In Sickness and in Health: The Broad Impact of Spousal Health Shocks

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Abstract

In this paper we provide new evidence on the spillover effects of health shocks within couples. Using administrative data from the Netherlands and a matching event-study framework, we estimate the causal effect of experiencing a health shock within a couple on the initially unaffected partner. Our findings reveal a significant deterioration in the partner's health outlook, characterized by substantial increases in hospital visits, overnight stays, and mortality. The health decline is broad in scope, encompassing higher risk of cancer, infections, accidents, and digestive and cardiovascular conditions. This deterioration is accompanied by substantial increases in stress and anxiety for both men a women, as well as depression and sleep disorders for women. Health shocks also trigger changes in household structure, including a increased likelihood of divorce. We do not find evidence of risky behaviors. On the contrary, we document a rise in exercise among men and a reduction in smoking and drinking among women.

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I. Introduction

Health shocks affect the well-being and economic lives of millions around the world. Approximately 7% of the population in high-income countries visits a hospital in a given year (CDC, 2018; CIHI, 2021; Statistics-Netherlands, 2023), and by age 55, at least 42.6% of the population will have experienced a hospitalization event at least once (Statistics-Netherlands, 2023). Health shocks lead to permanent health deterioration and declines in employment and income (García-Gómez et al., 2013; Dobkin et al., 2018). These shocks have spillovers for other family members, specifically partners, whose labor force participation (Lee, 2020; Fadlon and Nielsen, 2021; Jeon and Pohl, 2017; Jeon et al., 2020) and preventive care (Fadlon and Nielsen, 2019; Hoagland, 2022) have been found to be shaped by their affected spousal's health. This deterioration in economic conditions and added distress in the household, can further lead to a deterioration in one's health.

In this paper, we estimate the health effects of having a partner who experiences a health shock, and we delve into the coping mechanisms and changes in household structure that it triggers. We use rich administrative data from the Netherlands from October 1st 1994 to December 31st 2021 that link resident and household structure records for 26.5 million residents, to employment, hospital discharge, medication and survey data. To identify the counterfactual outcomes of couples experiencing health shocks, we use a matching event-study framework. We define a health shock as a hospital visit not related to childbirth or pregnancy which follows at least 5 years during which the individual had never visited a hospital, and we restrict our attention to shocks whose onset cannot be predicted, following García-Gómez et al. (2013). We focus on those experiencing a health shock between 25 and 55 years of age and couples who have been together for at least three years at the time of the health shock.

We start by documenting the effects on the person experiencing the initial health shock. Similar to the previous literature, we find that there is a permanent increase in the probability of future hospitalizations even five years after the original shock. The health deterioration for sick partners has spillovers to conditions other than the initially diagnosed one. Survival rates five years after the shock are 3.7 percentage points (pp) and 4.5 pp lower for women and men, respectively. Sick partners experience permanent declines in employment rates, with their employment rate being 2.5 pp lower five years after the shock. Examining the intensive margin for those who are employed, we estimate sustained declines in hours that peak in the second year after the shock. In terms of employment income, we find long-term declines of 3% for women and 4.6% for men.

We next turn to the effects on the initially healthy partner. We find that hospital visits increase permanently, and by year five after the shock, the initially unaffected partner is 10.8% and 10.9% more likely to visit a hospital for men and women, respectively. We find no evidence that these visits are wasteful or unnecessary; rather, they are indeed

the result of worsening health. For example, we find that unaffected female and male partners are 14.3% and 14.1% more likely, respectively, to themselves experience a severe health shock—defined as an unexpected hosital visit for which admission was classified as urgent and which entailed a hospital stay of at least three nights. The conditions that drive hospital admissions are varied. We find an increased likelihood of nervous, circulatory, digestive and respiratory conditions as well as injuries. This health deterioration translates into a lower survival probability; for women the decline in survival rates is of 0.14 pp and for men is of 0.07 pp. In terms of labor market outcomes, we do not find any economically significant changes in employment, hours worked or income.

Furthermore, these shocks also lead to changes in household structure. The probability of divorce increases by 24.7% when women experience the shock and by 16.6% when men do. Additionally, healthy men are twice as likely to remarry as healthy women. Five years after the shock, the total number of children is lower when women experience the shock, whereas it remains unaffected when men do.

We link our sample to prescription drug data and health surveys, to study the psychological and behavioral changes that these health shocks triggered and that accompany the deterioration in health. We find permanent increases in the probability of filling prescriptions for stress and anxiety for both men and women. Additionally, for women, there are permanent increases in the use of antidepressants. This pattern is also reflected in the survey data, where both men and women report feeling more nervous, and women report increased sadness. In some cases, stronger interventions are required, leading to a higher probability of hospital admissions for mental health conditions in the short term. Sleep quality worsens, as indicated by increased use of medication for sleep disorders. We do not find evidence of negative coping behaviors. Instead, women report not drinking more frequently and those who smoke reduce their cigarette consumption. Men on the other hand increase their exercise levels both at the extensive and intensive margins.

We probe the validity of our identification strategy with multiple exercises. A natural threat to our identification relates to the possibility that, given assortative matching in health outlooks, the health of the initially healthy partner was on track to deteriorate even in the absence of the other partner's health shock. To address this concern, we first show that there is no evidence of anticipation of the shock in "unmatched" health and economic variables such as medication prescriptions, employment, hours worked and income. Second, we examine the health trends of extended family members such as parents and siblings, with whom genetic endowments and health habits are shared, and observe no differential trends in hospital visits or survival rates. Third, we restrict our sample to a subset of shocks that are either more likely to be sudden or less likely to be the result of correlated health behaviours, such as acute appendicitis, injuries, emergency room entries, and shocks with uniform incidence across the week. We find that the patterns and magnitudes are very similar. Finally, we also show that our results are

robust to changes to our sample restrictions, econometric specification and definition of a health shock.

This paper contributes to the literature on the determinants of health and the role of external shocks and spousal spillovers in altering behaviors, increasing mortality and deteriorating well-being. We document that the determinants of health extend beyond genetics (Currie and Moretti, 2007; Visscher et al., 2008), and economic and environmental conditions (Cutler and Lleras-Muney, 2006; Currie, 2009; Heckman, 2006; Chay and Greenstone, 2003; Luttmer, 2005). The well-being of those around us, particularly the impact of partner health shocks, plays a significant role in influencing spousal health behaviors and outcomes. Furthermore, given the extent of couples assortative matching (Greenwood et al., 2014; Eika et al., 2019), and the higher incidence of health shocks for low socio-economic status individuals, this intra-household transmission of health can further exacerbate health inequities.

We also contribute to the literarure on the effects of health shocks on other family members. Previous research has documented spillover effects on health behaviors and investments. Fadlon and Nielsen (2019) show that after a nonfatal heart attack and stroke, family members increase their consumption of cholesterol-lowering medication. Similarly, Hodor (2021) finds evidence of positive behavioral spillovers following a heart attack or stroke, and she further demonstrates that these behavior changes and added expenditures constitute health investments. In contrast, Hoagland (2022) shows that the diagnosis of a chronic condition within a household leads family members to significantly and persistently increase both overall healthcare utilization and investments in disease-specific preventive care, albeit primarily through the uptake of low-value healthcare. This body of work highlights learning about one's own health and the salience of the health shock as important mechanisms, but which can sometimes lead to overreaction. Our contribution to this literature is providing evidence on the direct health deterioration resulting from a partner's health shock, which itself can drive changes in care, behaviors, and health investments.

Finally, recent work has studied the gendered spillover effects of health shocks from children to parents and from parents to adult children on economic outcomes (Costa-Ramón, 2021; Adhvaryu et al., 2023; Brito and Contreras, 2023). Evidence from Chile, Denmark, and Finland points to a decline in income and employment that is larger for mother/daughter than for father/son dyads. In the Dutch context, however, Rellstab et al. (2020) find null labor market effects on adult children of either gender when parents are hospitalized. In this paper, we find that among healthy partners, there are no significant differences in effects by sex on economic outcomes, but we do observe substantial heterogeneity by sex in coping behaviors, the incidence of depression, and divorce and remarriage.

The remainder of the paper is organized as follows. In Section II. we describe our

data, sample selection and empirical strategy. Section III. presents the results and is followed by the robustness checks in Section IV.. Section V. discusses the implications of our findings and concludes.

II. Empirical Strategy and Data

The identification challenge in this paper is to estimate the counterfactual outcomes of couples who experienced a health shock had the shock not occurred. Health shocks are not randomly distributed across the population, specifically, medical care, health investments, and habits correlate with socio-economic variables. A large body of literature documents the income and education health gradients, even in contexts with universal healthcare, such as the Dutch system (Cutler et al., 2008; De Gelder et al., 2017). As a result, the incidence and timing of health shocks can obscure other underlying health and economic trends. This creates a challenge in appropriately constructing a control group.

We address this challenge by first selecting a subset of shocks deemed unexpected by physicians (García-Gómez et al., 2013), and employing a matching event-study specification. Specifically, using rich administrative data, we estimate these counterfactuals by matching each couple in which one person experienced a health shock in year $t = k$, to a couple from the comparison group with identical demographics and similar economic variables during year $t = -3$ relative to the shock. The identification assumption in this setting is that, in the absence of the partner's shock, both the initially healthy treated and control pair would exhibit the same health trends. Because we do not match on trends in the pre-period, the pretrends remain flexible and can be used to evaluate potential bias due to selection on unobservables. This section describes our data sources, details of our sample and shocks selection, and our empirical strategy.

A. Data

Our data are linked administrative records from Statistics Netherlands for the entire Dutch population from October 1st 1994 to December 31st 2021. We use the Municipality Register (GBA), the hospital discharge register (LMR-LBZ), employment records (EWLBUS, POLISBUS, SPOLISBUS), the register of dispensed prescribed drugs (MEDICIJNTAB), and health surveys (POLS, GECON).

Resident and Household Register

The Municipality Register reports the date of birth, date of death and most recently recorded gender for all individuals registered in the Dutch Municipality Register at any point since October 1st, 1994, until December 31st 2021, for a total population of 26.5 million residents. The individual information is linked to household records that list household characteristics for every household formation recorded since October 1st,

1994. A separate household record exists after every change in household composition. For every household, we observe (i) the start and end dates of the recorded household, (ii) the individual identifiers of all household members, and (iii) the household type and the role of each person in the household. We use these data to identify couples in our sample and to construct our family formation outcomes such as divorce and remarriage.[1]

Hospital and Prescriptions Data

The hospital discharge register contains data on both inpatient and day care patients of all general and university hospitals and most of the specialized hospitals in the Netherlands from 1995 to 2019. Each year, there are approximately two million hospitalizations of some 1.6 million distinct individuals. For the entire Dutch population, we observe (i) whether the individual entered the hospital, (ii) whether it was an acute admission, (iii) the admission and discharge date, and (iv) the main diagnosis.[2]

The register of dispensed prescribed drugs reports whether any individual received a particular drug at least once in a given year, for all prescribed drugs covered by the basic insurance package, from 2006 to 2021.[3] We use these data to construct indicators for whether individuals were prescribed different types of drugs.

Health Survey

The health survey provides information on lifestyle, behaviors and a broad set of health measures for a sample of the population. For the years 1997–2009, we use the Continuing Survey on Living Conditions (POLS) and its health module. For the years 2010–2021 we only use the Health Survey, which was conducted independently during this period. These surveys provide self-reported information on weight, smoking and alcohol consumption habits, sport activities, and mental health.

Labor Market Data

The employment records report information for approximately half of all jobs held in the Netherlands for the years 1995–2005 (EWLBUS) and for the universe of jobs for the years 2006–2021 (POLISBUS, SPOLISBUS). For every job recorded in the data, we observe (i) the employee and firm identifiers, (ii) the start and end dates of the employment contract, (iii) the total number of days and hours worked, (iv) gross salary, gross overtime pay and one-time monetary rewards, and (v) sector and type of contract.

[1] As we are using municipal records which report household composition, we do not directly observe marriage and divorce. We use this terminology in the paper to refer to the beginning and end of a cohabitation between a couple. Additionally, we only consider couples who live in the same household.

[2] Health insurance coverage in the Netherlands is universal, comprehensive and mandatory. It covers general practitioner (GP) care, specialist care, hospital care, mental care and medication.

[3] As benzodiazepines were excluded from the basic health insurance package starting from 2009 - with some few exceptions - we only have information on sleeping medication and tranquilizers for the years 2006–2008.

The employment records provide the economic outcomes: namely, employment, hours and income.

B. Sample Construction

We define our treated sample as all couples in which at least one of the spouses ever suffered an unexpected health shock. For each couple, we select the first such shock to occur in our records as the main event for our analysis. As mentioned before, we restrict the treated sample to couples in which the age of both spouses is between 25 and 55 at the time of the health shock. Additionally, we consider only couples formed at least three years prior to the health shock. Finally, we restrict the sample to couples in which neither spouse nor any child residing in the household has any hospital visits recorded for the 5 years preceding the exact date of the main health shock used in the analysis.[4] To make sure that this restriction captures all hospital visits in this period, we restrict the sample to couples that are continuously observed in the Netherlands for at least the 5 years before the health shock. As our records begin in 1995, this restriction effectively implies that the health shocks in our final sample occurred in 2000 and onwards. We also exclude cases in which both spouses experienced a health shock concurrently.

