind our results. In particular, we rule out that our findings are driven by changes in childcare access or parenthood status.

Especially in developing countries, grandparents –and primarily grandmothers– are a relevant source of informal childcare. Therefore, a parental health shock could affect

[47] For this exercise, we define stacks only by the year of the first parental cancer hospitalization. The year of the first parental cancer hospitalization is defined as $t-6$ for controls.

daughters' labor market outcomes by reducing informal childcare provision.[48] We present two pieces of evidence that rule this out. First, we show that the effects of a parental health shock do not differ based on the presence or absence of a child aged 0-6 years at the time of the parental health shock, which is the group most in need of child care (Figure A15). Second, the sudden death of a parent –an event that reduces childcare provision but does not increase parental care needs– does not affect the labor market outcomes of sons or daughters (Figure A9).

Additionally, we rule out that the impact of a parental health shock on children's labor market outcomes is mediated by changes in fertility.[49] The birth of the first child decreases (increases) women's (men's) employment and earnings (Angelov et al. 2016; Kleven et al. 2019; Goldin et al. 2022). If a parental health shock affects children's fertility –especially the birth of the first child– this could, at least partially, explain our results. We estimate equation 1 using parenthood as an outcome. A parental health shock does not affect children's parental status (Figure A16).

Alternative Specifications. Our results are robust across various alternative specifications. In our preferred specification, we rely only on within-group variation –where groups are composed of families similar in composition, age, and socioeconomic status– and we control nonparametrically for age. However, our results are robust to using between and within-group variation, and excluding control variables. The main gain from leveraging only within-group comparisons is precision (Table 3).[50] Similarly, the dynamic effects of a parental health shock are robust to alternative choices regarding weights (Figure A17) and control variables (Figure A18).

Lastly, we present results using various dynamic differences-in-differences methods recently discussed in the literature. In particular, we compare the results from our preferred specification to a stacked event study without matching on covariates, to the Callaway &

[48] Talamas (2023) shows that after the death of a cohabiting mother, women with children aged 0-6 years old reduce their employment by 12 p.p. in Mexico.

[49] Income shocks affect fertility decisions (Alam and Pörtner 2018; Huttunen and Kellokumpu 2016). A parental health shock could thus affect fertility.

[50] Tables A7 and A8 show the same results for equations 1 and 3, respectively, in levels.

Sant'Anna estimator, and to the de Chaisemartin & D'Haultfoeuille estimator. In our setting, all four estimators use never-treated units as controls and differ only in the weights used for aggregation and the variation used for estimation –only within families similar in covariates or between different families (Roth et al. 2023). Our results are robust to the choice of a particular method (Figure A19).

7. Conclusion

Progress in narrowing the gender pay gap has stagnated in recent decades, despite the disappearance of gaps in education-related (Blau and Kahn 2017). In this context, the unequal distribution of unpaid care has emerged as a central explanation for current gender disparities in the labor market. In recent years, several studies have established that women pay high and persistent penalties associated with motherhood (Angelov et al. 2016; Kleven et al. 2019; Goldin et al. 2022; Cortés and Pan 2023). Meanwhile, the role of adult caregiving in shaping gender disparities in the labor market remains largely unexplored.

Adult caregiving is increasing rapidly due to an aging population. In most of the world, adult care is provided almost exclusively by families. Most countries, especially low and middle-income countries, are facing rising adult care demands relying primarily on families for care provision, in the absence of long-term care policies or well-developed markets (Feng 2019).

In this study, we show that adult care affects gender disparities in the labor market. We center the analysis on working-age children who provide care to a sick parent. Using data for 75% of the Chilean population and a difference-in-differences event study design, we show that a parental health shock –the first parental cancer hospitalization– leads to a gender specialization within families. Daughters face reductions in their employment and earnings, while earnings are unaffected or even increase for sons. The penalties that arise from adult caregiving are both sizable and comparable to the child penalties estimated in the literature. A parental health shock increases the gender gap in earnings by 4 percentage points, equivalent to a 9% increase. Within low-employment population, the increase reaches 10 percentage points.

We also show that differences in opportunity costs alone cannot explain the disproportionate impact of adult caregiving on women, suggesting that gender norms influence the allocation of care work within families. Moreover, care work is mostly concentrated among daughters who are mothers, suggesting that care work is correlated across the life cycle, especially between child care and parent care.

When adult caregiving falls mostly on families, it has the potential to widen gender disparities in the labor market. This contrasts with recent findings for European countries with high expenditure on long-term care where adult caregiving does not contribute to gender disparities and has overall null to moderate impacts on labor market outcomes.

Our work underscores the importance of considering how undergoing demographic changes impact gender inequality in the labor market, particularly in low and middle-income countries, and for lower-income populations. As the burden of adult care will only intensify in the coming decades, adult caregiving is likely to become an increasing source of gender inequality in the labor market, with the potential to slow down or even reverse progress made toward the convergence of earnings between men and women.

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8. Tables and Figures

TABLE 1. Distribution of Caregivers by Relationship with Care Recipient. Adults over 50 Years with Moderate to Severe Dependency

Relationship with Care Recipient	Percentage
Children	49.18%
Spouse or partner	25.13%
Siblings or siblings-in-law	5.51%
Grandchildren	5.00%
Other relatives	8.79%
Other non-relatives	4.37%
Personal health service	1.11%
Domestic Service	0.92%

Notes: Numbers in each row represent percentages over the total population of adults over 50 years old with moderate to severe dependency who receive help from at least one person due to their health status. Own calculations based on data from the Disability and Dependency Survey (ENDIDE) 2022, Ministry of Social Development and Family.

TABLE 2. Measures of Care Needs by Cancer Diagnosis, Adults over 50 Years

	Adults with a Cancer Diagnosis	Adults without a Cancer Diagnosis
A. Dependency		
No dependency	83.87%	66.22%
Mild to moderate dependency	10.95%	20.48%
Severe dependency	5.19%	13.30%
B. Disability		
No disability	74.03%	50.58%
Mild to moderate disability	6.98%	7.66%
Severe disability	18.99%	41.77%
C. Level of difficulty in daily activities		
No difficulty	14.03%	3.98%
Mild to moderate difficulty	62.27%	47.06%
Severe difficulty	23.70%	48.96%

Notes: Numbers in each panel represent percentages over total population (adults over 50 years with a cancer diagnosis and adults without a cancer diagnosis over 50 years). Own calculations based on data from the Disability and Dependency Survey (ENDIDE) 2022, Ministry of Social Development and Family.

TABLE 3. Effect of Parental Health Shock on Adult Children's Labor Market Outcomes. Dynamic Event-study

	Employment Rate			Earnings		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Sons						
Pre-trends	0.003	0.003	0.003	0.004	0.002	0.002
	(0.007)	(0.006)	(0.006)	(0.010)	(0.007)	(0.007)
Average effect	0.002	0.004	0.004	0.012	0.015*	0.015*
	(0.007)	(0.005)	(0.005)	(0.012)	(0.008)	(0.008)
Mean at baseline	0.58	0.58	0.58	8,691	8,691	8,691
Observations	1,274,240	1,274,240	1,274,240	1,274,240	1,274,240	1,274,240
Panel B: Daughters						
Pre-trends	0.008	0.008	0.008	-0.008	-0.008	-0.008
	(0.011)	(0.008)	(0.008)	(0.014)	(0.009)	(0.009)
Average effect	-0.031***	-0.033***	-0.033***	-0.038**	-0.038***	-0.038***
	(0.011)	(0.008)	(0.008)	(0.016)	(0.011)	(0.011)
Mean at baseline	0.37	0.37	0.37	4,212	4,212	4,212
Observations	1,372,481	1,372,481	1,372,481	1,372,481	1,372,481	1,372,481
Matching		✓	✓		✓	✓
Controls			✓			✓

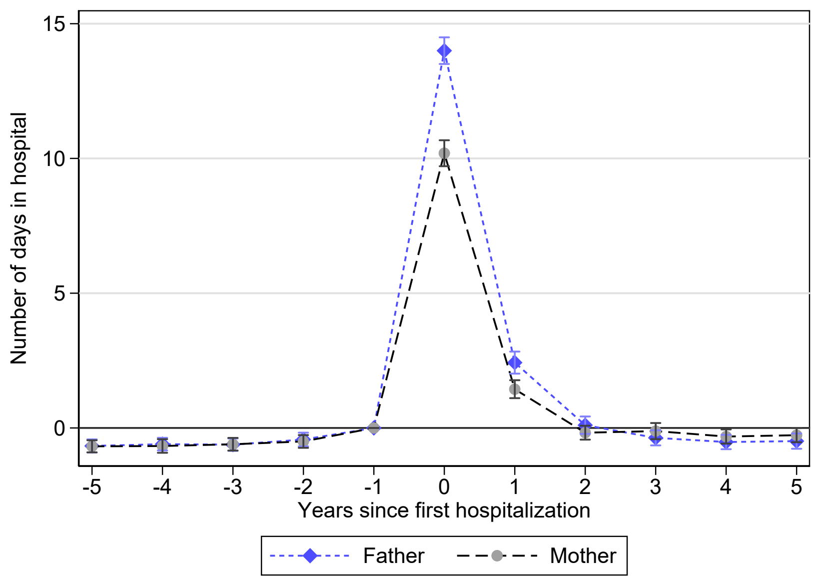
Note: Estimates from equation 1 varying controls and fixed effects. Pre-trends is the average effect for $t = \{-5, -4, -3, -2\}$. Average effect considers $t = \{0, 1, 2, 3, 4, 5\}$. Estimates correspond to P_t^m for men and P_t^w for women as defined in Section 3. Estimates represent percent changes. All specifications include two sets of fixed effects: individual × stack, and year × stack. In columns (1) and (4) stacks are defined only by the year of treatment. When matching is indicated, stacks are defined by year of treatment and socio-economic characteristics. When controls are indicated, age dummies are used to control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. *, **, and *** indicate statistical significance at the 90%, 95%, and 99% percent level. Earnings (mean at baseline) are measured in US dollars (annual exchange rate in 2014 = $CH 570,01 (source: Central Bank of Chile)).

TABLE 4. Labor Market Penalties from Adult Caregiving

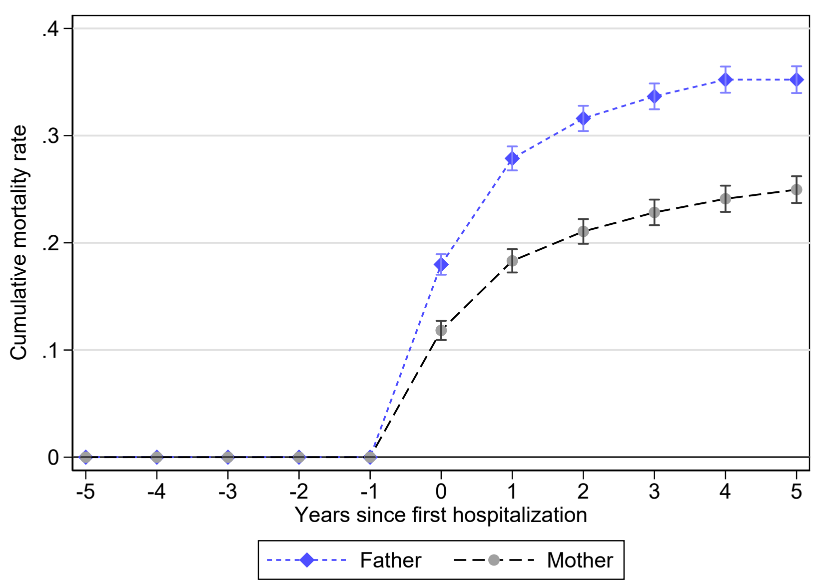
Period	$\hat{\beta}_t^m$	$\hat{\beta}_t^w$	$\hat{\beta}_t^m - \hat{\beta}_t^w$	$E[\tilde{Y}_{icst}^w \mid t]$	P_t
Panel A: Employment rate					
-5	-0.001	0.002	0.003	0.356	0.008
-4	0.001	0.004	0.003	0.360	0.007
-3	0.002	0.004	0.002	0.360	0.005
-2	0.004	0.002	0.003	0.361	-0.007
-1				0.362	
0	-0.003	-0.010	0.006	0.364	0.017
1	-0.003	-0.012	0.009	0.367	0.025
2	0.001	-0.015	0.015	0.369	0.042
3	0.002	-0.010	0.012	0.373	0.033
4	0.005	-0.013	0.018	0.377	0.048
5	0.008	-0.011	0.019	0.382	0.049
Panel B: Earnings					
-5	-49.3	-67.6	18.3	3,907	0.005
-4	60.4	-26.5	86.9	4,070	0.021
-3	15.6	-19.0	34.6	4,209	0.008
-2	42.0	-25.3	67.3	4,346	0.015
-1				4,475	
0	9.8	-115.9	125.7	4,597	0.027
1	80.5	-185.3	265.6	4,710	0.056
2	99.4	-173.6	273.0	4,810	0.057
3	134.6	-140.8	275.4	4,903	0.056
4	181.8	-253.4	434.9	4,991	0.087
5	326.9	-231.8	558.4	5,070	0.110

Note: The table shows the estimates needed to compute labor market penalties as defined by equation 2. $\hat{\beta}_t^m$ and $\hat{\beta}_t^w$ correspond to estimates from equation 1 for men and women respectively, for each period. $E[\tilde{Y}_{icst}^w \mid t]$ is the predicted outcome for women in the absence of the parental health shock, which is used to scale the results. All estimates come from regressions controlling non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. *, **, and *** indicate statistical significance at the 90%, 95%, and 99% percent level. Earnings are measured in US dollars (annual exchange rate in 2014 = \$CH 570,01 (source: Central Bank of Chile)).