We impose similar sample restrictions on the control sample, such that all control couples also satisfy the conditions related to age, couple's tenure and previous hospital visits relative to the year of the health shock of their matched treated couple. The restriction on previous hospital visits for the control sample is particularly important in our context given our focus on the initially healthy partner's health, as it ensures that we are matching couples in which the partners are comparably healthy. Notice that this restriction does not allow us to perform an empirical strategy using only treated couples, as we need to impose the condition of no hospital visits for a similar number of years in both treated and control couples.[5]

In Table 1 we present summary statistics for 4.6 million people, corresponding to the population of 25 to 55-year-olds who have been in a couple for at least three years, in 2015. The average age in our sample is 41.7 for women and 42.6 for men, with 25.3% of the population under 35 for women and 21.2% for men. Partners of women are, on average, 2.9 years older, while for men, they are 2.2 years younger. Women in this population earn approximately 50% less employment income than their partners and are the main earner in the couple only 25% of the time. Employment rates for women are 72.5%, and for men, they are 80.5%. The one-year divorce rate is around 2.8%, increasing to approximately 10% five years later. The average family size in this population is 3.5. Table 1 also

[4] As young children have a much higher frequency of hospital visits for less serious conditions, we construct this restriction as no hospital visits entailing a hospitalization of one or more nights for children 0-4 years old, and as any hospital visit for children 5 years old and older.

[5] An extreme example of this restriction is that when examining the effects on mortality, not yet treated controls will necessarily be alive.

reports summary statistics for our final sample, as compared to the general population in 2015. As expected, there is a negative selection in the population that experiences a health shock. Income levels and hours worked are lower and age is higher.

B..1 Health Shocks

Over our observed period, on average, 7.6% of the adult population 25 to 55 years old, has a hospital visit in a given year. This share is higher for women, of whom 8.2% experience a hospital visit in a year, as compared to 6.9% of men (see Table 1). Around half of these visits entail an overnight stay in the hospital. Following García-Gómez et al. (2013), we study health shocks whose onset is exogenous and cannot be medically predicted. Additionally, under our health shock definition, we exclude all hospital visits related to pregnancy or childbirth. This group of diagnoses account for 41.8% of all observed hospital visits. The incidence of this shock in our population is 3% a year.

In Tables 2 and 3, we present the most common diagnoses that we will consider as health shocks in our analysis. For women, these are: benign tumors in the uterus (8.9%), malignant breast tumors (8.7%), eye infections (4.3%), and appendicitis (3.8%). There is variation in the average onset of these shocks, with cancer appearing at age 46.5, whereas appendicitis affects women earlier, on average, at 40.4 years old. The severity of the shock also exhibits variation, both in the mortality risk and in the duration of the hospital stay length they entail. For breast cancer, the five-year survival probability is 85.5%, the lowest among the most common shocks. However, in the year of diagnosis, on average, patients only spend 0.7 nights in the hospital, with hospital visits increasing to 2.7 in the year after. On the other hand, acute appendicitis has a 98.5% five-year survival rate but entails 3.3 hospital nights in the year of diagnosis. For men, the most common shocks are heart attacks (7.3%), followed by appendicitis (4.3%), cardiac arrhythmias (4.2%), and benign tumors in the digestive system (3.3%). Similarly, across the most common shocks, five-year survival rates vary from 88.3% to 98.6%, and average hospital stays in the year of the shock range from 0.1 to 6.7 nights. When aggregating into diagnostic categories, in Tables B1 and B2, we find that cancer is the largest group (38%) for women, followed by injuries (15.1%). For men injuries are the top category (25.9%), followed by cardio-vascular conditions (23.4%).

C. Matching

We match our treated and control samples at the couple level in year -3 relative to the health shock. We use an exact match on the gender of each spouse, age of each spouse, employment status of each spouse, an indicator for in-year fertility, number of children living in the household, region of residence, number of alive parents for each spouse, and year. Then, we apply a probability-score match on the employment income percentile

of each spouse, employment income of each spouse, total hours worked of each spouse, employment tenure of each spouse, income ratio, family size, tenure of the couple, and number of children in age groups 0-3, 4-11, and 12 and above. We successfully matched 84% of our shocks to both men and women, to control couples. The matched sample consists of 167,091 unexpected hospital visits for men and 173,229 for women (columns 3 and 4 in Table 1).[6]

D. Event-Study Specification

We identify the health, economic and household structure consequences of health shocks by comparing the evolution of each outcome y among couples who experience the event in index year t with the evolution of that outcome among the matched comparison group:

$$y_{imt} = \alpha_i + \sum_{t=-5, t\neq -2}^{t=5} \beta_t D_t + \sum_{t=-5, t\neq -2}^{t=5} \gamma_t D_t T_i + \varepsilon_{imt} \tag{1}$$

where y_{imt} represents our outcomes for individual i in match m at time to treatment t. $D_t = (\text{time to treatment}_t = t)$ represents dummies for each time to treatment between -5 and +5, T_i is an indicator for treated individuals, and α_i is an individual fixed effect. We are interested in the coefficients γ_t and we cluster standard errors at the individual level.

III. Results

In Figures 1 to 9 we take Eq. 1 to the data and show our results. We present the results for men in blue and for women in orange. Filled markers refer to results for sick partners, and empty markers correspond to those for initially healthy partners.

A. Direct Effects of Health Shocks

We begin by documenting the effects on the person experiencing the initial health shock, this constitutes the *treatment* for the initially healthy partner. Similar to a large body of literature using comparable identification strategies (e.g., Meyer and Mok (2019); Dobkin et al. (2018); Jeon and Pohl (2017); García-Gómez (2011); among others), in Figure 1, we find that following a health shock, there is a permanent decline in health status and labor market attachment. We estimate increases in the probability of future hospital visits, hospitalizations, and future health shocks even five years after the original event. The health deterioration for sick partners has spillovers to conditions other than the initially diagnosed one. In Figure A2, we document that there are increases in the incidence

[6]The unmatched sample (columns 5 and 6 in Table 1), has higher income, is younger, and has lower employment rates, for both partners.

of diagnoses across multiple categories. Survival rates five years after the shock are 3.7 percentage points (pp) and 4.5 pp lower for women and men, respectively. When splitting the sample by income terciles, in Figure A5 we find that effects on future hospitalization are lower for those in the highest income group, particularly in the first three years.

In terms of economic effects, we find that these partners experience significant and permanent declines in employment rates, with their employment rate being 2.5 percentage points lower five years after the shock (Panel a of Figure 2). Within our study window of five years, we do not estimate any recovery from this decline in labor force attachment. Regarding income heterogeneity, we find that employment effects are 40% lower for those in the top tercile of the income distribution (Figure A5). The decline in employment is also greater for more severe shocks. Specifically, we divided the sample into two groups based on the mortality risk associated with the diagnosed condition. We found that among individuals in the higher mortality group, the decrease in employment is 4.2 percentage points for men and 5.5 percentage points for women, compared to 1.2 and 0.8 percentage point, respectively, in the lower mortality group (Figure A6). In terms of the intensive margin for those employed, we also estimate permanent declines in hours. The drop is largest in the second year after the shock, after which hours stabilize in years three to five with a decline of 2.5% to 3%. Both of these changes translate into a permanent decline in employment income of 3% for women and 4.6% for men.

B. Spillover Effects on Partners

The previous results depict a context wherein the initially unaffected partner experienced the deterioration of their partners health and labor market attachment. Next, we evaluate the evolution of their health.

We start by looking at the probability of a hospital visit following the partner's shock. In Panel a of Figure 3, we estimate a positive effect on the probability of hospital visits for years one to five after the shock.[7] By year five, partners of shocked individuals experience 11% higher hospital visits compared to the control group for both women and men. When examining couples from different income groups, Figure A1 shows that, for the most part, the income-health gradient is not very strong.

Recent research suggests that family members may overreact to health shocks experienced by others in the household, and such behavior may not lead to health benefits (Hoagland, 2022). It is therefore reasonable to consider that some of the effects seen in

[7]As we match the treated and control groups at the year level, we need to impose the restriction of no hospital visits until the time of the shock at the year level for the control group. Instead, this restriction is imposed until the precise day of the health shock for partners in the treated sample. For this reason, we cannot meaningfully interpret our estimates in year zero for all outcomes related to hospital visits. Matching at the daily level would allow us to estimate meaningful effects for year zero, but is computationally unfeasible.

Figure 3 could be attributed to this behavior rather than a change in health status. To evaluate this hypothesis, we examine a subset of more severe hospital visits, including overnight stays (Panel b), hospitalizations resulting from diagnoses deemed unexpected by physicians (Panel c), and urgent visits that entail three or more nights at the hospital (Panel d). Across these three categories, we observe significant short and long-term increases in the incidence of more serious hospitalizations.

In Figure 4 we examine the causes for hospital visits by category. We find that a broad range of diagnostic categories drives the increase in hospital visits. For both women and men, there is an increase in the incidence of cancer, digestive, nervous, cardiovascular, musculoskeletal, and respiratory conditions, as well as injuries. The observation of effects in conditions such as cancer within one year of the partner's shock may seem unexpected. This can be explained by both an increase in detection prompted by greater interaction with the healthcare system, but also by the quick development of serious conditions. There is evidence that traumatic events can trigger the onset of cancer (Palesh et al., 2007) and increase cancer mortality (Elwert and Christakis, 2008).

This health deterioration leads to higher mortality risk. In Figure 5 we find evidence that compared to the control group, these initially healthy partners face lower survival rates for the next five years after the shock. Specifically, at the five year mark, the increase in one-year mortality risk for women is 6.12% and 1.5% for men. This evidence points towards a deterioration of health, rather than an overreaction to perceived risk or moral hazard.

Even though the severity of the partner's shock—measured as the shock mortality rate being above the median—is important in determining the extent of health deterioration and economic effects for the sick partner, Panels a and b of Figure 6 show that there is no meaningful heterogeneity on the incidence of hospitalizations for the healthy partner on this dimension. On the other hand, regarding the healthy partner's mortality, we find that men are more affected by less severe shocks, and women by more severe shocks.

Economic Spillovers

We examine whether these events lead to changes in the labor market engagement of this population. Theoretically, one could expect both increases and declines in employment rates and hours worked resulting from either the added-worker effect or the caregiver effect. That is, given the decline in income that the health shock generated, there may be an added necessity for additional income in the household, inducing the initially healthy partner to enter employment or increase the number of hours worked. Alternatively, if there are added caregiving responsibilities that demand considerable amounts of time, the partner may leave employment or reduce hours worked. Previous work has found

mixed evidence, and most of the literature points towards only small adjustments. In Figure 7, we confirm these previous findings, and do not find any evidence of employment adjustment either in the extensive or intensive margins. Given the size of our sample we can reject that responses in terms of employment are larger than 0.0027pp and 0.0054pp for women and men, respectively. This finding holds even when we split the sample by severity of the shock (Figure A7).

Household Structure Changes

These health shocks have significant implications for household structure. As depicted in Figure 8, one year after the shock, the experience of a health shock increases the probability of divorce by 23.7% when women experience the shock and by 24% when men do. By year five, the risk of divorce is 24.7% and 16.6% higher than for the control group, for women and men respectively.

We document substantial heterogeneity in divorce effects by shock severity, family composition and income. In Figure A3, we split the sample by initial shock severity and find that experiencing more severe shocks substantially increases the probability of divorce. These rates are 59% higher for women and 80% higher for men. The sex difference is stronger for severe shocks, after which women face a 45% higher divorce hazard. Regarding family composition, divorce effects are 3.3% higher for women and 1.1% higher for men in couples without children compared to those with children (Figure A4). Across income levels, divorce risk falls as family income rises (Figure A5). These differences are notable: couples in the bottom tercile experience divorce effects that are more than two times higher than those in the top tercile when women experience the shock, and 24% higher when men do. Furthermore, the difference in divorce effects by sex is driven entirely by women in the bottom tercile, who experience divorce risks almost double to those of men.

Finally, we also find large increases in the probability of remarriage. We do not find a difference by sex for sick partners, but for those who did not experience the initial health shock, men are 47.7% more likely to remarry than women. Similar to divorce effects, positive effects on remarriage are higher for those without children (Figure A8). However, given that remarriage rates are higher in couples without children (4.5% for both men and women) compared to those with children (1.8% for women and 2.3% for men), in terms of effect size, the estimates are larger for couples with children. Lastly, five years after the shock, the total number of children is lower when women experience the shock, whereas it remains unaffected when men do.

C. What Explains This Deterioration in Health Status?

The mechanisms behind the health decline of the initially healthy partner can be physiological, psychological, and behavioral (Cohen et al., 2007). Stress-related physiological effects can arise from the body's endocrine responses. These stress responses can potentially increase the risk of both physical and psychiatric disorders by impacting various bodily systems, such as the cardiovascular and immune systems (McEwen, 1998).[8] Supporting this, experimental research in animals has found that stress contributes to the initiation and progression of select tumors and coronary artery disease (Rozanski et al., 1999; Antoni et al., 2006). In addition, the emotional strain from witnessing the decline in the partner's health can contribute to an increased risk of depression (Schulz and Sherwood, 2008; Pinquart and Sörensen, 2003), which can further worsen health status (Moussavi et al., 2007). Finally, behavioral changes often occur as adaptation or coping mechanisms, such as increased smoking, decreased exercise and sleep, poorer diet, and reduced adherence to medical regimens. To empirically evaluate these mechanisms, we use drug prescriptions data and surveys on habits and self-reported health.

Increased Stress Levels

In Panel b of Figure 9, we find an increase in the probability of filling a prescription for stress management immediately after the shock for both women and men.[9] This increase, which remains relatively constant even five years after the shock, corresponds to a 3.1 and 3.6% rise for women and men, respectively. Using our linked survey data, we further support this mechanism. In Panel e of Figure 9, we note that after the shock, healthy partners have an increased likelihood of reporting feelings of nervousness in the past four weeks. Additionally, higher stress levels are indicated by a rise in medications used to treat conditions triggered or worsened by stress, such as hypertension, ulcers, and diarrhea 11.

Incidence of Depression

[8] Physiological effects can arise from stressor-elicited endocrine responses, particularly the hypothalamic-pituitary-adrenocortical (HPA) axis and the sympathetic-adrenal-medullary (SAM) system. The HPA axis is activated by cortisol, which regulates various physiological processes including anti-inflammatory responses, metabolism, and gluconeogenesis. Conversely, the SAM system responds by releasing catecholamines, which work with the autonomic nervous system to regulate systems such as the cardiovascular, pulmonary, hepatic, skeletal muscle, and immune systems. These processes potentially increase the risk of physical and psychiatric disorders.

[9] We identify stress medication as all prescribed drugs classified with ATC codes NC07A (Beta-blocking agents), N02B (Analgesics and antipyretics, other than opioids and anti-migraine preparations), N03A (Antiepileptics), N05B (Anxiolytics), N05C (Hypnotics and sedatives), and N06A (Antidepressants).

To investigate psychological distress we examine the probability of having a prescription for antidepressants in Panel a of Figure 9.[10] We find that women experience a gradual increase in the likelihood of being prescribed antidepressants, and by year five, they are 3.7% more likely to be taking antidepressants than women in the control group. For men, we do not find statistically significant effects. In Panel d of Figure 9, we find that after the shock, healthy women also have an increased likelihood if stating they felt sad or depressed in the past four weeks.

The severity of some of these experiences is high enough to entail a hospital visit. Panel f of Figure 9 shows the probability of a hospital visit with a mental health diagnosis. We detect an increased probability of a hospital visit due to a mental health condition in the year after the shocks for both women and men, for the subset of shocks that entail higher mortality rates. We do not find any effect on hospital visits with a mental health diagnosis for non severe shocks.

Behavior Changes and Coping Mechanisms

A large body of literature has documented the importance of sleep as a major determinant of health (Luyster et al., 2012; Grandner, 2022). Increased stress and depression have been linked to worsening sleep quality and duration (Kalmbach et al., 2018; Oh et al., 2019). We use the three years in our data (2006–2008), when sleeping medications were covered by public health insurance, to document changes in sleeping disorders.[11] As we only have three years of data for this medication group we cannot construct a panel of sleep medication use for the full 11-year time period around the time of the shock. For this reason, we add a control for calendar year to our specification. In Panel c of Figure 9, we find an immediate increase in the likelihood of filling a prescription for sleep medication in the year of the whock. For women, we also estimate a statistically significant effect for the first three years following the shock.[12]

Next, we link 0.11% of our sample to the health surveys and find that this linkage is balanced in terms of treatment and control status, time to shock, and sex. Given the smaller sample size, we pool years together for our regression analysis, and include controls for survey year, log of employment income for both spouses in $t = -3$, employment tenure for both spouses in $t = -3$, couple's tenure in $t = -3$, age of both spouses in $t = -3$, region of residence in $t = -3$, as well as two continuos measures of severity based on the rate of subsequent mortality and hospital visits. These controls, which were part of

[10] We identify antidepressants as prescribed drugs classified with ATC code N06A.

[11] We identify sleep medication as all prescribed drugs classified with ATC codes N05B (Anxiolytics) and N05C (Hypnotics and sedatives).

[12] Figure A10 reports our estimates from an alternative specification which does not include individual fixed effects. As compared to our preferred specification, these estimates are larger in magnitude but more precise in the period following the shock.

the propensity score matching in our main specification, contribute to balance treatment and control groups in this exercise, where the sample size is too small to construct the exact and propensity matching of our main analysis. Using these data, we further explore changes in behaviors and coping mechanisms, such as drinking, smoking, and exercising. In terms of risky behaviors, in Table 4 we estimate that shortly after the shock, women are more likely to report that they never drink and also reduce the number of cigarettes they smoke. For men, on the other hand, we do not find any significant effects on smoking or alcohol consumption. When examining exercise habits, we find that around the time of the shock, men increase their amount of exercise, both in terms of frequency and intensity. The probabilty than men report being overweight also decreases, while we do not find any significant effects for women.

IV. Robustness

In this section we provide evidence of the validity of our identification strategy and conduct different robustness checks.

A natural threat to our identification relates to the possibility that, given assortative matching in health outlooks, the health of the initially healthy partner would have deteriorated even in the absence of the other partner's health shock. To address this concern, we show that there is no evidence of anticipation of the shock in "untargeted" health and economic variables such as medication prescriptions, employment, hours worked and income. This can be observed when we examine the in Figure 7 for economic outcomes and Figures 9 and 11 for medication. The coefficients of the pre-trends are statistically insignificant both individually and jointly. There is also no clear pattern or trend in the data.

Second, we examine the health trends of extended family members such as parents and siblings, with whom genetic endowments and health habits are shared. This excercise is possible given the richness of Dutch municipal registers, which allow to identify the parents and siblings of the individuals in our sample, in order to follow the health outcomes of the entire family tree. In Figure 10 we plot event study estimates for hospital visits and overnight hospital stays. We find there is not any meaningful difference between sibling and parents across treatment and control groups before the onset of the shock. This evidence further suggests that the health effects we estimate for the initially healthy partner, are the result of the shock measured at $t = 0$, and not the result of an underlying and contemporaneous health decline.

Third, we show that our results remain consistent when we examine a subset of shocks that are either more likely to be sudden or less likely to result from correlated health behaviors. To demonstrate this, we construct four different sets of shocks. First,

we restrict our shocks to those that begin in the emergency room (41%) or have an urgent code from the referring physician. Second, we consider "undeferrable" shocks, that occur with the same frequency across all days of the week (4.1%).[13] Third, we limit our sample to acute appendicitis events (4%). Fourth, we restrict our sample to injuries (20.5%). Figure 13 presents the results on hospital visits and hospitalizations for these sets of shocks. We find that, the patterns are similar to our baseline specification across all definitions, even when the sample size is substantially smaller and the severity of the shocks varies significantly. Results for appendicitis are smaller and shorter lived, which is expected given the overall low severity and ambulatory nature of the shock.

An alternative explanation is that our effects are the result of common shocks (i.e car accident, poisonings, etc) rather than spillovers. To address this concern, in Figure A11, we exclude couples who experienced hospital visits less than one week or one month apart, respectively. We find that our results remain invariant to this exclusion. Similarly, a concern is that our results might reflect correlated risks rather than spillover effects. In Figure 12 we provide evidence against this hypothesis by examining effects on hospital visits for diagnosis categories different from the initial shock. For these cases, we find substantial increases in the probability of a hospital visit, consistent across multiple diagnosis categories. Specifically, we observe that 92% of the hospital visits arise from conditions where this was not the category of the partner's initial shock.

Finally, in Figure A9 we further refine the definition of the shock to assess the sensitivity of the effects to different definitions. The first definition includes only shocks that entail a hospital stay of three days or longer, and the second adds the further restriction of an urgent intake. We find that our estimated spillovers are present across all shock definitions and that the point estimates are very similar.

V. Discussion

In this paper, we show how one's health is profoundly influenced by the well-being of those around them, particularly one's partner. Our findings underscore the significant health repercussions experienced by both the initially affected partner and their initially healthy counterpart. We observe a sustained increase in hospital visits for the initially healthy partner, increased likelihood of hospitalization, and higher mortality rates.

Furthermore, our analysis estimates the broader spillover effects on family dynamics and structure. We find evidence of elevated divorce probabilities following a partner's health shock, particularly among women. Additionally, the discrepancy in remarriage

[13]Specifically, for each shock diagnosis, we use the full hospital records and test if the proportion of weekend admissions is equal to the proportion of weeday admissions (Rellstab et al., 2020). We identify a shock diagnosis as "undeferrable" if we do not reject the null hypothesis at the 1% level. Most of the shocks classified as"undeferrable" are injury diagnoses.

rates between healthy men and women underscores the gendered nature of post-shock adjustments within households.

Overall, the behavioral adaptations, emotional strain, and physiological responses we document illustrate the complex interplay of factors contributing to increased risks and worsening health. The data show significant rises in stress and depression, as reflected in higher prescription rates for stress management and antidepressants, particularly among women. This health deterioration is present even amidst improvements in healthy habits. Women report reductions in alcohol consumption and smoking, while men increase their physical activity and are less likely to be overweight

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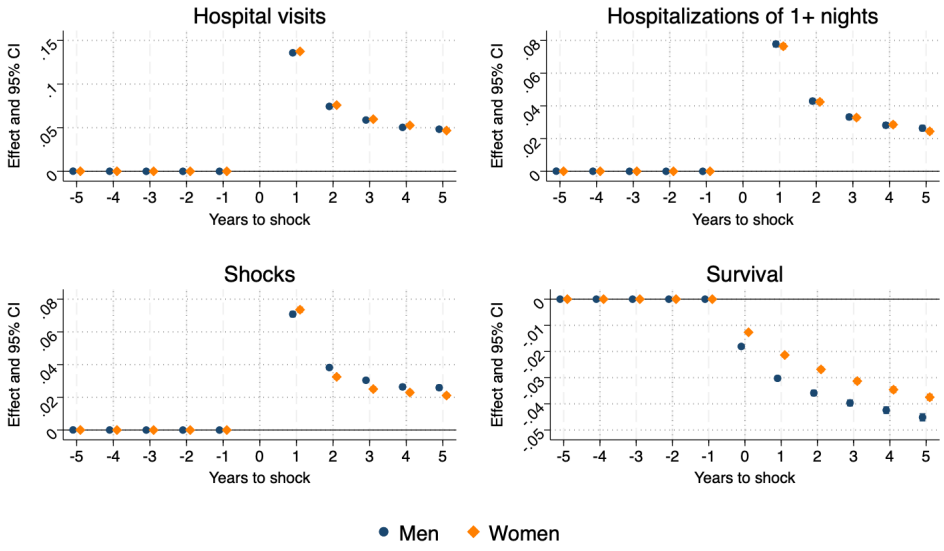
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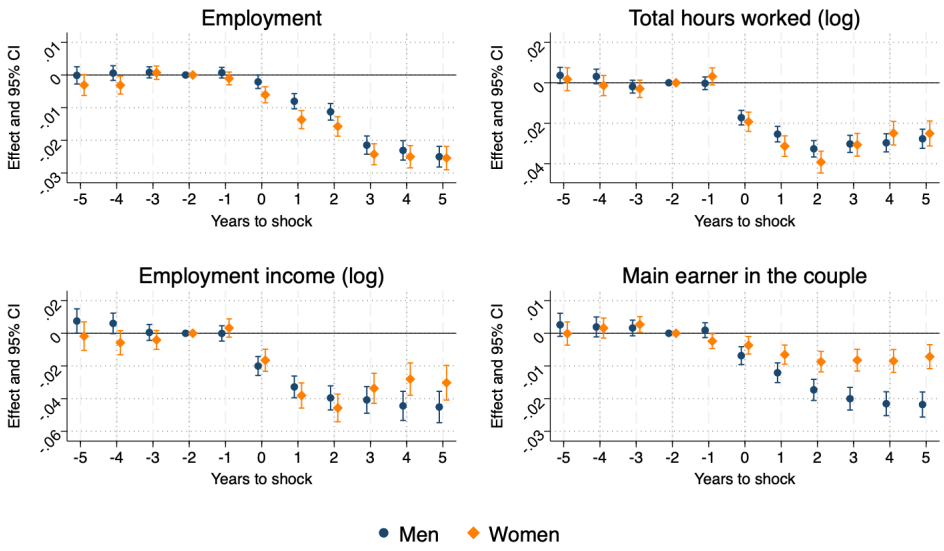
VI. Figures