Figure 1. Effect of a Parental Health Shock on Parental Health



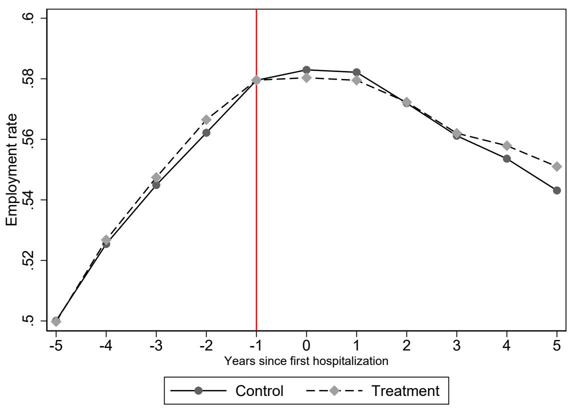
(a) Days in Hospital



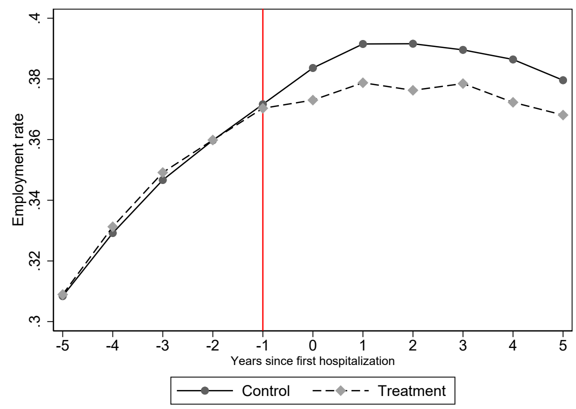
(b) Mortality

Note: Estimates from equation 1. Outcomes are measures of parental health. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

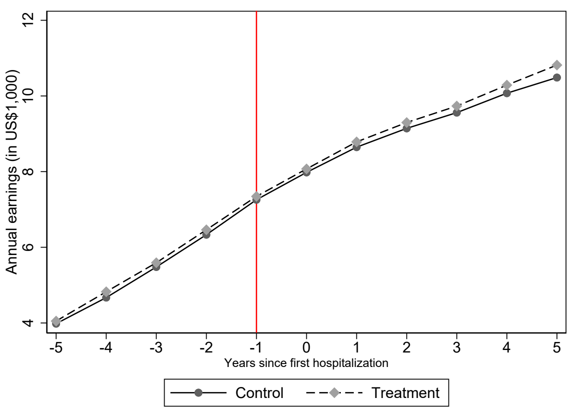
Figure 2. Average Employment and Earnings of Adult Children by Gender and Treatment Status over Time



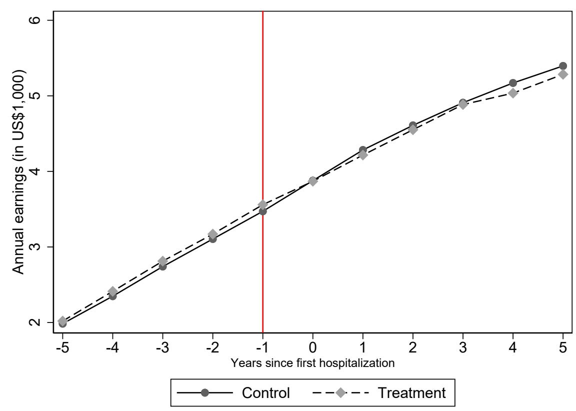
(a) Employment rate, Men



(b) Employment rate, Women



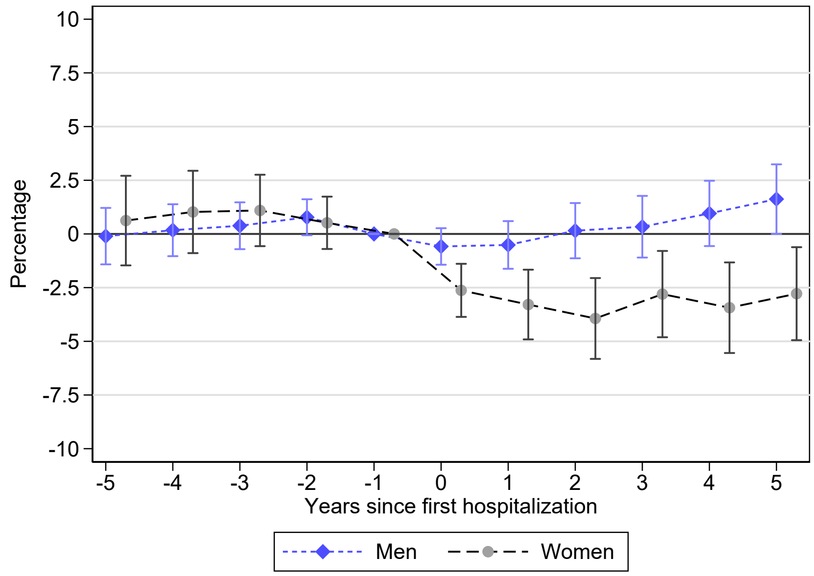
(c) Annual earnings, Men



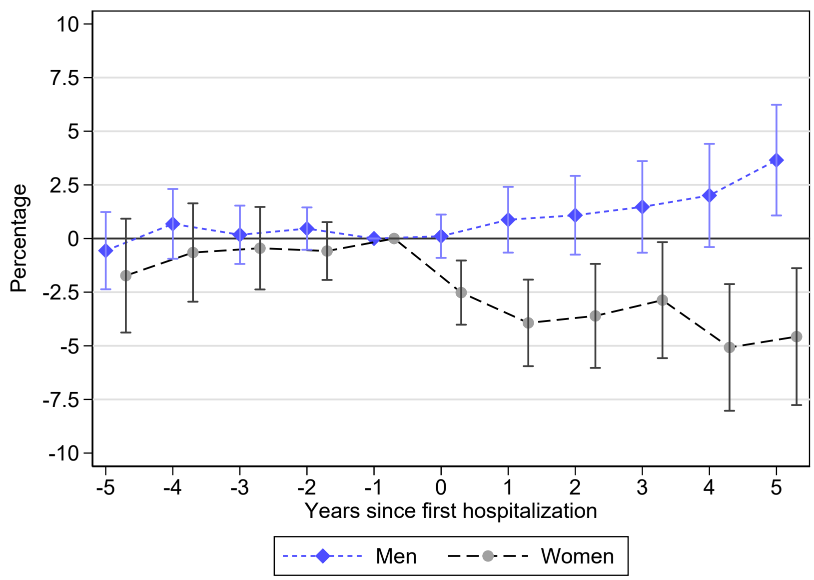
(d) Annual earnings, Women

Note: Estimates from equation 1. Outcomes are labor market outcomes for children. Panel (a) and (c) are estimates for cases with one cancer hospitalization ($N_h = 1$). Panel (b) and (d) are estimates for cases with multiple cancer hospitalizations ($N_h > 1$). All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

FIGURE 3. Effect of a Parental Health Shock on Adult Children's Labor Market Outcomes



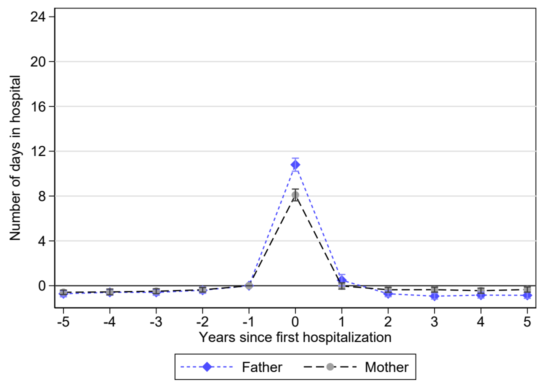
(a) Employment rate



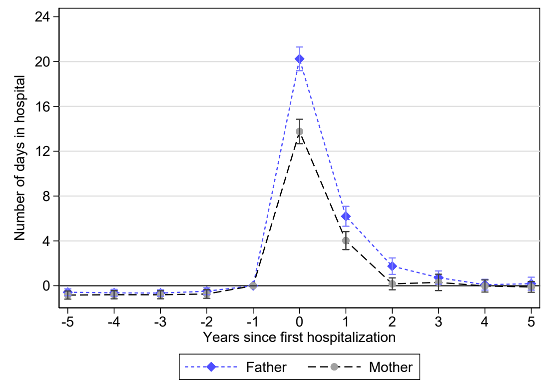
(b) Annual earnings

Note: Estimates from equation 1. Outcomes are labor market outcomes for children. Estimates correspond to P_t^m for men and P_t^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

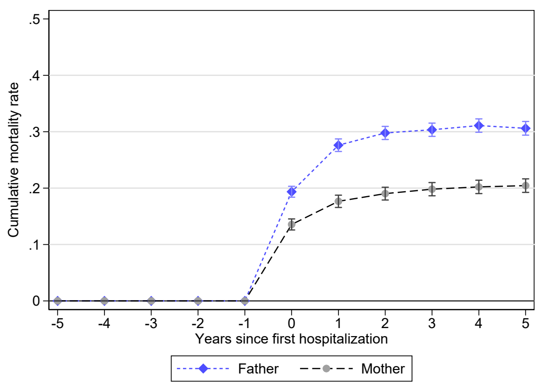
Figure 4. Effect of a Parental Health Shock on Parental Health by Re-hospitalization



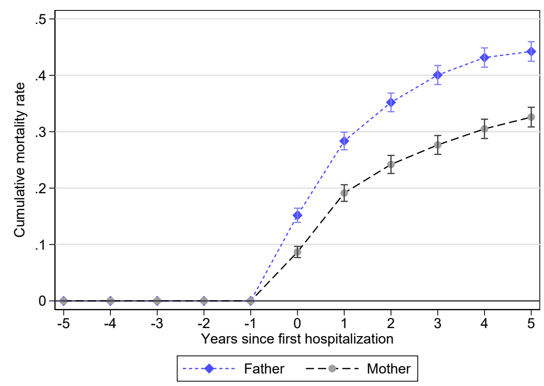
(a) Days in Hospital, $N_h = 1$



(b) Days in Hospital, $N_h > 1$



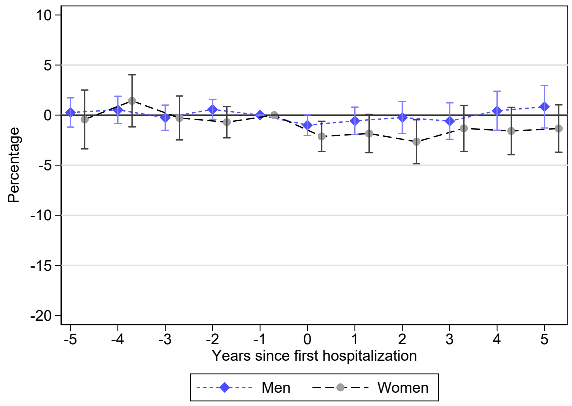
(c) Mortality, $N_h = 1$



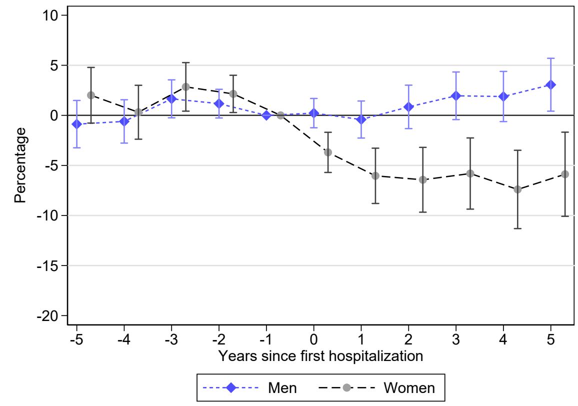
(d) Mortality, $N_h > 1$

Note: Estimates from equation 1. Outcomes are measures of parental health. Panel (a) and (c) are estimates for cases with one cancer hospitalization ($N_h = 1$). Panel (b) and (d) are estimates for cases with multiple cancer hospitalizations ($N_h > 1$). All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

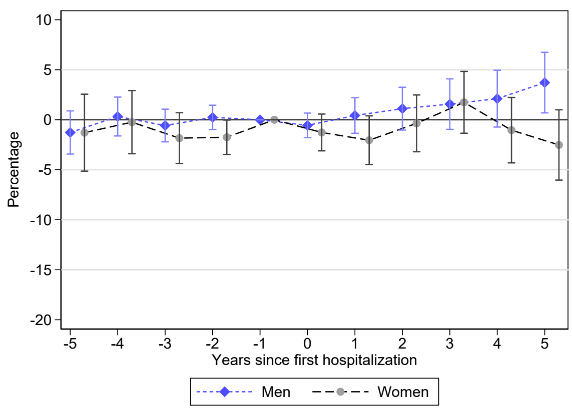
Figure 5. Effect of a Parental Health Shock on Adult Children's Labor Market Outcomes by Number of Cancer Hospitalizations



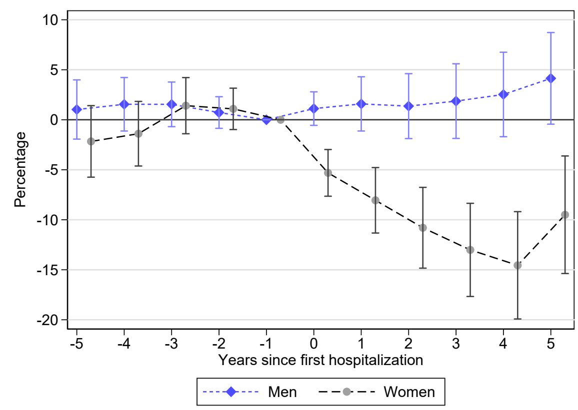
(a) Employment rate, $N_h = 1$



(b) Employment rate, $N_h > 1$



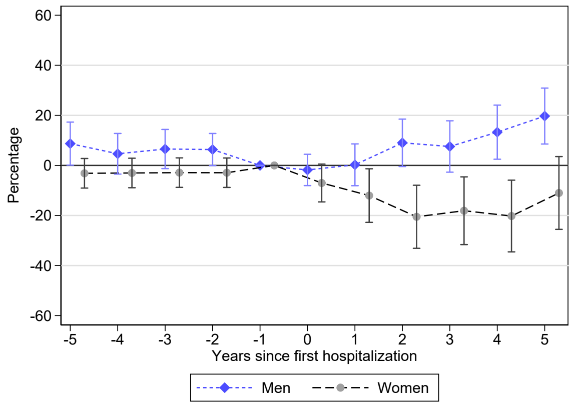
(c) Annual earnings, $N_h = 1$



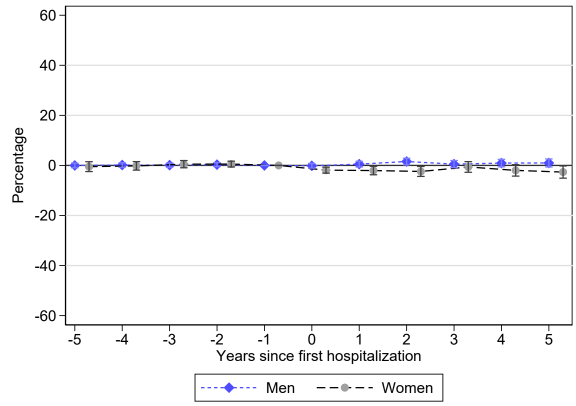
(d) Annual earnings, $N_h > 1$

Note: Estimates from equation 1. Outcomes are labor market outcomes for children. Panel (a) and (c) are estimates for cases with one cancer hospitalization ($N_h = 1$). Panel (b) and (d) are estimates for cases with multiple cancer hospitalizations ($N_h > 1$). Estimates correspond to P_t^m for men and P_t^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