Figure 1: Health Effects of Own Health Shock



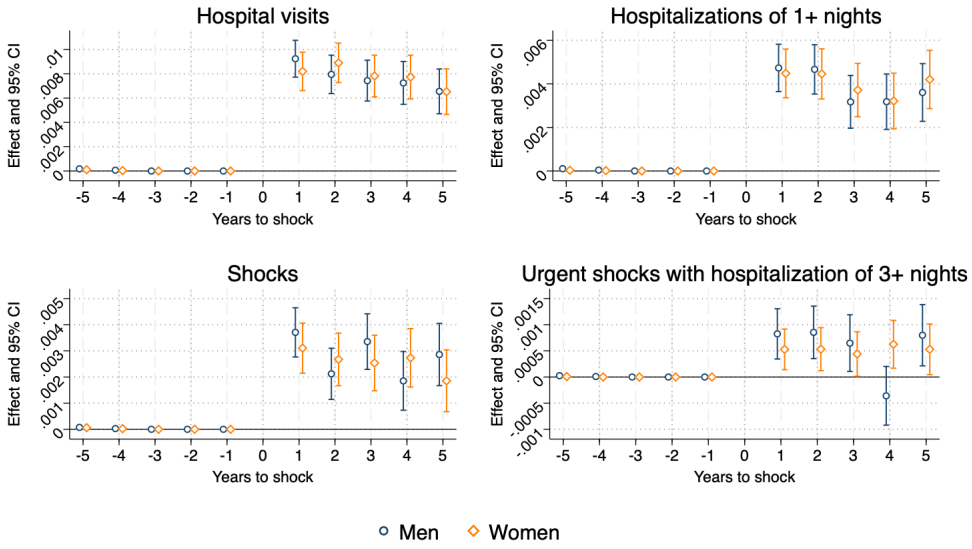
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on hospital visits, hospitalizations, health shocks, and survival in the subsequent 5 years for the shocked individual. Hospital visits include all visits to the hospital, with the exception of visits with a diagnosis related to pregnancy or childbirth. Hospitalizations include all hospital visits, with the exception of visits with a diagnosis related to pregnancy or childbirth, for which the patient was discharged one day or more after admission. Following García-Gómez et al. (2013) shocks identify hospital visits whose onset is exogenous and cannot be medically predicted, based on the diagnosis. We construct survival based on individual's year of death. Coefficients for $t = -5$ to -1 are zero by construction due to our sample restrictions. Coefficients for $t = 0$ for hospital visits, hospitalizations, and health shocks are outside of the scale of the graph. The coefficient is 1 for all specifications by construction. Standard errors are clustered at the individual level. This figure is referenced in Section III.A.

Figure 2: Economic Effects of Own Health Shock



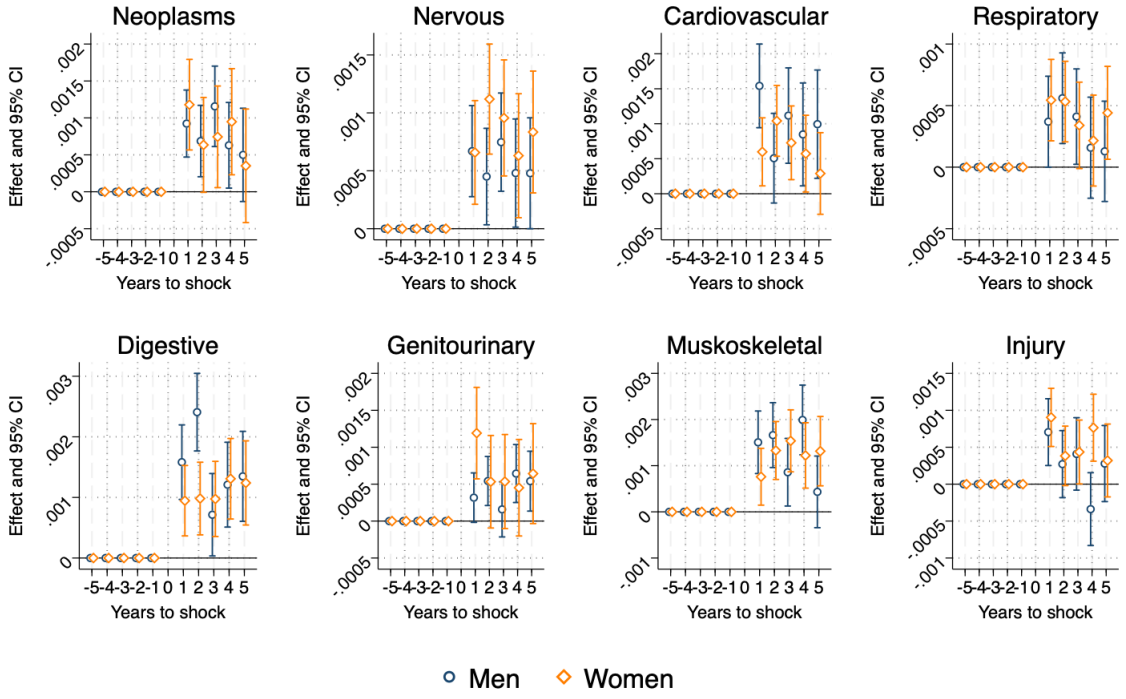
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on employment, the log of the total number of hours worked, the log of employment income, and an indicator for the main earner in the couple in the subsequent 5 years for the shocked individual. Employment is only defined for years 2006 onwards, as we do not have data on the universe of jobs for the previous years. Total hours worked and employment income are conditional on the individual being employed; these variables are defined for the entire period. The variable main earner in the couple is constructed as an indicator which is equal to one if the individual is employed and earns more than their spouse. Standard errors are clustered at the individual level. This figure is referenced in Section III.A.

Figure 3: Health Spillover Effects



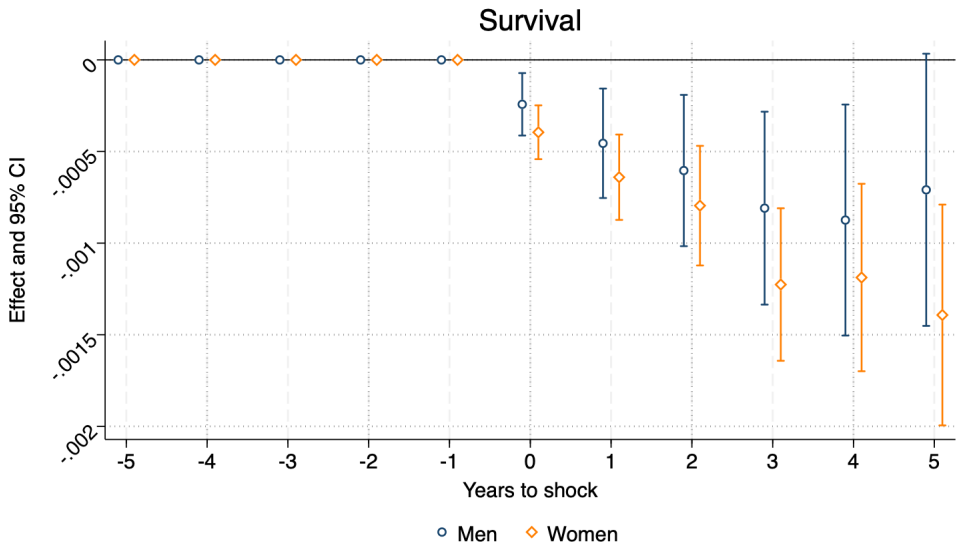
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on hospital visits, hospitalizations, shocks and urgent shocks that were followed by a hospitalization of at least 3 nights in the subsequent 5 years for the partner of the shocked individual. Hospital visits include all visits to the hospital, with the exception of visits with a diagnosis related to pregnancy or childbirth. Hospitalizations include all hospital visits, with the exception of visits with a diagnosis related to pregnancy or childbirth, for which the patient was discharged one day or more after admission. Following García-Gómez et al. (2013) shocks identify hospital visits whose onset is exogenous and cannot be medically predicted, based on the diagnosis. Urgent shocks with a hospitalization of 3 or more nights include all shocks for which the hospital visit started at the Emergency Room or that have an urgent code from the referring physician, and for which the patient was discharged three days or more after admission. Coefficients for $t = -5$ to -1 are zero by construction due to our sample restrictions. Coefficients for $t = 0$ cannot be interpreted meaningfully given the different sample restrictions imposed on partners in the treated and control groups. In particular, we match treated and control couples at the yearly level due to computational feasibility. This implies that we need to impose the restriction of no previous hospital visits until the year of the shock for partners in the control sample, while the restriction is imposed until the precise date of the shock for partners in the treated sample. Standard errors are clustered at the individual level. This figure is referenced in Section III.B.

Figure 4: Hospital Visits by Diagnosis Category: Initially Healthy Partner



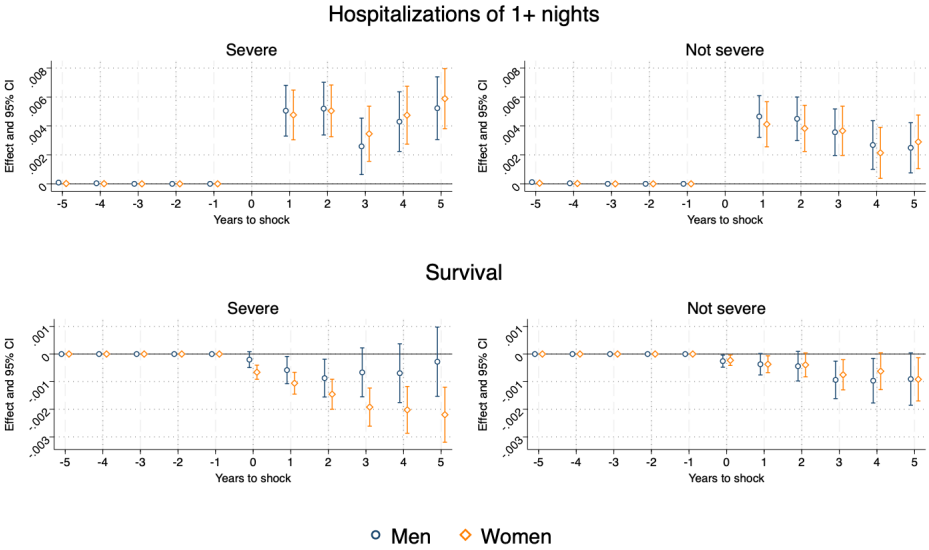
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on hospital visits by broad diagnosis category in the subsequent 5 years for the partner of the shocked individual. Hospital visits include all visits to the hospital, with the exception of visits with a diagnosis related to pregnancy or childbirth. We show results for hospital visits in the following diagnosis categories: neoplasms (ICD-9 codes 140-239), diseases of the nervous system and sense organs (320-389), diseases of the circulatory system (390-459), diseases of the respiratory system (460-519), diseases of the digestive system (520-579), diseases of the genitourinary system (580-629), diseases of the musculoskeletal system and connective tissue (710-739), injury (800-999). Coefficients for $t = -5$ to -1 are zero by construction due to our sample restrictions. Coefficients for $t = 0$ cannot be interpreted meaningfully given the different sample restrictions imposed on partners in the treated and control groups. In particular, we match treated and control couples at the yearly level due to computational feasibility. This implies that we need to impose the restriction of no previous hospital visits until the year of the shock for partners in the control sample, while the restriction is imposed until the precise date of the shock for partners in the treated sample. Standard errors are clustered at the individual level. This figure is referenced in Section III.B.

Figure 5: Health Spillover Effects: Survival Rates



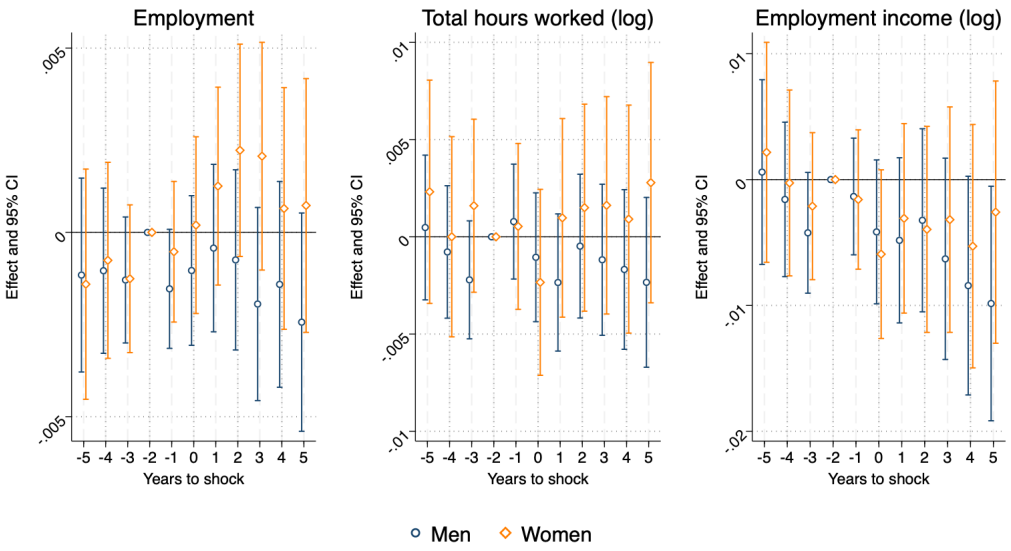
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on survival in the subsequent 5 years for the partner of the shocked individual. We construct survival based on individual's year of death. Coefficients for $t = -5$ to -1 are zero by construction due to our sample restrictions. Standard errors are clustered at the individual level. This figure is referenced in Section III.B.

Figure 6: Health Spillovers by Shock Severity



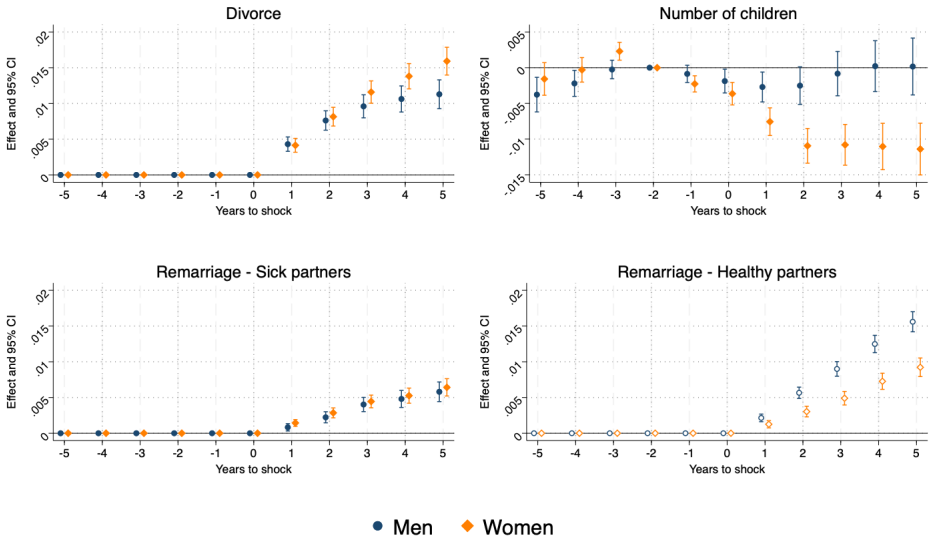
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on hospitalizations and survival in the subsequent 5 years for the partner of the shocked individual. Hospitalizations include all hospital visits, with the exception of visits with a diagnosis related to pregnancy or childbirth, for which the patient was discharged one day or more after admission. We construct survival based on individual's year of death. The effects are shown separately by severity of the initial shock. We classify shocks as severe if the mortality risk associated with the diagnosed condition for the control group is above the median. Coefficients for $t = -5$ to -1 are zero by construction due to our sample restrictions. Coefficients for hospitalizations in $t = 0$ cannot be interpreted meaningfully given the different sample restrictions imposed on partners in the treated and control groups. In particular, we match treated and control couples at the yearly level due to computational feasibility. This implies that we need to impose the restriction of no previous hospital visits until the year of the shock for partners in the control sample, while the restriction is imposed until the precise date of the shock for partners in the treated sample. Standard errors are clustered at the individual level. This figure is referenced in Section III.B.

Figure 7: Economic Spillovers: Initially Healthy Partner



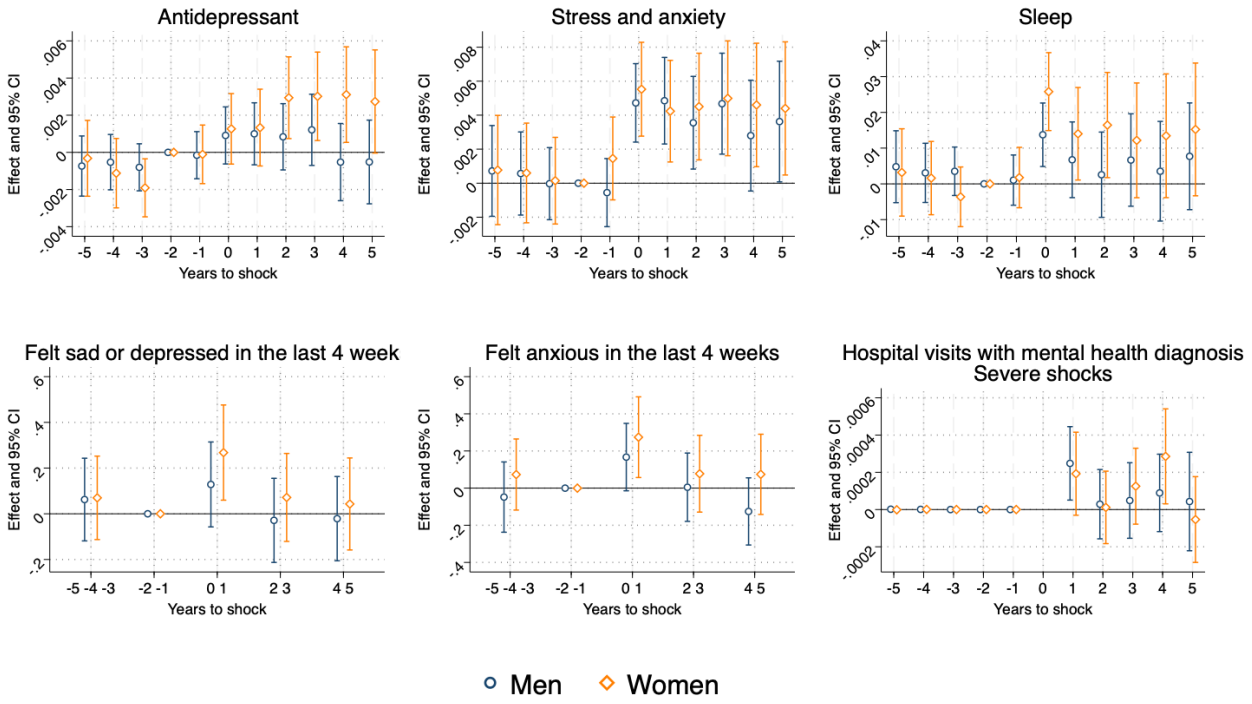
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on employment, the log of the total number of hours worked, and the log of employment income, in the subsequent 5 years for the partner of the shocked individual. Employment is only defined for years 2006 onwards, as we do not have data on the universe of jobs for the previous years. Total hours worked and employment income are conditional on the individual being employed; these variables are defined for the entire period. Standard errors are clustered at the individual level. This figure is referenced in Section III.B.

Figure 8: Household Structure Effects of Health Shocks



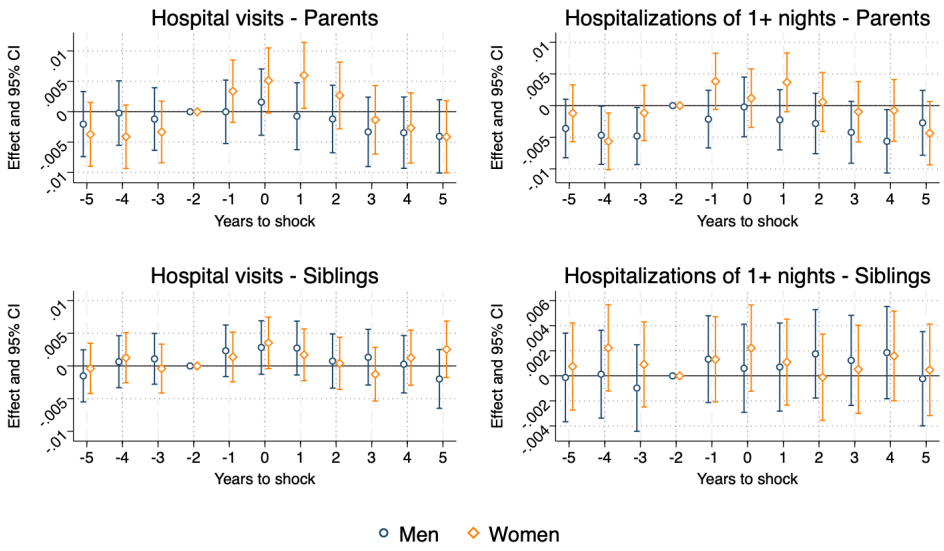
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ in the subsequent 5 years on divorce, and the log of the total number of children for the affected couple, and on remarriage separately for the shocked individual and for their partner. Coefficients for $t = -5$ to -1 for divorce and remarriage are zero by construction due to our sample restrictions. Standard errors are clustered at the individual level. This figure is referenced in Section III.B.

Figure 9: Health Spillover Effects: Mental Health



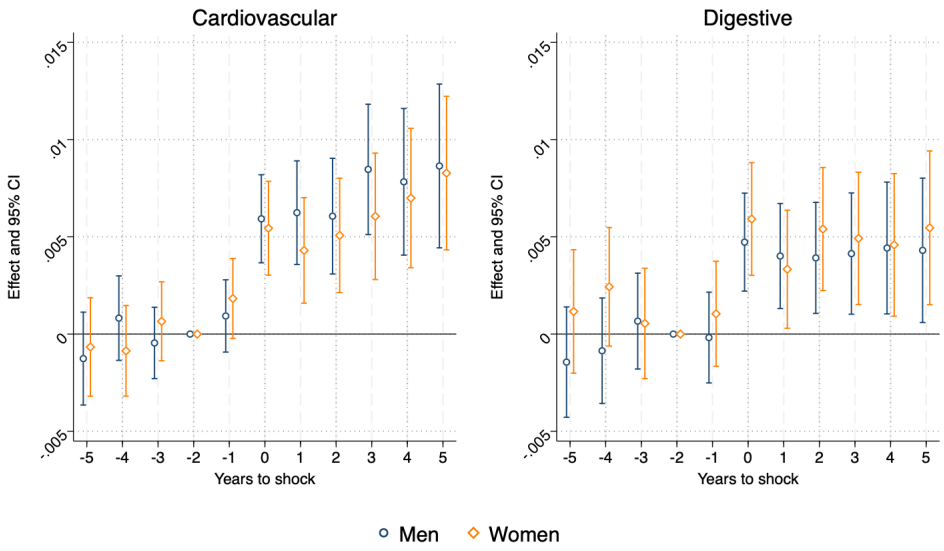
Notes: The graphs in Panels a and b of this figure show our estimates for the coefficients γ_t from Eq. 1, for the effect of a health shock in $t = 0$ on consumption of antidepressants and stress management medication in the subsequent 5 years for the partner of the shocked individual. We construct the outcomes as indicators equal to 1 if the individual filled any prescription for a stress medication (ATC codes NC07A, N02B, N03A, N05B, N05C, N06A) or antidepressants (ATC code N06A) during the year. Panel c shows our estimates for the coefficients γ_t from a specification analogous to Eq. 1, where we add a control for calendar year. We make this adjustment as we only observe the prescription of sleeping medication for three years (2006–2008), when they were covered by public health insurance, so we cannot construct a panel of sleeping medication usage for the full 11-year period around the time of the shock. Specifically, the figure shows the effect of a health shock in $t = 0$ on the prescription of sleping medication (ATC codes N05B and N05) in the subsequent 5 years for the partner of the shocked individual. The indicator for sleep medication is equal to 1 if the individual filled any prescription for a drug in this category during the year. Panels d and e show our estimates for the coefficients γ_t from a specification analogous to Eq. 1, where we pool together single years to treatment. Specifically these panels show the effect of health shocks in $t = 0$ on two self-reported mental health measures for the partner of the shocked individual. Respondents answered the following two questions on a scale of 1 to 5 based on frequency:"In the past 4 weeks I felt depressed and gloomy" and "In the past 4 weeks I felt very anxious". We standardize these variables and estimate the effects of the health shock in the subsample which we are able to link to the health survey. Panel f shows our estimates for the coefficients γ_t from Eq. 1 for hospital visits with a mental health diagnosis (ICD9 codes 290-319) for the subsample of initial shocks classified as severe. We classify shocks as severe if the mortality risk associated with the diagnosed condition for the control group is above the median. Coefficients for $t = -5$ to -1 are zero by construction due to our sample restrictions. Coefficients for $t = 0$ cannot be interpreted meaningfully given the different sample restrictions imposed on partners in the treated and control groups. In particular, we match treated and control couples at the yearly level due to computational feasibility. This implies that we need to impose the restriction of no previous hospital visits until the year of the shock for partners in the control sample, while the restriction is imposed until the precise date of the shock for partners in the treated sample. This figure is referenced in Section III.C.