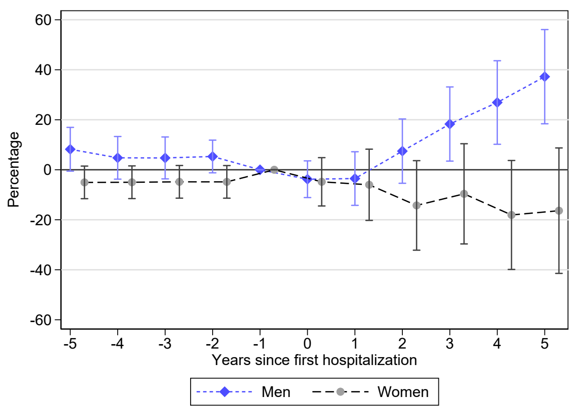
FIGURE 6. Effect of a Parental Health Shock on Adult Children's Labor Market Outcomes, by Employment Tercile



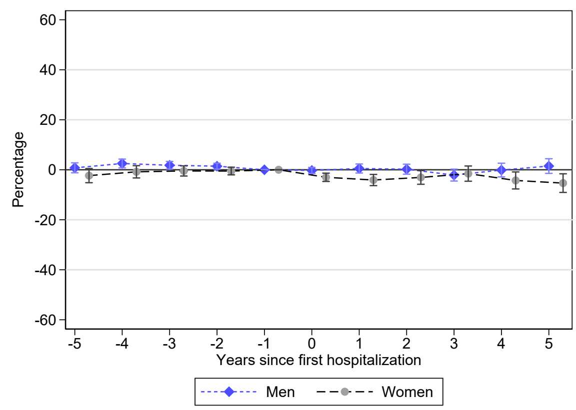
(a) Employment, First Tercile



(b) Employment, Third Tercile



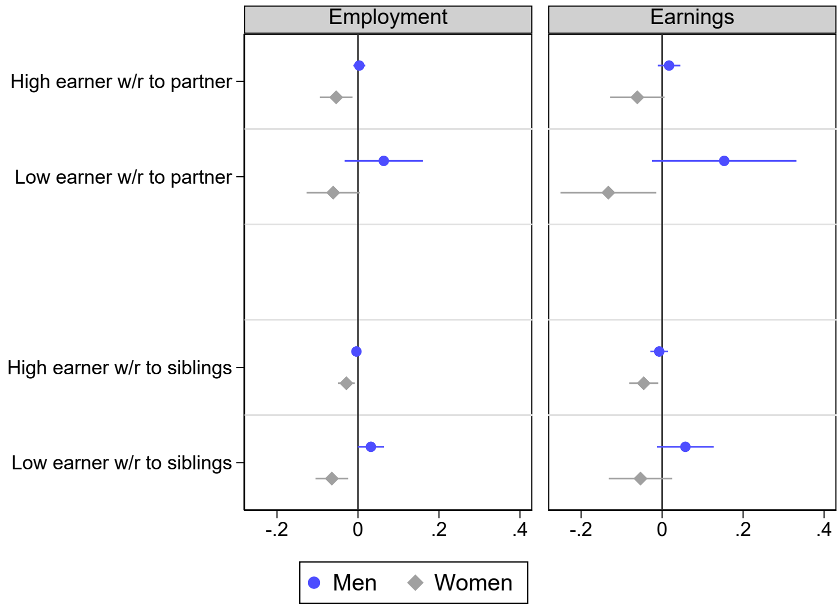
(c) Annual Earnings, First Tercile



(d) Annual Earnings, Third Tercile

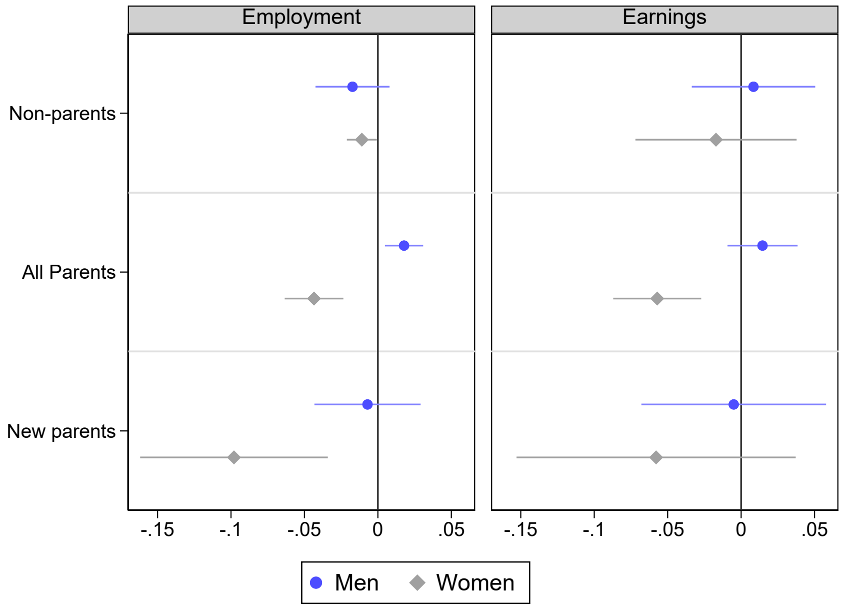
Note: Estimates from equation 1. Outcomes are labor market outcomes for children. Panels (a) and (c) show estimates for individuals in the first tercile of pre-shock employment, corresponding to the group of children with the lowest employment rates before the parental health shock. Panels (b) and (d) show estimates for individuals in the third tercile of pre-shock employment, corresponding to the group of children with the highest employment rates before the parental health shock. The scale of the y axis is similar across panels to ease comparison. Estimates correspond to P_t^m for men and P_t^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

FIGURE 7. Effects of a Parental Health Shock by Relative Earnings



Note: Estimates from equation 3. Outcomes are labor market outcomes for children. Estimates correspond to P^m for men and P^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

FIGURE 8. Effects of a Parental Health Shock by Parenthood



Note: Estimates from equation 3. Outcomes are labor market outcomes for children. Estimates correspond to P^m for men and P^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals. Annual exchange rate in 2014 = \$CH 570,01 (Source: Central Bank of Chile)

Appendix A. Tables and Figures

Table A1. Distribution of Parents with a Cancer Hospitalization by Cancer Type

Cancer Diagnosis	Fathers	Mothers	Total
Breast	0.2%	30.3%	15.2%
Prostate	29.4%	0.0%	14.7%
Colorectal	10.7%	8.4%	10.6%
Stomach	13.2%	5.1%	10.3%
Uterine cervical	0.0%	12.4%	6.2%
Gallbladder	2.2%	3.6%	3.1%
Bronchus and Lung	4.1%	2.3%	3.6%
Leukimia	3.3%	1.9%	2.6%
Pancreas	2.1%	1.7%	1.9%
Liver	1.8%	1.0%	1.6%
Esophagus	1.5%	0.8%	1.3%
Other	32.5%	33.0%	32.8%
Total	4,349	3,753	8,102

Notes: Distribution of treated fathers and mothers in our sample by type of cancer. Percentages over total treatment sample by gender of parent.

Table A2. Descriptive Statistics for Parents Sample

	Treated	Control
A. Fathers		
Age at first cancer hospitalization	64.1	63.8
Age at first child	27.4	27.3
Number of children	2.6	2.6
Number of sons	1.3	1.3
Number of daughters	1.3	1.3
Level of education		
Less than high school	71.8%	71.8%
High school or some college	20.9%	20.9%
College	7.3%	7.3%
Observations	8,162	146,131
B. Mothers		
Age at first cancer hospitalization	61.3	61.0
Age at first child	24.6	24.5
Number of children	2.6	2.6
Number of sons	1.3	1.3
Number of daughters	1.3	1.3
Level of education		
Less than high school	74.8%	74.8%
High school or some college	18.9%	18.9%
College	6.3%	6.3%
Observations	8,162	146,131

Notes: Main summary statistics for treated and control parents.

Table A3. Descriptive Statistics for Children Sample

	Treated	Control
A. Sons		
Age at parental first cancer hospitalization	35.3	35.2
Has children	70.4	69.8
Age at first child (conditional on having children)	26.9	27.0
Level of education		
Less than high school	24.3%	24.2%
High school or some college	46.2%	46.3%
College	29.5%	29.5%
Employment and earnings		
Employment rate	57.8%	57.8%
Earnings	$US 8,691	$US 8,586
Earnings (conditional on employment)	$US 12,764	$US 12,526
Observations	6,863	108,977
B. Daughters		
Age at parental first cancer hospitalization	35.4	35.4
Has children	80.6%	80.5%
Age at first child (conditional on having children)	24.7	24.4
Level of education		
Less than high school	20.9%	20.8%
High school or some college	50.6%	50.7%
College	28.5%	28.5%
Employment and earnings		
Employment rate	37.0%	37.1%
Earnings	$US 4,212	$US 4,108
Earnings (conditional on employment)	$US 9,071	$US 8,775
Observations	7,182	117,589

Notes: Main summary statistics for treated and control children. Employment and earnings are measured the year before the first parental cancer hospitalization. Annual exchange rate in 2014 = $CH 570,01 (Source: Central Bank of Chile).

Table A4. Characteristics of Parents and Children with a Parental Cancer Hospitalization by Cancer Re-hospitalization

	One Cancer Hospitalization	Multiple Cancer Hospitalizations
Panel A. Sons		
Age at first cancer hospitalization	36.3	36.1
Employment rate	59.1%	55.9%
Annual earnings	$US 8,855	$US 8,386
Observations	4,452	2,411
Panel B. Daughters		
Age at first cancer hospitalization	36.5	36.2
Employment rate	36.7%	37.5%
Annual earnings	$US 4,109	$US 4,404
Observations	4,684	2,498

Notes: Age and labor market outcomes for treated children by whether the parent is re-hospitalized due to cancer. Annual exchange rate in 2014 = $CH 570,01 (Source: Central Bank of Chile).

Table A5. Distribution of Residents in Public Long-Term Care Centers by Type of Disease

Disease	Percentage
Mental and Behavioral Disorders	69.7%
Circulatory System	65.2%
Musculoskeletal System	32.3%
Nervous System	29.5%
Endocrine, Nutritional, and Metabolic Disorders	25.2%
Eye	46.7%
Ear	43.7%
Congenital Malformations and Deformities	16.3%
Respiratory System	21.7%
Genitourinary System	11.4%
Injuries, Poisonings, Other External Causes	6.7%
Tumors	3.7%
Total	465

Notes: Percentage of residents in public long-term care centers by disease. Percentages add to over 100% as residents can have multiple diseases. The sample includes residents from 11 long-term centers. Source: "Living Conditions of Elderly Individuals within SENAMA's Long-Term Care Facilities" (2017), SENAMA (National Service for the Elderly).

TABLE A6. Cancer Diagnoses by Re-hospitalization Rate

	High re-hospitalization rate	Low re-hospitalization rate
Diagnosis:		
Breast	2.5%	13.4%
Bronchus and Lung	1.2%	4.0%
Colorectal	20.2%	2.0%
Esophagus	2.7%	0.1%
Gallbladder	0.1%	6.2%
Leukemia	5.7%	6.6%
Liver	0.2%	2.4%
Pancreas	2.0%	0.7%
Stomach	12.6%	2.4%
Uterine cervical	8.3%	0.6%
Other	44.4%	28.5%
Re-hospitalization rate		
Share re-hospitalized	50.0%	20.5%
Total	3,262	3,267

Note: Distribution of cancer cases with high and low re-hospitalization rate by diagnosis type. The classification of diagnosis in each group (high and low re-hospitalization rate) is performed using ICD10 with 4 digits. Different cancers within the same diagnosis type can fall into different groups. Re-hospitalization rates for each group are also displayed.

TABLE A7. Effect of Parental Health Shock on Adult Children's Labor Market Outcomes. Dynamic Event-study (Estimates in Levels)

	Employment Rate			Earnings		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Sons						
Pre-trends	0.002	0.002	0.002	32.5	18.1	17.2
	(0.004)	(0.003)	(0.003)	(86.1)	(59.6)	(59.5)
Average effect	0.001	0.002	0.002	112.0	134.6*	138.8*
	(0.004)	(0.003)	(0.003)	(110.5)	(75.4)	(75.3)
Mean at baseline	0.58	0.58	0.58	8,691	8,691	8,691
Observations	1,274,240	1,274,240	1,274,240	1,274,240	1,274,240	1,274,240
Panel B: Daughters						
Pre-trends	0.003	0.003	0.003	-33.9	-33.3	-34.6
	(0.004)	(0.003)	(0.003)	(56.8)	(38.7)	(38.6)
Average effect	-0.011***	-0.012***	-0.012***	-183.5**	-184.3***	-183.6***
	(0.004)	(0.003)	(0.003)	(75.6)	(51.8)	(51.8)
Mean at baseline	0.37	0.37	0.37	4,212	4,212	4,212
Observations	1,372,481	1,372,481	1,372,481	1,372,481	1,372,481	1,372,481
Matching		✓	✓		✓	✓
Controls			✓			✓

Note: Estimates from equation 1 varying controls and fixed effects. Pre-trends is the average effect for $t = \{-5, -4, -3, -2\}$. Average effect considers $t = \{0, 1, 2, 3, 4, 5\}$. All specifications include two sets of fixed effects: individual × stack, and year × stack. In columns (1) and (4) stacks are defined only by the year of treatment. When matching is indicated, stacks are defined by year of treatment and socio-economic characteristics. When controls are indicated, age dummies are used to control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. *, **, and *** indicate statistical significance at the 90%, 95%, and 99% percent level. Estimates are presented in levels: percentage points for employment rate and US dollars for earnings (annual exchange rate in 2014 = $CH 570,01 (source: Central Bank of Chile)).