Figure 10: Health Evolution of Other Family Member



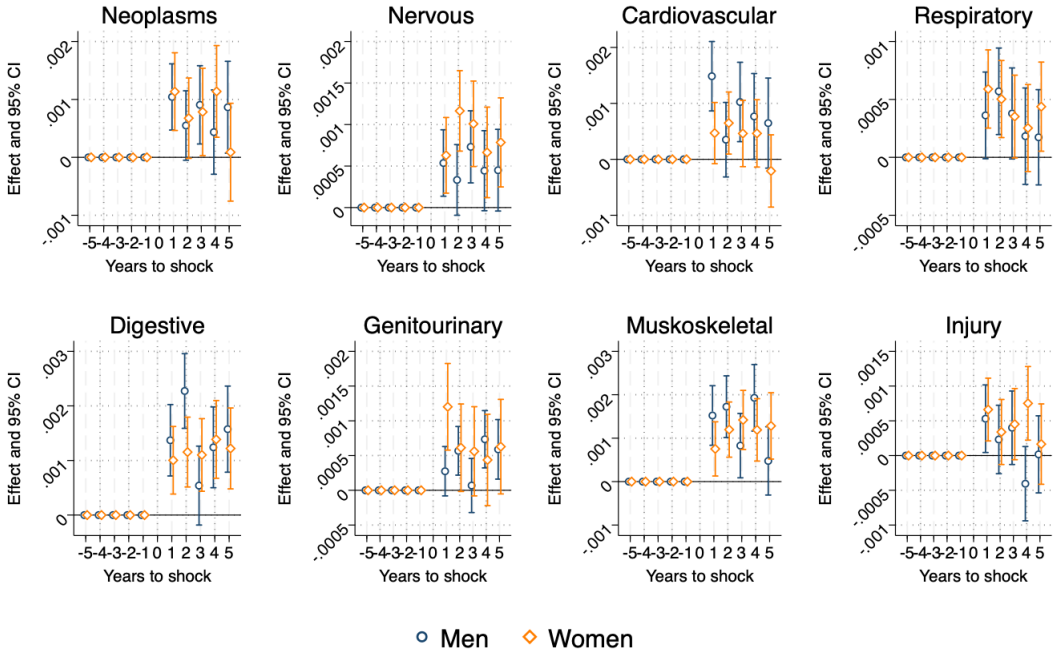
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on hospital visits and hospitalizations in the subsequent 5 years for relatives of the partner of the shocked individual. Hospital visits include all visits to the hospital, with the exception of visits with a diagnosis related to pregnancy or childbirth. Hospitalizations include all hospital visits, with the exception of visits with a diagnosis related to pregnancy or childbirth, for which the patient was discharged one day or more after admission. Panels a and b show these effects for the parents of the partner of the shocked individual, while Panels c and d show these effects for their siblings. The indicators for hospital visits and hospitalizations are equal to 1 if any of the parents (or any of the siblings) experienced the event during the year. Standard errors are clustered at the individual level. This figure is referenced in Section IV.

Figure 11: Health Spillover Effects: Medication Prescriptions



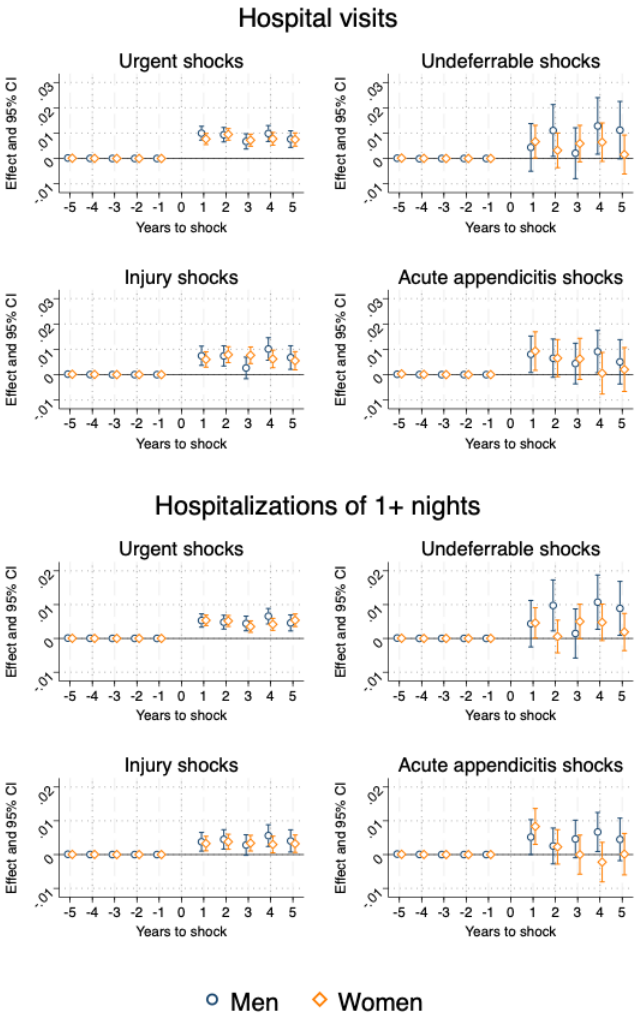
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on the prescription of medication for cardiovascular (ATC codes C) and digestive (ATC codes A) conditions in the subsequent 5 years for the partner of the shocked individual. The indicators for are equal to 1 if the individual filled any prescription for a drug in this category during the year. Standard errors are clustered at the individual level. This figure is referenced in Section IV.

Figure 12: Health Spillover Effects: Hospital Visit for Categories Different that the Original Shock



Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on hospital visits by broad diagnosis category in the subsequent 5 years for the partner of the shocked individual. For each diagnosis category, we exclude couples for whom the diagnosis of the sick individual's initial shock belongs to that same category. For example, when we look at the effects on hospital visits with a cardiovascular diagnosis, we exclude couples in which the sick partner experienced a heart attack in $t = 0$. Coefficients for $t = -5$ to -1 are zero by construction due to our sample restrictions. Standard errors are clustered at the individual level. This figure is referenced in Section IV.

Figure 13: Health Spillover Effects: Subset of "Sudden" Shocks



Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on hospital visits and hospitalizations in the subsequent 5 years for the partner of the shocked individual. Hospital visits include all visits to the hospital, with the exception of visits with a diagnosis related to pregnancy or childbirth. Hospitalizations include all hospital visits, with the exception of visits with a diagnosis related to pregnancy or childbirth, for which the patient was discharged one day or more after admission. Each panels restricts to a different set of shocks which are less likely to be expected or correlated with the partners health. Urgent shocks are shocks for which the hospital visit starts at the Emergency Room or that have an urgent code from the referring physician. Undeferrable shocks correspond to shock diagnoses that occur with the same frequency across all days of the week. Specifically, for each shock diagnosis, we use the full hospital records and test if the proportion of weekend admissions is equal to the proportion of weeday admissions (Rellstab et al., 2020). We identify a shock diagnosis as undeferrable if we do not reject the null hypothesis at the 1% level. Injury shocks include all shocks with an injury diagnosis (ICD-9 codes 800-959). Acute appendicities shocks are hospital visits with a diagnosis for acute appendicitis (ICD-9 code 540). Coefficients for $t = -5$ to -1 are zero by construction due to our sample restrictions. Coefficients for $t = 0$ cannot be interpreted meaningfully given the different sample restrictions imposed on partners in the treated and control groups. In particular, we match treated and control couples at the yearly level due to computational feasibility. This implies that we need to impose the restriction of no previous hospital visits until the year of the shock for partners in the control sample, while the restriction is imposed until the precise date of the shock for partners in the treated sample. Standard errors are clustered at the individual level. This figure is referenced in Section IV.

VII. Tables

Table 1: Summary Statistics

Variable	**General Population 2015**		**Matched Sample at t=-1**		**Unmatched Sample at t=-1**	
	Women	Men	Women	Men	Women	Men
Age	41.7	42.6	42.6	44.6	40	42.4
Age 25-35	25.3%	21.2%	15.2%	11.6%	26.8%	18.7%
Age 36-45	34.7%	35.1%	38.5%	31.2%	40.4%	36.0%
Age 46-55	40.0%	43.7%	46.3%	57.2%	32.8%	45.3%
Age of partner	44.6	40.4	44.6	42.3	41.9	39.1
Employment income	22,314	41,898	17,002	36,900	24,131	43,397
Employment income of partner	42,193	22,057	23,899	11,207	33,919	18,168
Employed	72.5%	80.5%	77.0%	84.5%	65.6%	68.8%
Employed partner	78.6%	73.4%	84.9%	77.4%	70.1%	64.3%
Total hours per week	21.2	32.2	16.4	27.6	21.9	31.5
Divorce rate (one year)	2.7%	2.9%				
Divorce rate (five years)	9.80%	10.70%				
Family size	3.5	3.5	3.3	3.4	3.5	3.5
Main earner in the household	25.3%	75.8%	20.4%	78.3%	29.8%	69.4%
Hospital visit rate	8.2%	6.9%				
Hospitalization rate	4.3%	3.4%				
Any shock during the year	3.0%	2.9%				
Urgent shock with 3+ nights hosp.	0.5%	0.6%				
Survival rate (one year)	99.9%	99.9%				
Survival rate (five years)	99.4%	99.2%				
Observations	2,405,357	2,214,204	173,229	167,091	31,198	31,154

Notes: The Table reports summary statistics by gender. The first two columns report summary statistics for the population of 25-55-year-olds who had been in a couple for at least three years, in 2015. The third and fourth columns report statistics for the sick individuals in our main sample of analysis in the year preceding the health shock, $t = -1$. This corresponds to couples where both spouses are 25-55 years old in $t = 0$ with at least 3 years of couple's tenure by that time, and in which neither spouse nor any children residing in the household had any hospital visit for the 5 preceding years. The fifth and sixth columns report statistics for individuals who suffer a health shock and statisfy our sample restrictions, but for whom the matching algorithm does not find a suitable match among control couples. Employment is only defined for years 2006 onwards, as we do not have data on the universe of jobs for the previous years. Total hours worked per week and employment income are conditional on the individual being employed; these variables are defined for the entire period. The variable main earner in the household is constructed as an indicator which is equal to one if the individual is employed and earns more than their spouse. Divorce and health-related variables are not meaningful for the shocked population due to our sample restrictions. This Table is referenced in Section B.

Table 2: Most Common Diagnostic Codes: Women

Main Diagnoses in t=0	**Total Number of Diagnoses**	**Share of Total Diagnoses**	**Share of Totall Diagnoses in Control**	**Avg Age at Diagnosis in Control**	**Avg Nights in Hospital in Control**	**Avg Num Hosp. Visits Next Years in Control**	**5-Year Survival Probability in Control**
Uterine leiomyoma	15,342	8.9%	2.0%	44.8	2.6	0.2	98.6%
Malignant neoplasm of female breast	15,046	8.7%	5.8%	46.5	0.7	2.7	85.5%
Other disorders of eyelids	7,437	4.3%	0.9%	47.6	0.0	0.2	98.6%
Acute appendicitis	6,597	3.8%	0.8%	40.4	3.3	0.2	98.5%
Noninflammatory disorders of cervix	4,436	2.6%	0.8%	39.4	0.2	0.2	98.4%
Benign neoplasm of other parts of digestive system	4,021	2.3%	0.7%	47.6	0.5	0.5	97.2%
Other disorders of synovium, tendon and bursa	3,605	2.1%	1.0%	43.9	0.1	0.2	98.7%
Carcinoma in situ of breast and genitourinary system	3,546	2.0%	0.6%	44.1	0.9	0.6	97.9%
Lipoma	3,343	1.9%	0.4%	44.4	0.2	0.2	99.0%
Benign neoplasm of breast	3,024	1.7%	0.3%	41.5	0.2	0.2	98.3%
Fracture of ankle	2,808	1.6%	0.4%	44.3	2.1	0.4	98.5%
Fracture of radius and ulna	2,493	1.4%	0.3%	45.7	0.9	0.3	98.6%
Benign neoplasm of ovary	2,451	1.4%	0.3%	42.1	2.6	0.2	98.7%
Complications peculiar to certain specified procedures	2,441	1.4%	0.6%	44.3	2.3	0.6	94.4%
Cholelithiasis	2,399	1.4%	2.6%	42.0	1.8	0.2	98.6%
Average in control				**39.8**	**0.04**	**0.1**	**98.2%**

Notes: The Table reports the most common diagnoses that we consider as health shocks - i.e. hospital visits whose onset is exogenous and cannot be medically predicted, excluding visits related to pregnancy and childbirth - for the sick women in our main sample. For each diagnosis we report the total number of $t = 0$ shocks in the sample of sick individual and their share of total shocks. We also report a set of statistics based on the full sample of possible controls - i.e. the control sample which passes our sample restrictions, but that is not necessarily matched to a treated couple. Specifically, for each diagnosis we report the share of total shock diagnoses, the average age at diagnosis, the average number of nights spent in the hospital immediately following the diagnosis, the average number of hospital visits one year after a diagnosis, and the 5-year survival probability. The bottom line in the table reports these statistics for the full control sample. This Table is referenced in Section B..1