Table A8. Effect of Parental Health Shock on Adult Children's Labor Market Outcomes. Two-way Fixed Effects (Estimates in Levels)

	Employment Rate			Earnings		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Sons						
Average effect	0.000	0.000	0.000	109.3	120.2	125.0
	(0.004)	(0.003)	(0.003)	(127.6)	(85.8)	(85.7)
Mean at baseline	0.58	0.58	0.58	8,691	8,691	8,691
Observations	1,274,240	1,274,240	1,274,240	1,274,240	1,274,240	1,274,240
Panel B: Daughters						
Average effect	-0.013***	-0.014***	-0.014***	-129.6	-157.7***	-155.7***
	(0.004)	(0.003)	(0.003)	(84.9)	(58.6)	(58.6)
Mean at baseline	0.37	0.37	0.37	4,212	4,212	4,212
Observations	1,372,481	1,372,481	1,372,481	1,372,481	1,372,481	1,372,481
Matching		✓	✓		✓	✓
Controls			✓			✓

Note: Estimates from equation 3 varying controls and fixed effects. All specifications include two sets of fixed effects: individual × stack, and year × stack. In columns (1) and (3), stacks are defined only by the year of treatment. When matching is indicated, stacks are defined by year of treatment and socio-economic characteristics. When controls are indicated, age dummies are used to control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. *, **, and *** indicate statistical significance at the 90%, 95%, and 99% percent level. Estimates are presented in levels: percentage points for employment rate and US dollars for earnings (annual exchange rate in 2014 = \$CH 570,01 (source: Central Bank of Chile)).

Table A9. Effect of Parental Health Shock on Adult Children's Labor Market Outcomes by Availability of Partner Information. Two-way Fixed Effects (Estimates in Levels)

	Employment Rate		Earnings	
	Sample with partner	Full sample	Sample with partner	Full sample
	(1)	(2)	(3)	(4)
Panel A: Sons				
Parental Health Shock	0.005	0.000	249.4	125.0
	(0.005)	(0.003)	(162.9)	(85.7)
Mean at baseline	0.61	0.58	10,510	8,691
Observations	287,100	1,274,240	287,100	1,274,240
Panel B: Daughters				
Parental Health Shock	-0.013**	-0.014***	-207.6**	-155.7***
	(0.005)	(0.003)	(93.0)	(58.6)
Mean at baseline	0.29	0.37	3,483	4,212
Observations	358,567	1,372,481	358,567	1,372,481

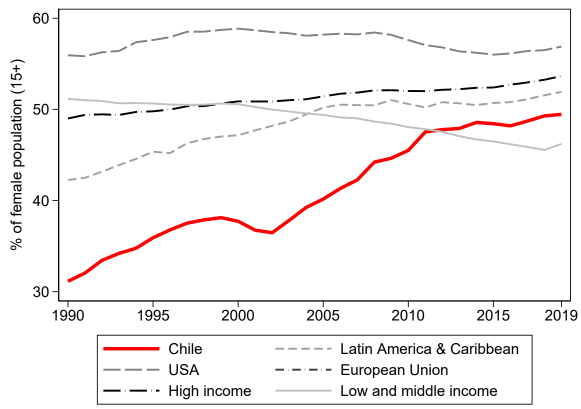
Note: Estimates from equation 3. Columns (1) and (3) show results for the sample of children from whom we can identify their partner either from marriage data. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. *, **, and *** indicate statistical significance at the 90%, 95%, and 99% percent level. Earnings are measured in US dollars (annual exchange rate in 2014 = \$CH 570,01 (source: Central Bank of Chile)).

Table A10. Effect of Parental Health Shock on Adult Children's Labor Market Outcomes. (Different Reference Periods)

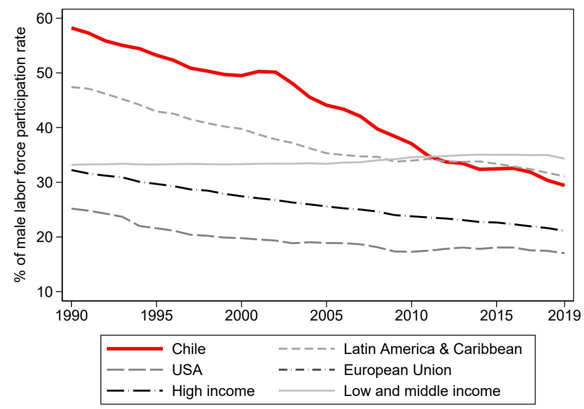
	Employment Rate		Earnings	
	(1)	(2)	(3)	(4)
Panel A: Sons				
Average effect	0.004	-0.006	0.015*	0.010
	(0.005)	(0.006)	(0.008)	(0.010)
Mean at baseline	0.58	0.58	8,691	8,691
Observations	1,274,240	1,274,240	1,274,240	1,274,240
Panel B: Daughters				
Average effect	-0.033***	-0.035***	-0.038***	-0.033***
	(0.008)	(0.009)	(0.011)	(0.012)
Mean at baseline	0.37	0.37	4,212	4,212
Observations	1,372,481	1,372,481	1,372,481	1,372,481
Reference Period	-1	-2	-1	-2

Note: Estimates from equation 1 with different reference periods ($t = -1$ or -2). Average effect considers $t = \{0, 1, 2, 3, 4, 5\}$. Estimates correspond to P_t^m for men and P_t^w for women as defined in Section 3. Estimates represent percent changes. All specifications include two sets of fixed effects: individual × stack, and year × stack, control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. *, **, and *** indicate statistical significance at the 90%, 95%, and 99% percent level. Earnings (mean at baseline) are measured in US dollars (annual exchange rate in 2014 = $CH 570,01 (source: Central Bank of Chile)).

FIGURE A1. Trends in Labor Force Participation (LFP) in Selected Countries and Regions (Population 15 Years and Over)



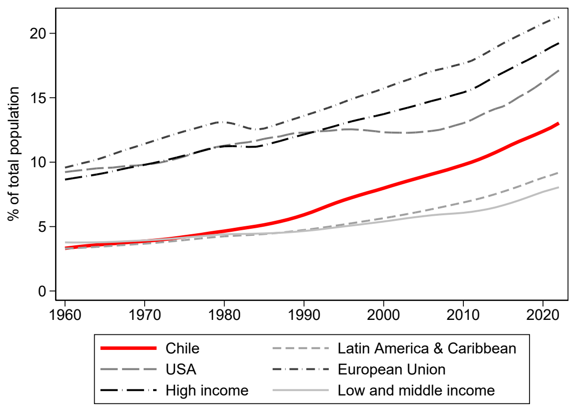
(a) Female LFP



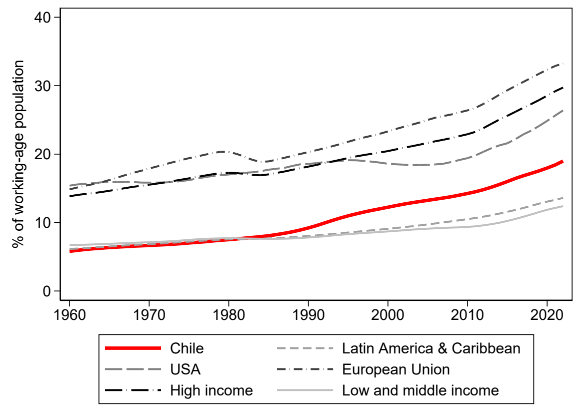
(b) Gender Gap in LFP

Note: Panel (a) shows the female labor force participation (as percentage of total female population). Panel (b) shows the gender gap in labor force participation rate (as percentage of the male labor force participation rate). Population aged 15 years and older. Source: World Development Indicators, World Bank.

Figure A2. Trends in Population Aging in Selected Countries and Regions



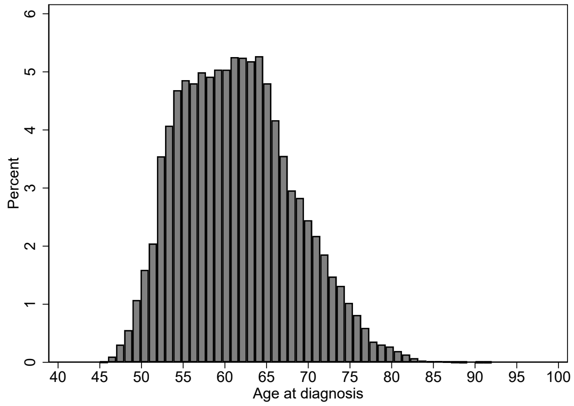
(a) Population Aged 65 and Older



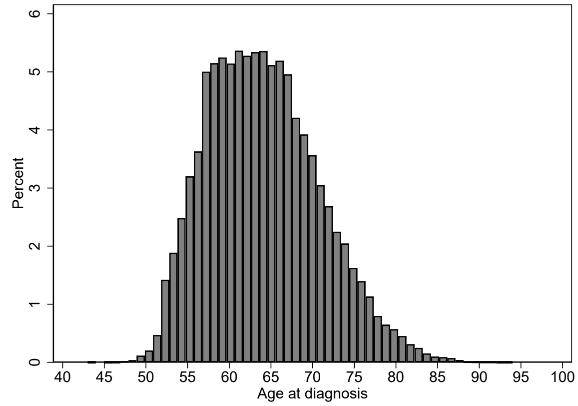
(b) Dependency Ratio

Note: Panel (a) shows the population aged 65 or older as percentage of total population. Panel (b) shows the dependency ratio, which is defined as the population aged 65 or older as percentage of working-age population (15-64 years old). Source: World Development Indicators, World Bank.

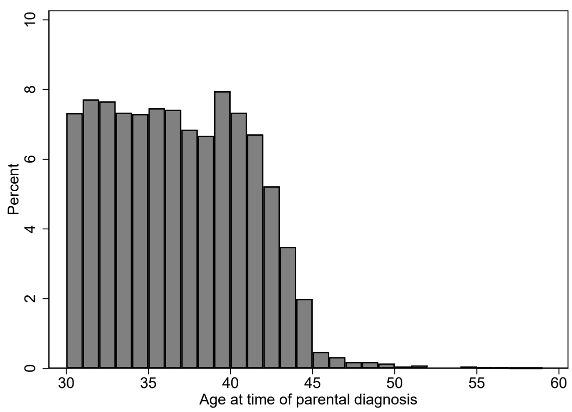
Figure A3. Distribution of Age at First Parental Cancer Hospitalization for Treated Families



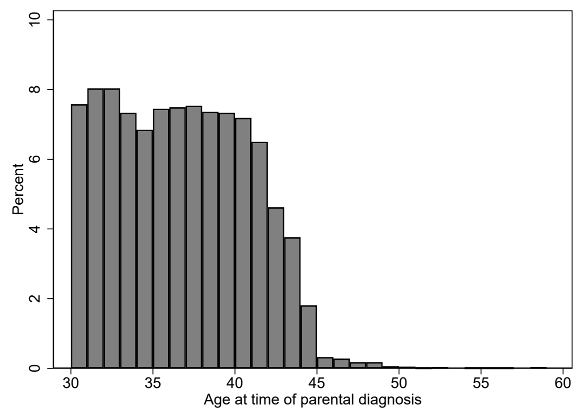
(a) Mothers



(b) Fathers



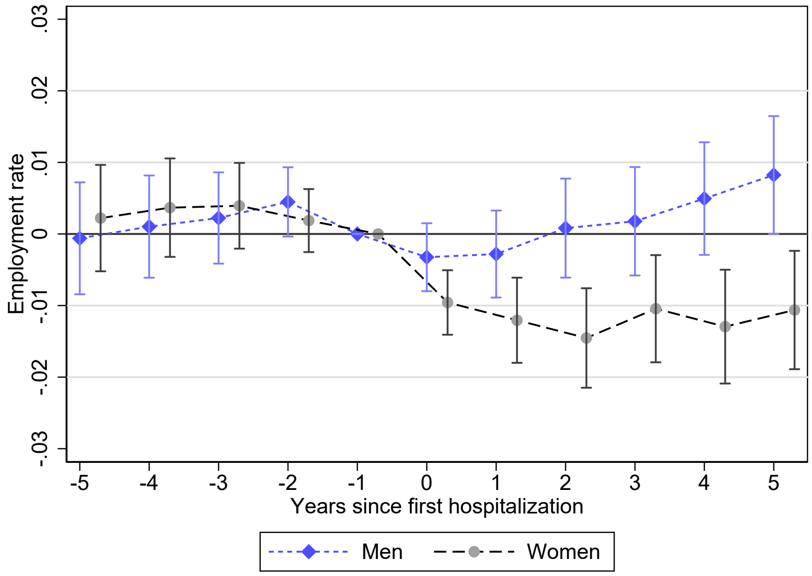
(c) Daughters



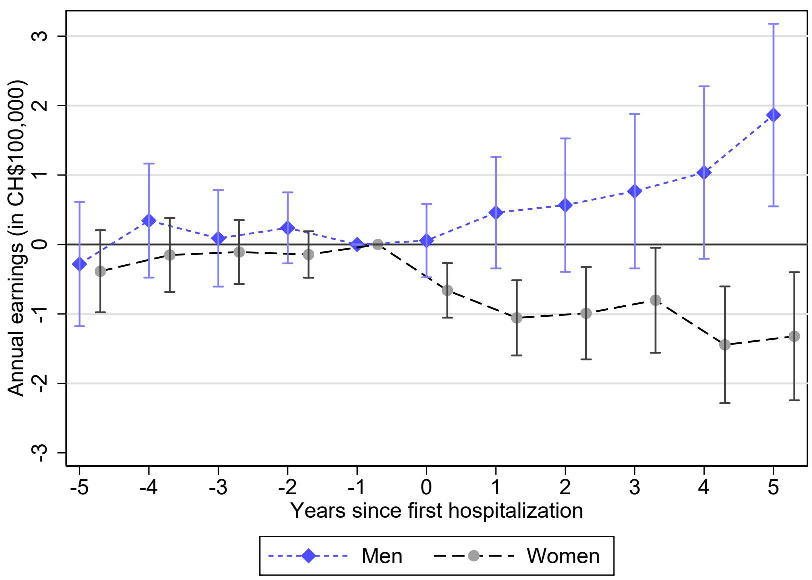
(d) Sons

Note: Distribution of age at year of the first parental cancer hospitalization for treated parents by gender (panel (a) for mothers and panel (b) for fathers) and for treated children by gender (panels (c) for daughters and panel (d) for sons). Each bin corresponds to one year. The low share of children aged over 45 years is related to data limitations for birth records for cohorts born before 1970.