Table 3: Most Common Diagnostic Codes: Men

Main Diagnoses in t=0	**Total Number of Diagnoses**	**Share of Total Diagnoses**	**Share of Totall Diagnoses in Control**	**Avg Age at Diagnosis in Control**	**Avg Nights in Hospital in Control**	**Avg Num Hosp. Visits Next Years in Control**	**5-Year Survival Probability in Control**
Acute myocardial infarction	12,116	7.3%	2.1%	49.8	4.4	0.4	94.7%
Acute appendicitis	7,103	4.3%	0.9%	42.2	3.3	0.2	98.4%
Cardiac dysrhythmias	7,089	4.2%	2.3%	49.3	1.5	0.7	95.2%
Benign neoplasm of other parts of digestive system	5,566	3.3%	1.1%	50.0	0.3	0.5	96.1%
Lipoma	4,108	2.5%	0.5%	46.0	0.1	0.1	98.1%
Symptoms involving respiratory system and other chest symptoms	3,832	2.3%	4.9%	46.9	0.7	0.4	97.0%
Sprains and strains of ankle and foot	3,680	2.2%	0.4%	42.6	0.8	0.1	98.6%
Angina pectoris	3,639	2.2%	0.9%	50.2	1.4	0.5	97.1%
Other forms of ischaemic heart disease	3,557	2.1%	0.7%	50.2	3.8	0.5	97.2%
Other disorders of synovium, tendon and bursa	3,258	1.9%	0.8%	45.3	0.3	0.2	98.4%
Abscess of anal and rectal regions	3,033	1.8%	0.5%	43.7	1.2	0.5	97.4%
Fracture of ankle	2,827	1.7%	0.4%	43.3	2.3	0.4	98.1%
Pneumonia, organism unspecified	2,584	1.5%	0.4%	46.7	5.7	0.5	88.3%
Fracture of radius and ulna	2,506	1.5%	0.3%	44.7	1.3	0.3	98.3%
Occlusion of cerebral arteries	2,374	1.4%	0.4%	50.1	6.7	0.4	90.4%
Average in control				**41.9**	**0.04**	**0.1**	**97.8%**

Notes: The Table reports the most common diagnoses that we consider as health shocks - i.e. hospital visits whose onset is exogenous and cannot be medically predicted, excluding visits related to pregnancy and childbirth - for the sick men in our main sample. For each diagnosis we report the total number of $t = 0$ shocks in the sample of sick individual and their share of total shocks. We also report a set of statistics based on the full sample of possible controls - i.e. the control sample which passes our sample restrictions, but that is not necessarily matched to a treated couple. Specifically, for each diagnosis we report the share of total shock diagnoses, the average age at diagnosis, the average number of nights spent in the hospital immediately following the diagnosis, the average number of hospital visits one year after a diagnosis, and the 5-year survival probability. The bottom line in the table reports these statistics for the full control sample. This Table is referenced in Section B..1

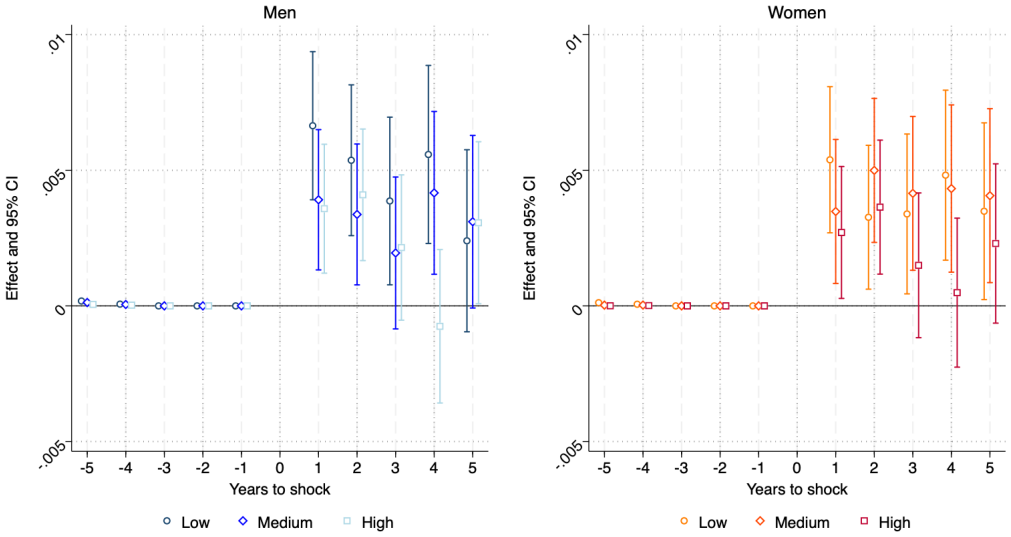
Table 4: Short-Term Coping Mechanisms and Behavior Changes

	Num. Cigarettes	Never Drinks	Any Sport	Sports 5h+	Overweight
Panel a: Healthy Women					
Post Shock	-0.554***	0.103*	-0.070	-0.008	-0.052
	(0.196)	(0.054)	(0.048)	(0.043)	(0.058)
Observations	341	1,008	2,655	1,820	1,434
Panel b: Healthy Men					
Post Shock	-0.042	0.015	0.092**	0.097**	-0.097*
	(0.215)	(0.036)	(0.046)	(0.047)	(0.057)
Observations	359	1,016	2,802	1,953	1,468

Notes: The Table reports our estimates from a Difference-in-Differences regression of short-term outcomes from the Health Surveys. Specifically, we report the coefficient of the interaction term between an indicator for the treated group and an indicator for years 0 and 1 relative to the shock, which captures the short term effect of the health shock. Number of cigarettes indicates the log of the reported number of cigarettes smoked per day. Never Drinks is an indicator equal to 1 if the respondent stated that they never drank alcohol in the previous year. Any sport is an indicator equal to 1 if the respondent indicated that they spent any time doing sports in the previous week or in the average week, depending on the survey year. Sports 5h+ is an indicator equal to 1 if the respondent indicated that they spent 5 or more hours doing sports. Overweight is an indicator equal to 1 if the BMI calculated based on reported weight and height is 25 or higher. We estimate these regressions on the subsample which we are able to match to the Health Surveys. The number of observations varies across outcomes due to different response rates and to the survey used. For the outcomes related to physical activiy, we use the Continuing Survey on Living Conditions (POLS) in years 1997–2008. The other outcomes are not available in the general survey so we use the health module of the survey, which is only administered to a subsample of respondents. We use the Health Survey for all outcomes for the years 2009–2021. Robust standard errors are reported in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. This Table is referenced in Section III.C.

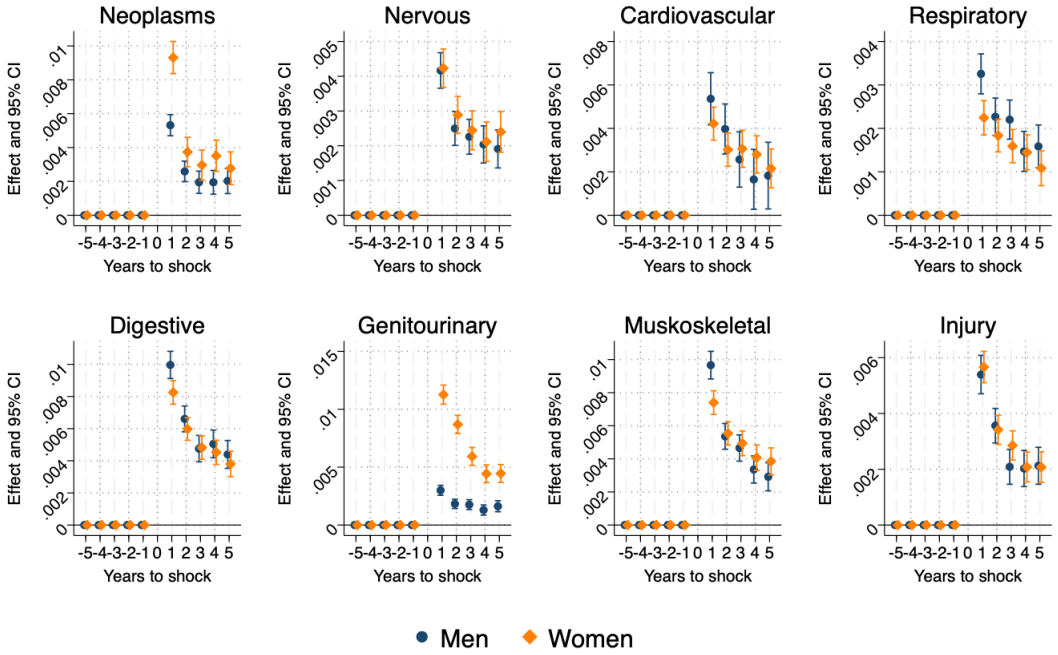
A Additional Figures

Figure A1: Healthy Partner Hospitalization Rates by Income



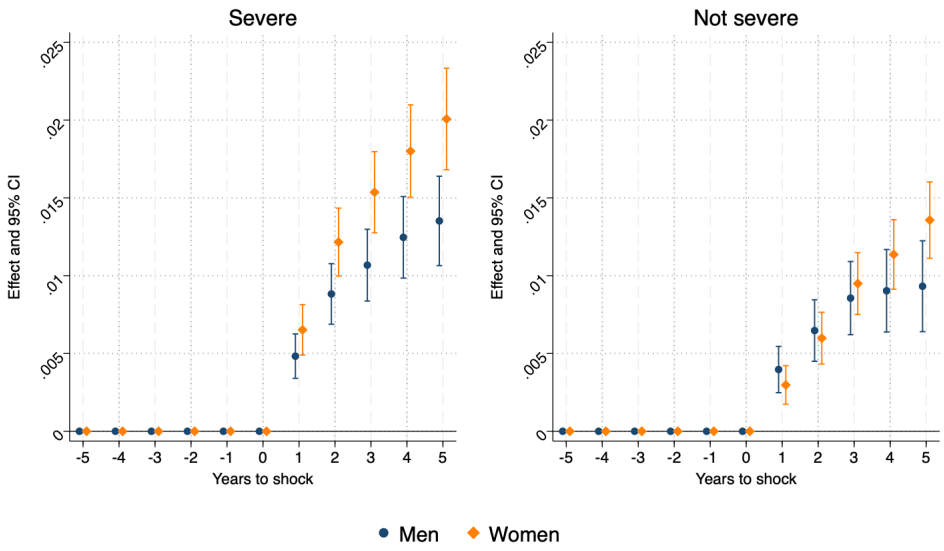
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on hospitalizations in the subsequent 5 years for the partner of the shocked individual. The effects are shown separately by couple employment income tercile in $t = -3$. Coefficients for $t = -5$ to -1 are zero by construction due to our sample restrictions. Coefficients for $t = 0$ cannot be interpreted meaningfully given the different sample restrictions imposed on partners in the treated and control groups. In particular, we match treated and control couples at the yearly level due to computational feasibility. This implies that we need to impose the restriction of no previous hospital visits until the year of the shock for partners in the control sample, while the restriction is imposed until the precise date of the shock for partners in the treated sample. Standard errors are clustered at the individual level. This figure is referenced in Section III.B.

Figure A2: Initial Health Shock Diagnosis Categories



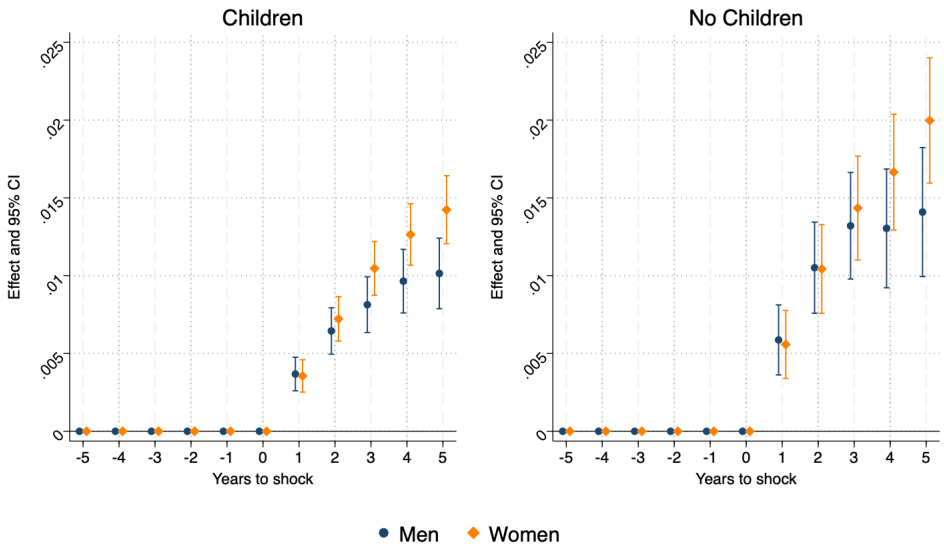
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on hospital visits by broad diagnosis category in the subsequent 5 years for the shocked individual. For each diagnosis category, we exclude individuals for whom the initial shock diagnosis belongs to that same category. For example, when we look at the effects on hospital visits with a cardiovascular diagnosis, we exclude individuals who experienced a heart attack in $t = 0$. Coefficients for $t = -5$ to -1 are zero by construction due to our sample restrictions. Coefficients for $t = 0$ cannot be interpreted meaningfully given the different sample restrictions imposed on individuals in the treated and control groups. In particular, we match treated and control couples at the yearly level due to computational feasibility. This implies that we need to impose the restriction of no previous hospital visits until the year of the shock for individuals in the control sample, while the restriction is imposed until the precise date of the shock for individuals in the treated sample. Standard errors are clustered at the individual level. This figure is referenced in Section IV.