FIGURE A4. Effect of a Parental Health Shock on Adult Children's Labor Market Outcomes (Estimates in Levels)



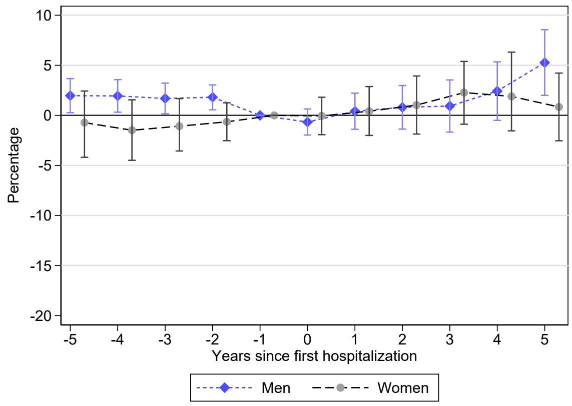
(a) Employment rate



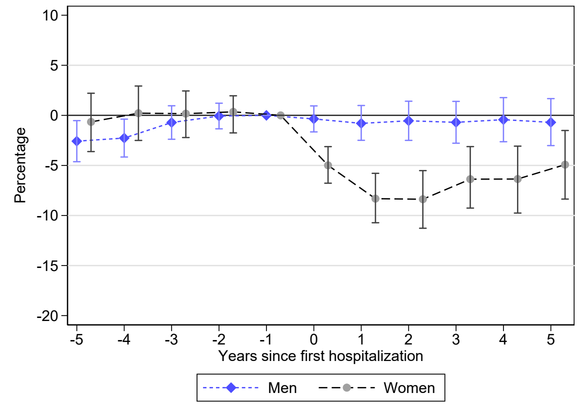
(b) Annual earnings

Note: Estimates from equation 1. Outcomes are labor market outcomes for children. Estimates are in levels. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. Chilean pesos exchange rate. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

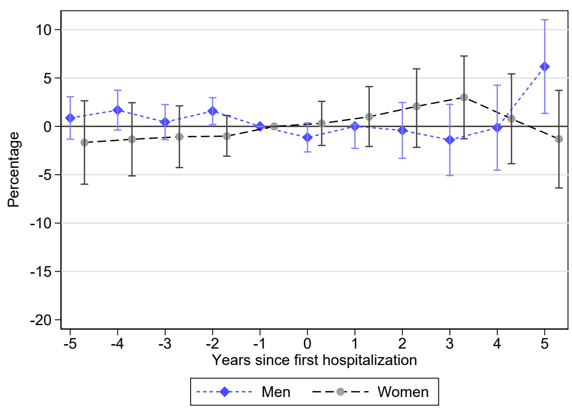
FIGURE A5. Effect of a Parental Health Shock on Adult Children's Labor Market Outcomes by Diagnosis with Different Re-hospitalization Rate



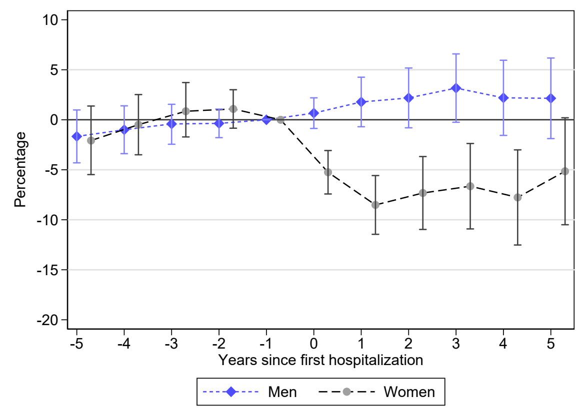
(a) Employment rate, low re-hospitalization rate



(b) Employment rate, high re-hospitalization rate



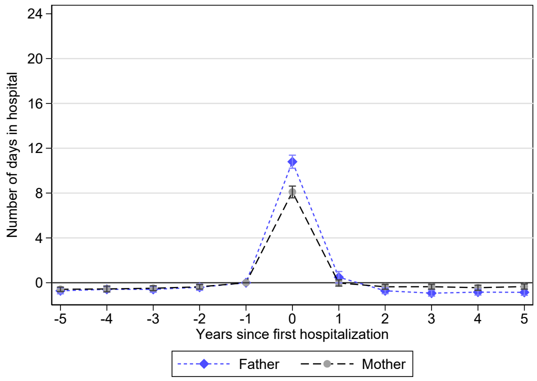
(c) Annual earnings, low re-hospitalization rate



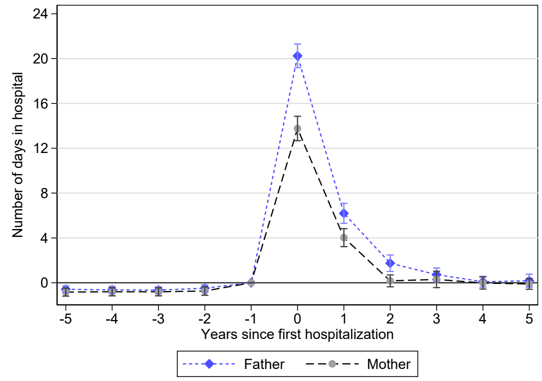
(d) Annual earnings, high re-hospitalization rate

Note: Estimates from equation 1. Outcomes are labor market outcomes for children. Panel (a) and (c) are estimates for diagnoses with low re-hospitalization rate. Treated units are restricted to the bottom 40% of diagnoses by probability of re-hospitalization. Panel (b) and (d) are estimates for diagnoses with high re-hospitalization rate. Treated units are restricted to the top 40% of diagnoses by probability of re-hospitalization. Estimates correspond to P_t^m for men and P_t^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

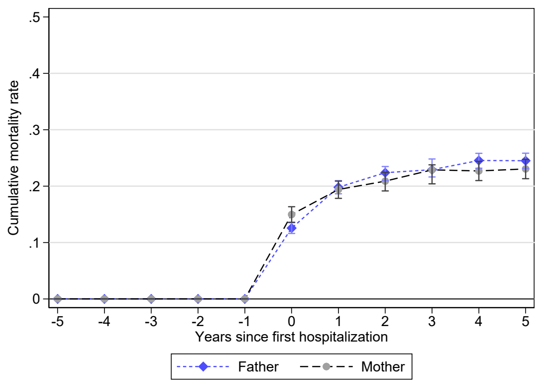
Figure A6. Effect of a Parental Health Shock on Parental Health by Diagnosis with Different Re-hospitalization Rate



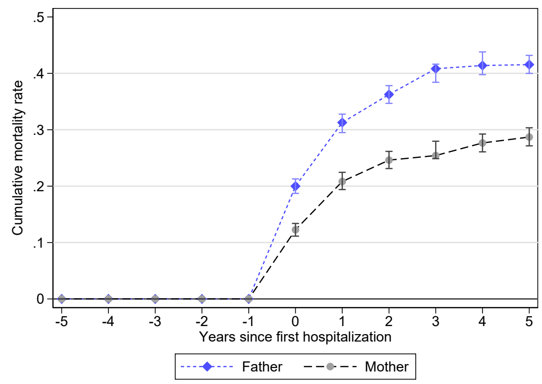
(a) Days in Hospital, low re-hospitalization rate



(b) Days in Hospital, high re-hospitalization rate



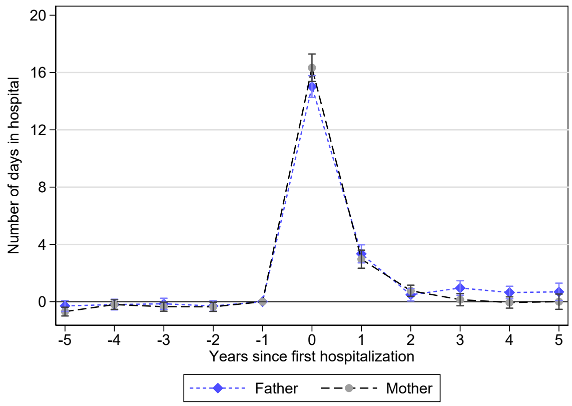
(c) Mortality, low re-hospitalization rate



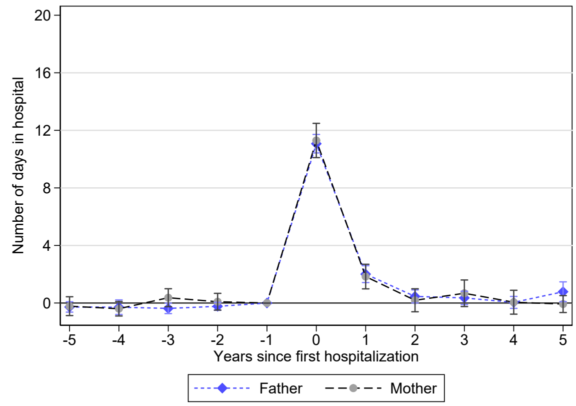
(d) Mortality, high re-hospitalization rate

Note: Estimates from equation 1. Outcomes are measures of parental health. Panel (a) and (c) are estimates for diagnoses with low re-hospitalization rate. Treated units are restricted to the bottom 40% of diagnoses by probability of re-hospitalization. Panel (b) and (d) are estimates for diagnoses with high re-hospitalization rate. Treated units are restricted to the top 40% of diagnoses by probability of re-hospitalization. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

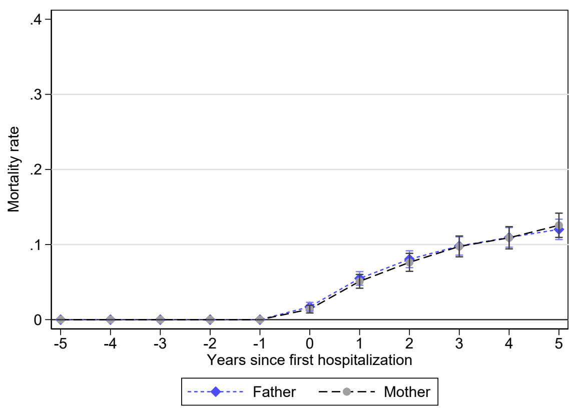
FIGURE A7. Effect of Other Parental Health Shocks on Parental Health



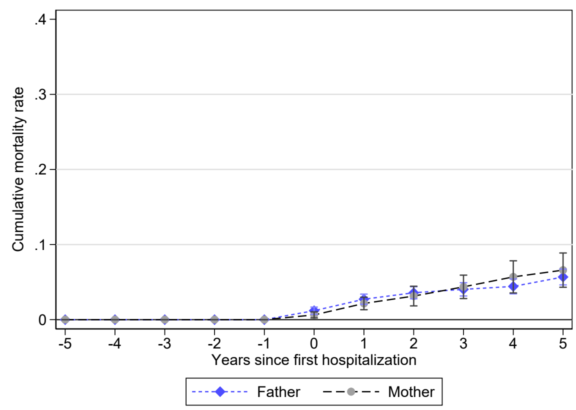
(a) Days in hospital, Stroke



(b) Days in hospital, Hear Attack



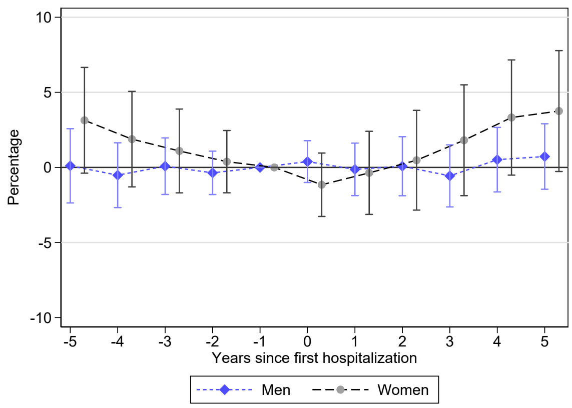
(c) Mortality rate, Stroke



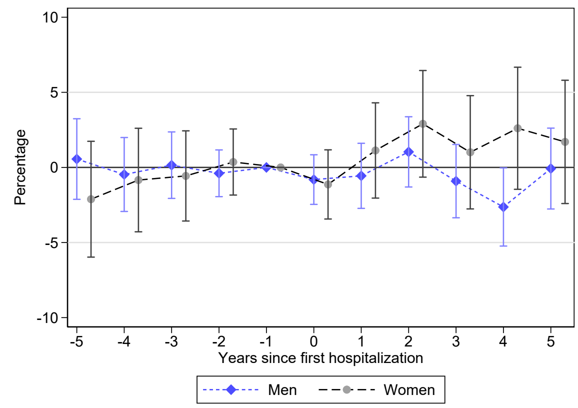
(d) Mortality rate, Heart Attack

Note: Estimates from equation 1. Outcomes are measures of parental health. Panels (a) and (c) show estimates for strokes as a parental health shock. Panels (b) and (d) show estimates for heart attacks as a parental health shock. In both cases, treatment is defined as a parental heart attack or stroke when the parent survives past the first month. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

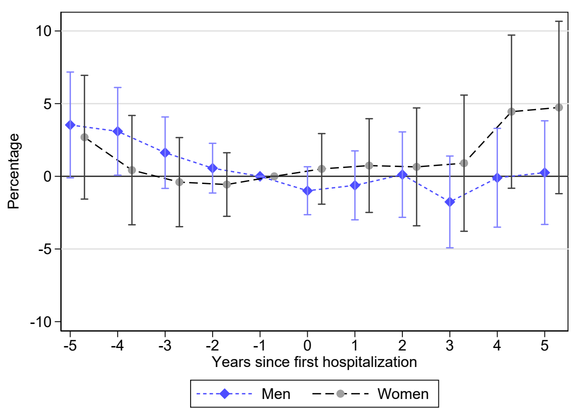
Figure A8. Effect of a Other Parental Health Shock on Adult Children's Labor Market Outcomes



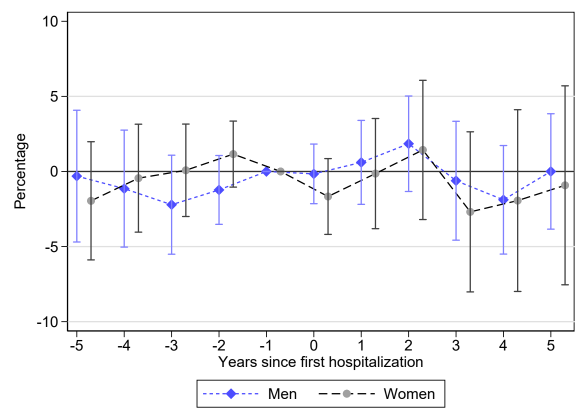
(a) Employment, Stroke



(b) Employment, Heart Attack



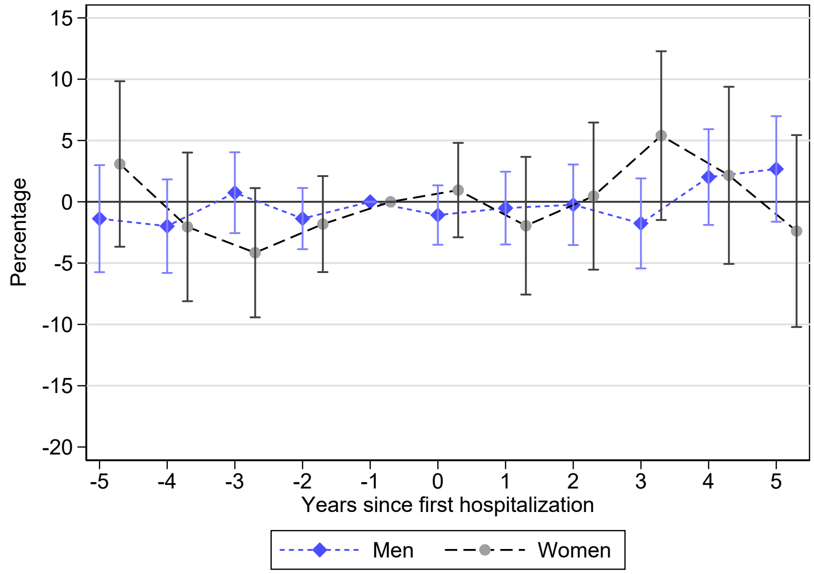
(c) Annual Earnings, Stroke



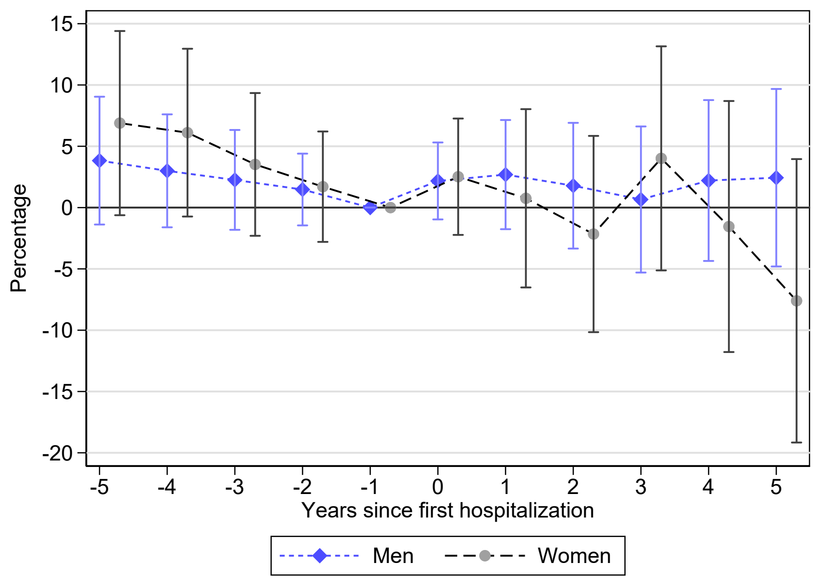
(d) Annual Earnings, Heart Attack

Note: Estimates from equation 1. Outcomes are labor market outcomes for children. Panels (a) and (c) show estimates for strokes as a parental health shock. Panels (b) and (d) show estimates for heart attacks as a parental health shock. In both cases, treatment is defined as a parental heart attack or stroke when the parent survives past the first month. Estimates correspond to P_t^m for men and P_t^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

FIGURE A9. Effect of a Parental Sudden Death on Adult Children's Labor Market Outcomes



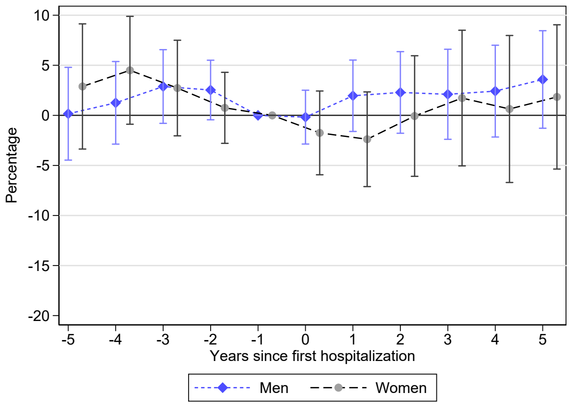
(a) Employment rate



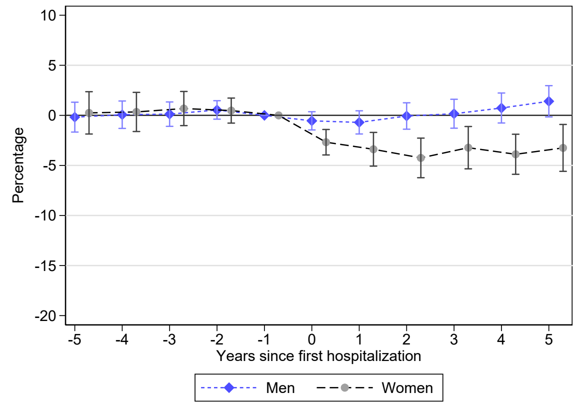
(b) Annual Earnings

Note: Estimates from equation 1 using a sudden parental death as treatment. A sudden parental death is defined as a death due to a stroke or a heart attack for parents with no previous hospitalizations. Outcomes are labor market outcomes for children. Estimates correspond to P_t^m for men and P_t^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

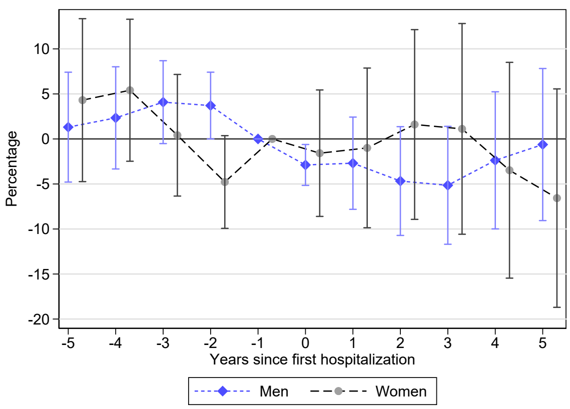
Figure A10. Effect of a Parental Health Shock on Adult Children's Labor Market Outcomes, by Timing on Death



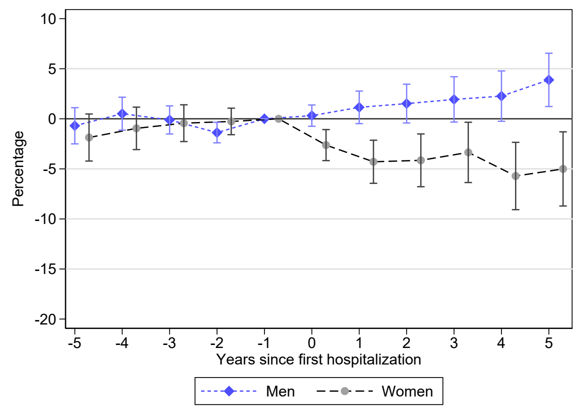
(a) Employment,
Parent dies during first month



(b) Employment,
Parent survives first month



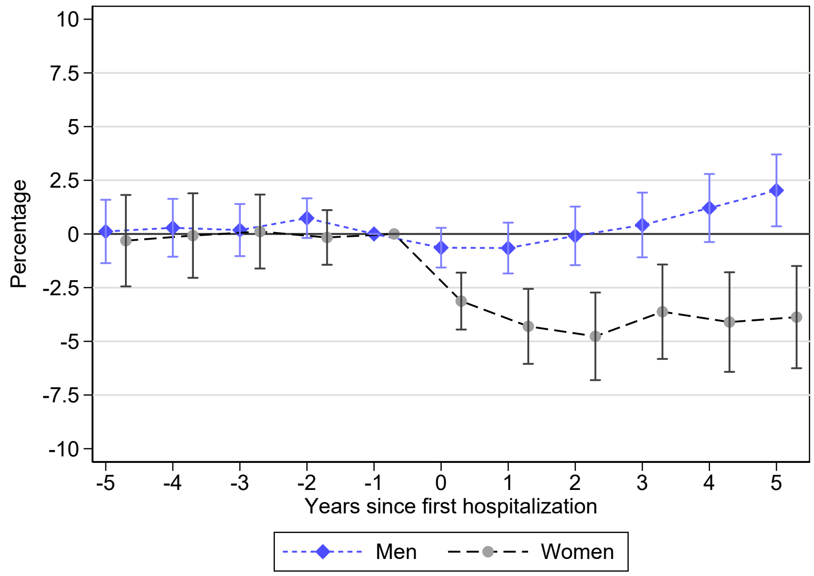
(c) Annual Earnings,
Parent dies during first month



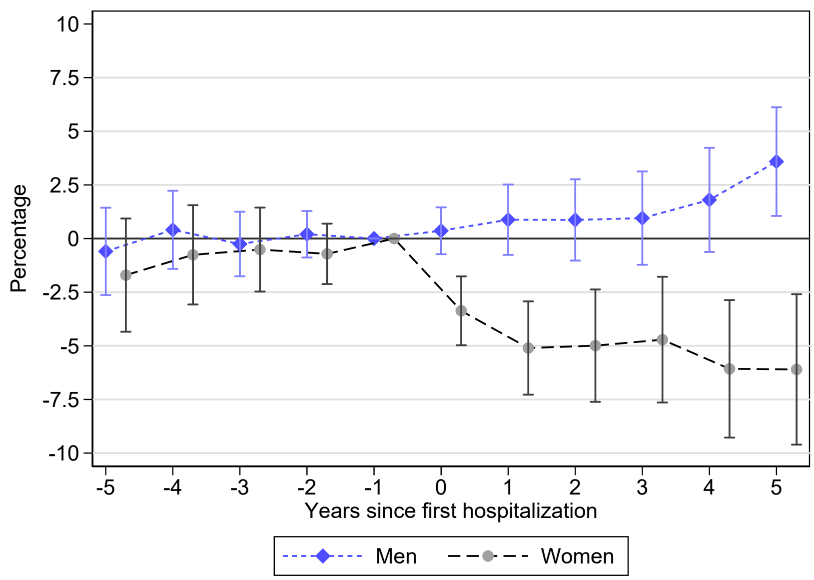
(d) Annual Earnings,
Parent survives first month

Note: Estimates from equation 1. Outcomes are labor market outcomes for children. Panels (a) and (c) show estimates for individuals whose parent dies within a month of the first cancer hospitalization. Panels (b) and (d) show estimates for individuals whose parent survives for at least a one since the first cancer hospitalization. The scale of the y axis is similar across panels to ease comparison. Estimates correspond to P_t^m for men and P_t^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

FIGURE A11. Effect of a Parental Health Shock on Adult Children's Labor Market Outcomes (Excluding Preventable Cancer Types)



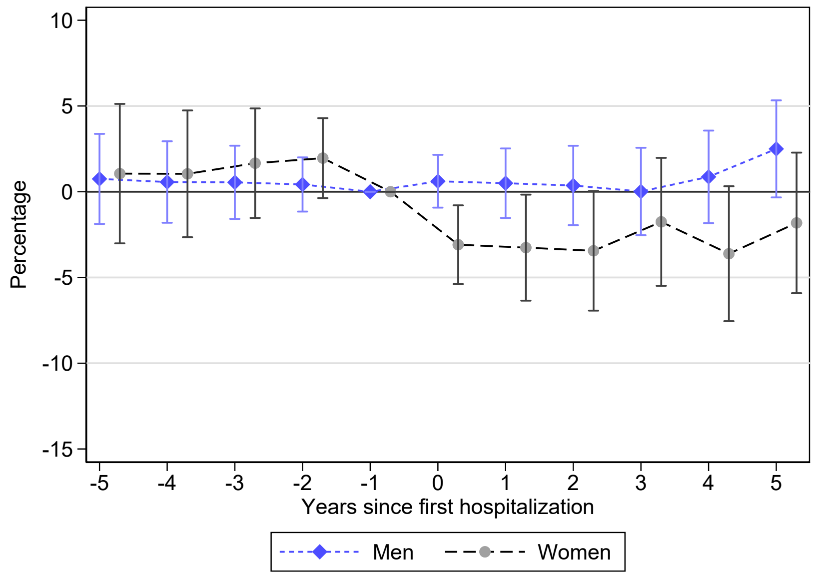
(a) Employment Rate



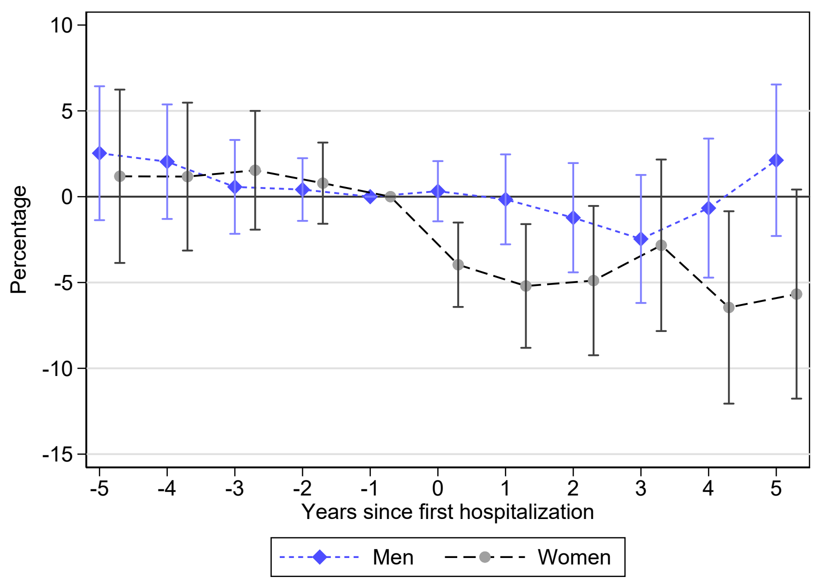
(b) Annual Earnings

Note: Estimates from equation 1. The treatment sample excludes parental cancer types mostly related to lifestyle or environmental factors, as defined by Tomasetti et al. (2017). Excluded cancer types are cervical, esophagus, head and neck, lung, melanoma, and stomach cancer. Outcomes are labor market outcomes for children. Estimates correspond to P_t^m for men and P_t^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

Figure A12. Effect of a Parental Health Shock on Adult Children's Labor Market Outcomes (Alternative Control Sample)



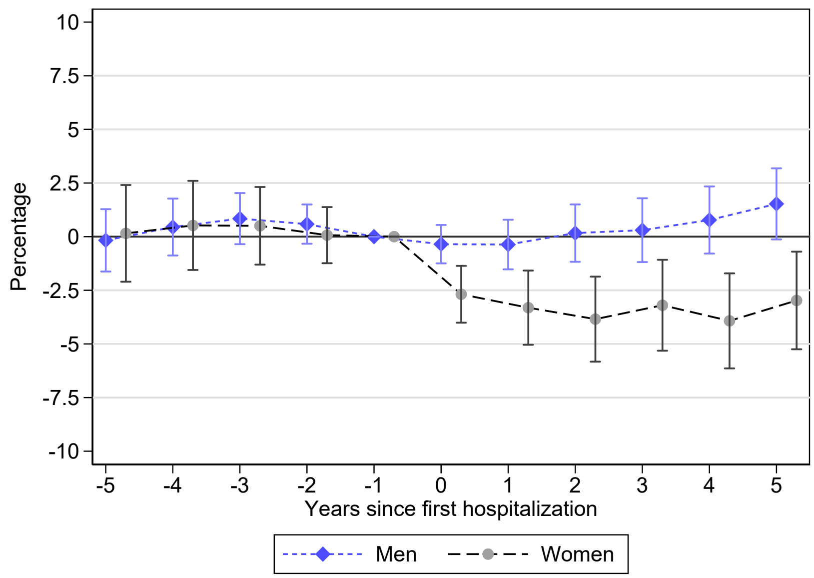
(a) Employment Rate



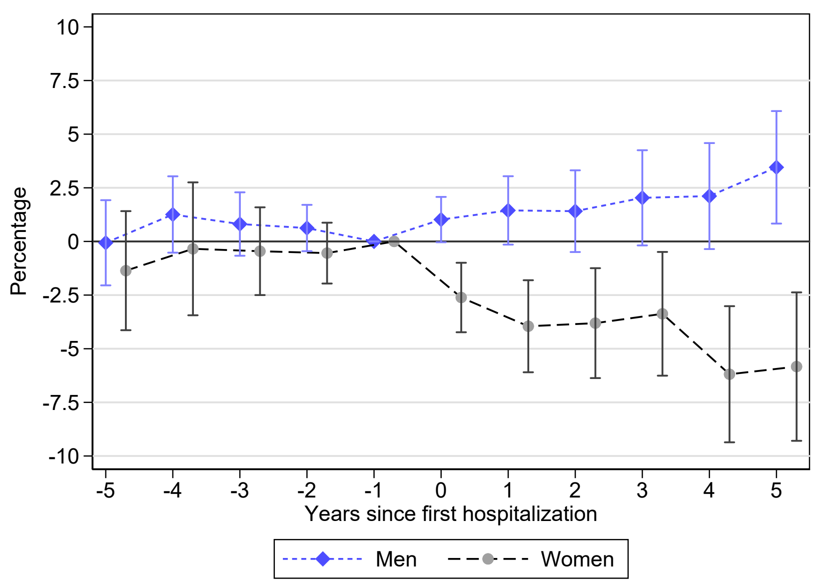
(b) Annual Earnings

Note: Estimates from equation 1, with stacks defined only by year of health shock as explained in section 6, paragraph 6. Control sample are not-yet-treated units. Outcomes are labor market outcomes for children. Estimates correspond to P_t^m for men and P_t^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

Figure A13. Effect of a Parental Health Shock on Adult Children's Labor Market Outcomes (Excluding Cases With Previous Hospitalizations)



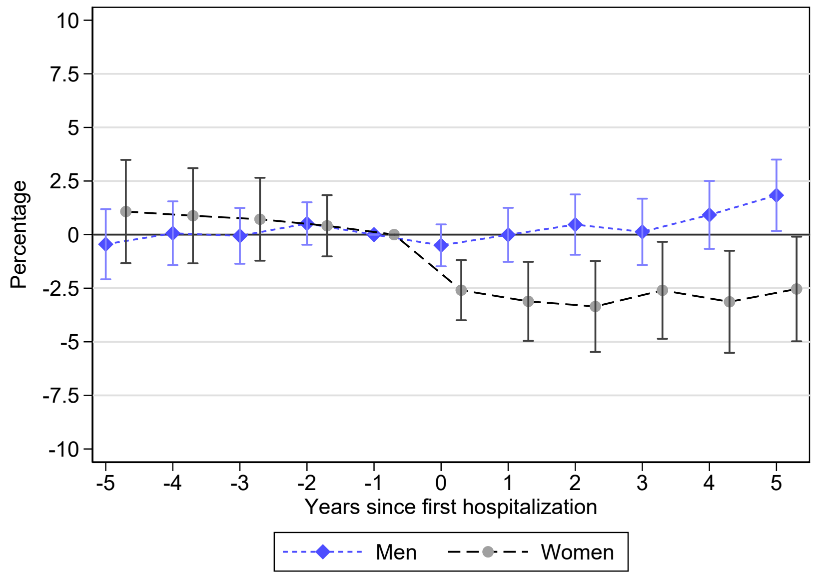
(a) Employment Rate



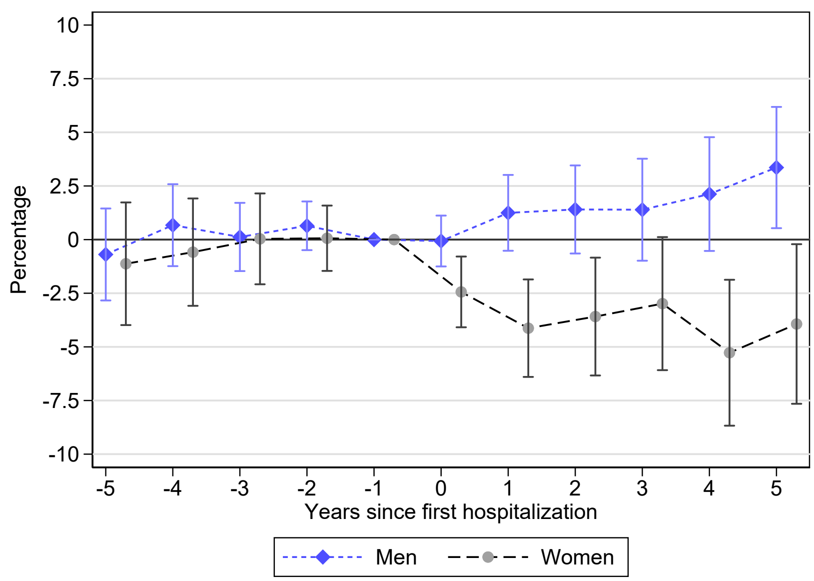
(b) Annual Earnings

Note: Estimates from equation 1. The sample excludes units whose parents had a hospital admission during $t = -1$. Outcomes are labor market outcomes for children. Estimates correspond to P_t^m for men and P_t^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

FIGURE A14. Effect of a Parental Health Shock on Adult Children's Labor Market Outcomes (Excluding Cases First Treated on Jan - March)



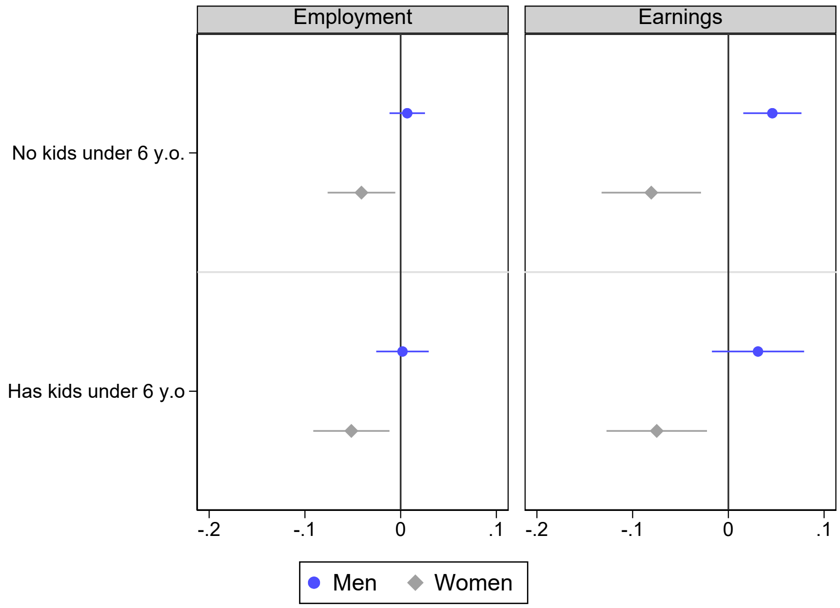
(a) Employment Rate



(b) Annual Earnings

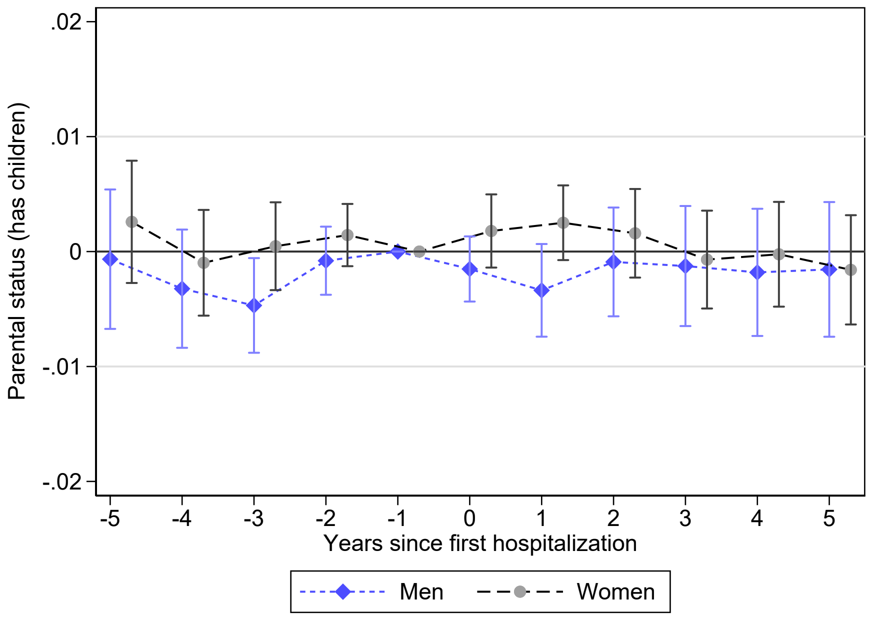
Note: Estimates from equation 1. The treatment sample excludes cases for which the first parental cancer hospitalization happened in January, February, or March. Outcomes are labor market outcomes for children. Estimates correspond to P_t^m for men and P_t^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

Figure A15. Effect of a Parental Health Shock by the Number of Children Aged 0-6 Years



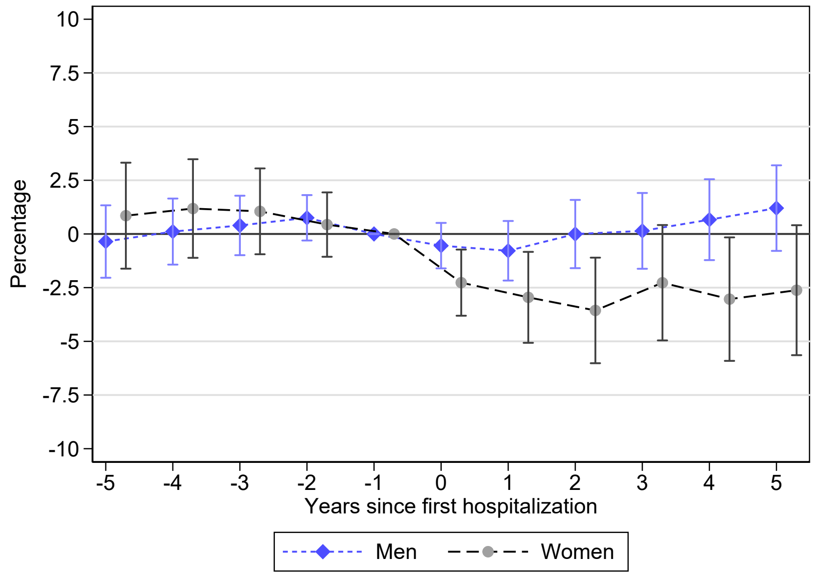
Note: Estimates from equation 3. Outcomes are labor market outcomes for children. Estimates correspond to P^m for men and P^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

Figure A16. Effect of a Parental Health Shock on Adult Children's Parental Status

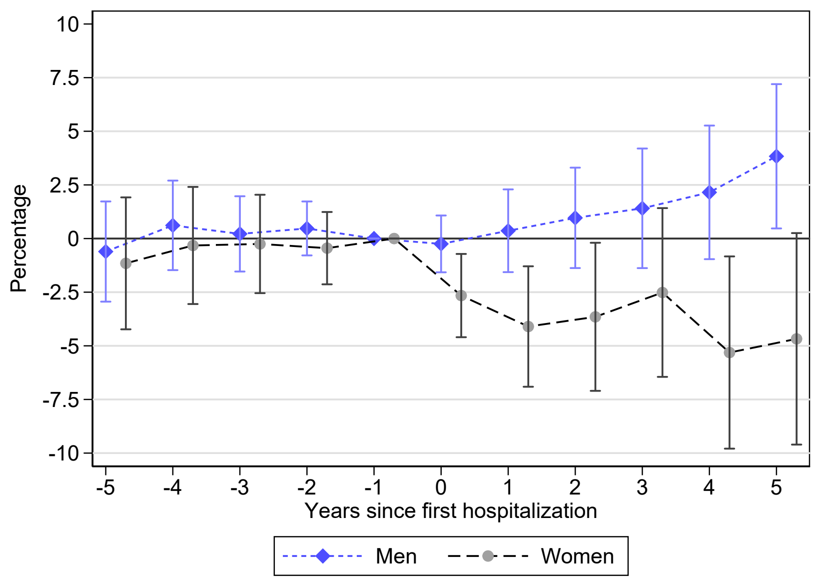


Note: Estimates from equation 3. Outcomes is parental status for children. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

FIGURE A17. Effect of Parental Health Shock on Children's Labor Market Outcomes (No Weights)



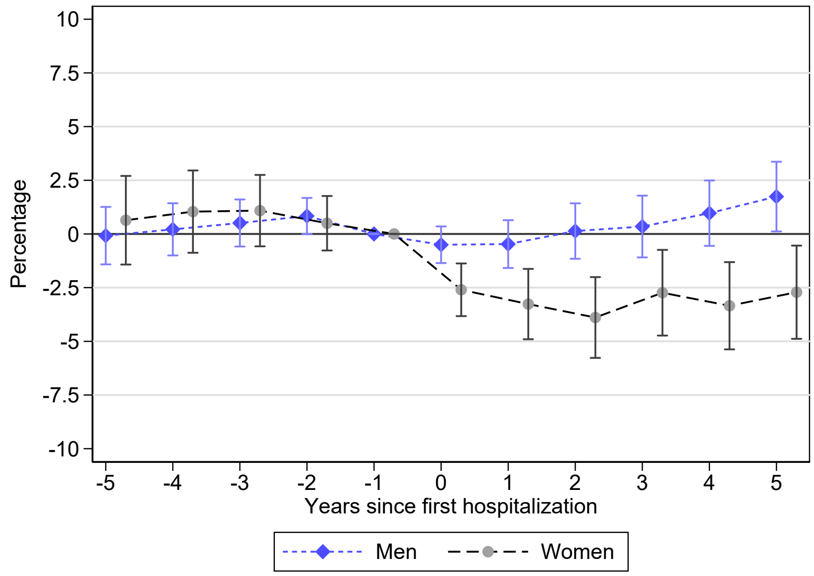
(a) Employment



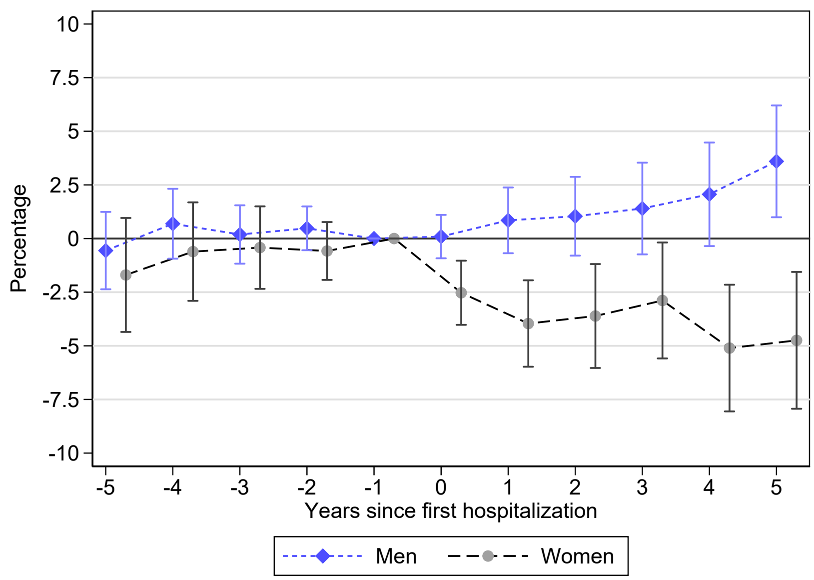
(b) Earnings

Note: Estimates from equation 1. Outcomes are labor market outcomes for children. Estimates correspond to P_t^m for men and P_t^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Clustered standard errors at the family level. 95% confidence intervals.

Figure A18. Effect of Parental Health Shock on Children's Labor Market Outcomes (No Controls)



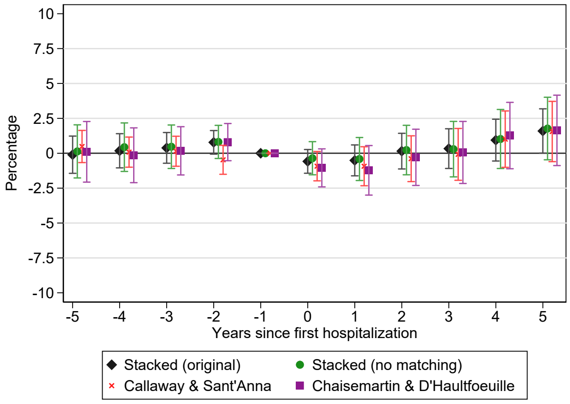
(a) Employment



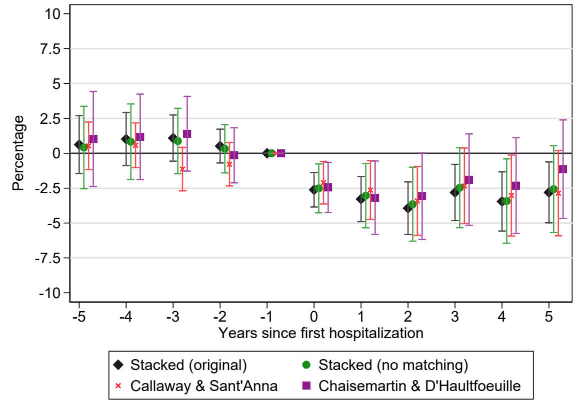
(b) Earnings

Note: Estimates from equation 1. Outcomes are labor market outcomes for children. Estimates correspond to P_t^m for men and P_t^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

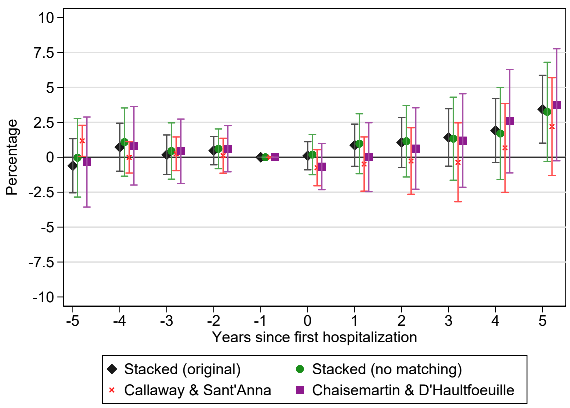
FIGURE A19. Effect of Parental Health Shock on Children's Labor Market Outcomes by Different Estimators



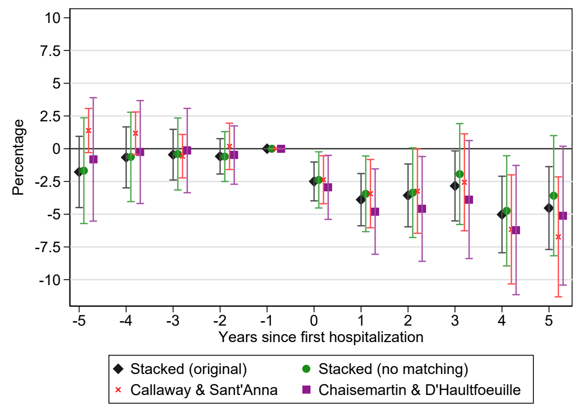
(a) Employment (Men)



(b) Employment (Women)



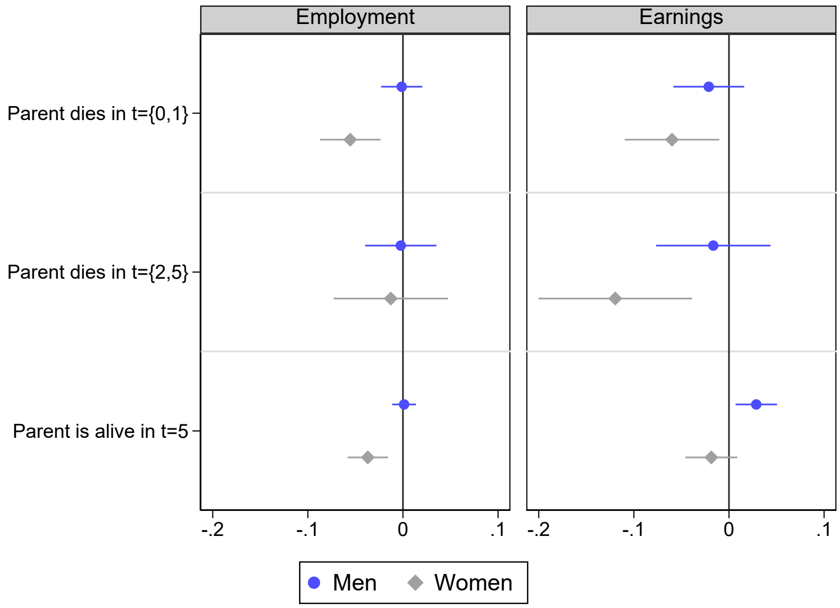
(c) Earnings (Men)



(d) Earnings (Women)

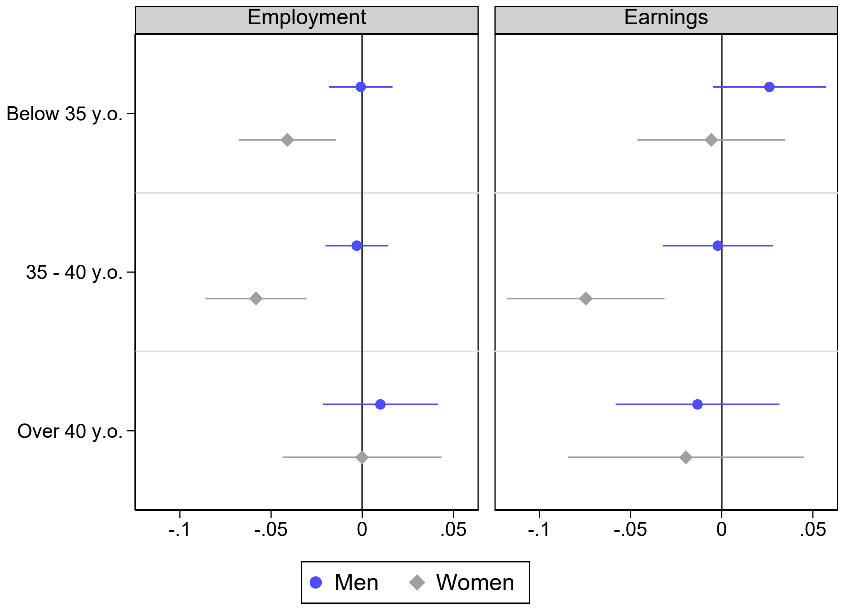
Note: Estimates from equation 1 using different event study estimators that are robust to heterogeneous effects across cohorts. In black the stacked event study estimator, with stacks defined by covariates and cohort; in green a stacked event study estimator with stacks only defined by cohort; in red the Callaway & Sant'Anna estimator; and in purple the de Chaisemartin & D'Haultfoeuille estimator. In this setting, all four estimators use never-treated units as controls and differ in the weights used for aggregation and the variation used (Roth et al. 2023). Outcomes are labor market outcomes for children. Estimates correspond to P_t^m for men and P_t^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

FIGURE A20. Effects of a Parental Health Shock by Timing of Parental Death



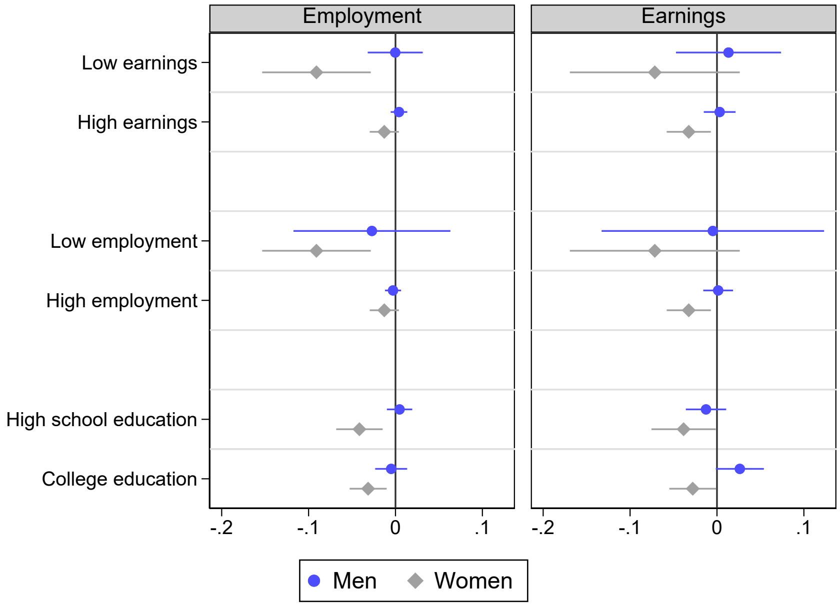
Note: Estimates from equation 3. Outcomes are labor market outcomes for children. Estimates correspond to P^m for men and P^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

Figure A21. Effects of a Parental Cancer Diagnosis by Age



Note: Estimates from equation 3. Outcomes are labor market outcomes for children. Estimates correspond to P^m for men and P^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.

FIGURE A22. Effects of a Parental Cancer Diagnosis by Socioeconomic Status



Note: Estimates from equation 3. Outcomes are labor market outcomes for children. Estimates correspond to P^m for men and P^w for women as defined in Section 3. Employment rate is defined as the average monthly employment rate for each year. Annual earnings are defined as total monthly earnings (including 0s) for each year. All regressions control non-parametrically for age. Control units are weighted by N_T/N_C, where N_T and N_C are the number of treated units and control units within stack. Clustered standard errors at the family level. 95% confidence intervals.