Figure A3: Divorce Effects by Shock Severity



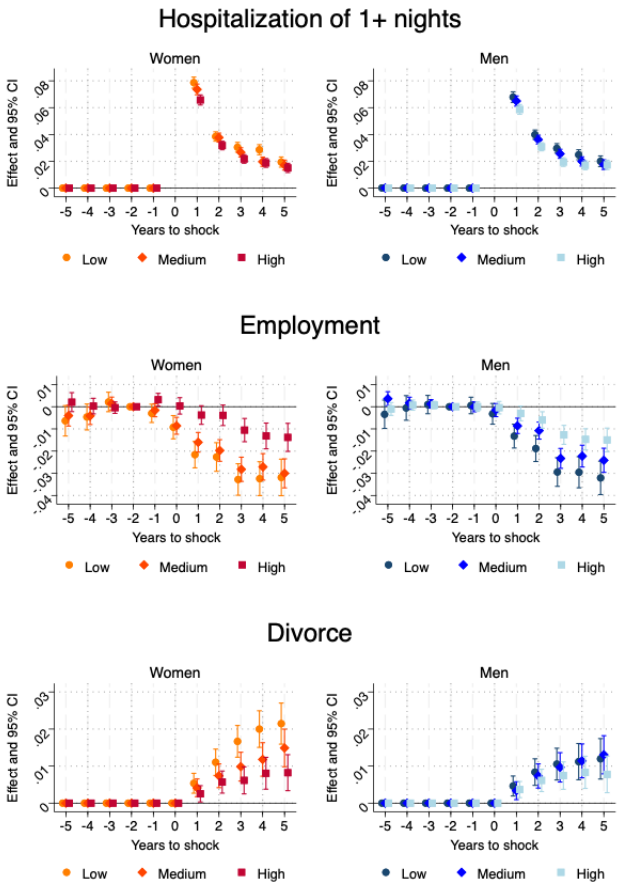
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on divorce in the subsequent 5 years for the affected couple. The effects are shown separately by severity of the initial shock. We classify shocks as severe if the mortality risk associated with the diagnosed condition for the control group is above the median. Coefficients for $t = -5$ to -1 are zero by construction due to our sample restrictions. Standard errors are clustered at the individual level. This figure is referenced in Section III.B..

Figure A4: Divorce Effects by Parental Status



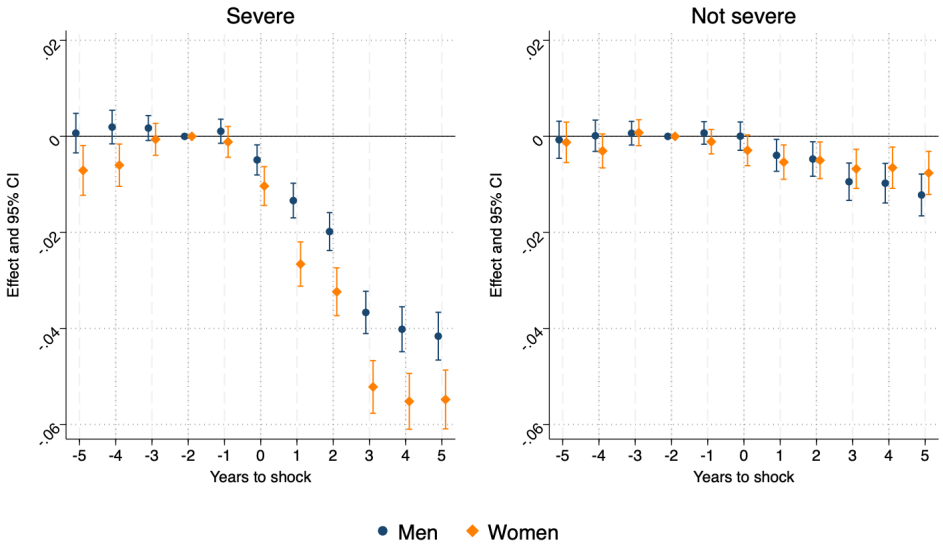
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on divorce in the subsequent 5 years for the affected couple. The effects are shown separately by parental status of the couple in $t = -3$. We classify couples as with children if there are any individuals under 18 years old living in the same household. Coefficients for $t = -5$ to -1 are zero by construction due to our sample restrictions. Standard errors are clustered at the individual level. This figure is referenced in Section III.B.

Figure A5: Hospitalization, Employment and Divorce Effects by Income Tercile



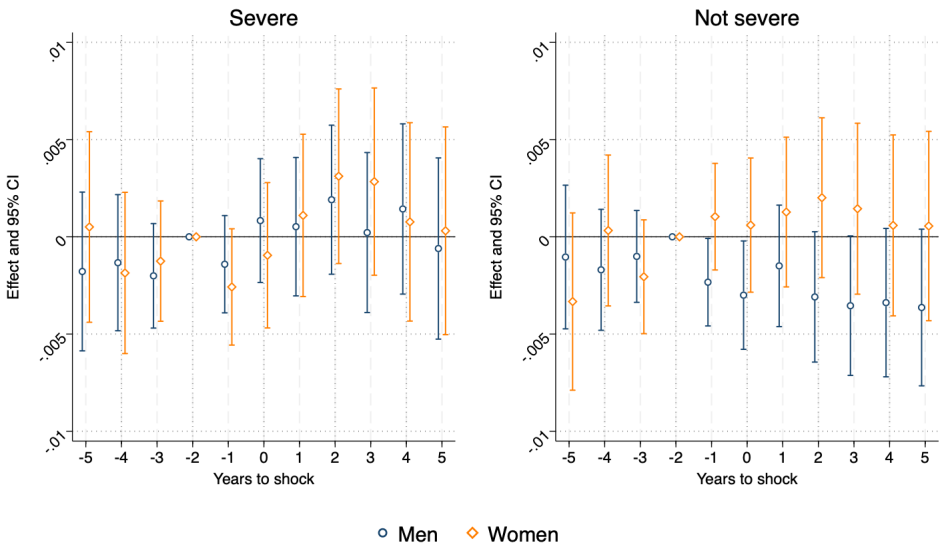
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on hospitalization, employment and divorce in the subsequent 5 years for the shocked individual. The effects are shown separately by couple employment income tercile in $t = -3$. Coefficients for $t = -5$ to -1 for hospitalization and divorce are zero by construction due to our sample restrictions. Coefficients for $t = 0$ for hospitalization are outside of the scale of the graph. The coefficient is 1 for all specifications by construction. Standard errors are clustered at the individual level. This figure is referenced in Sections III.A. and III.B.

Figure A6: Employment Effects by Shock Severity



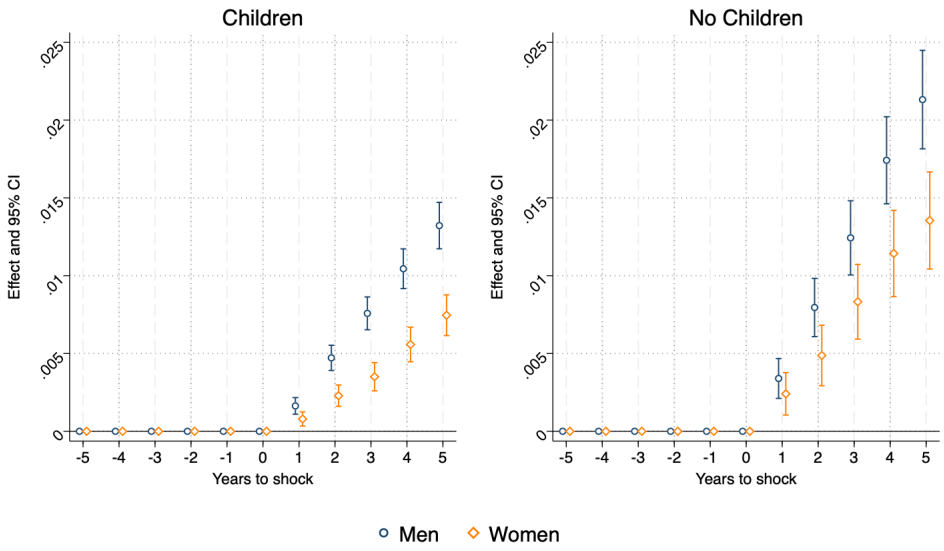
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on employment in the susequent 5 years for the shocked individual. The effects are shown separately by severity of the initial shock. We classify shocks as severe if the mortality risk associated with the diagnosed condition for the control group is above the median. Standard errors are clustered at the individual level. This figure is referenced in Section III.A.

Figure A7: Healthy Partner Employment Effects by Shock Severity



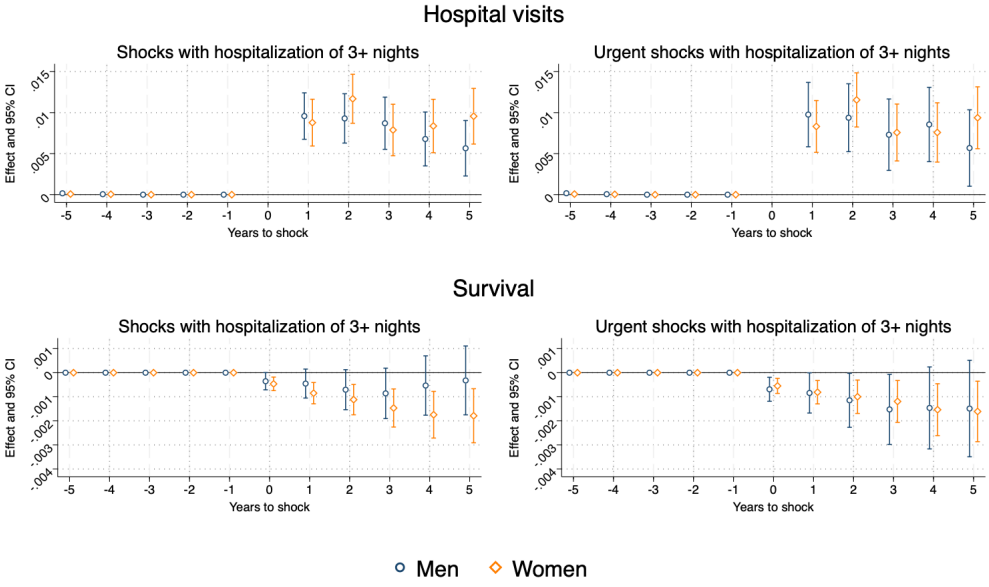
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on employment in the susequent 5 years for the partner of the shocked individual. The effects are shown separately by severity of the initial shock. We classify shocks as severe if the mortality risk associated with the diagnosed condition for the control group is above the median. Standard errors are clustered at the individual level. This figure is referenced in Section III.B.

Figure A8: Healthy Partner Remarriage Effects by Parental Status



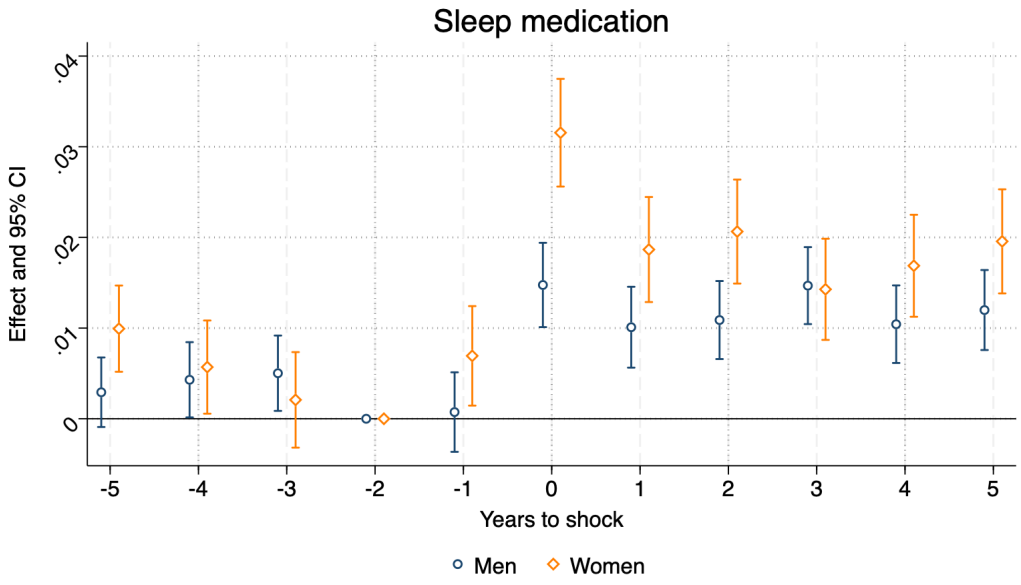
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on remarriage in the subsequent 5 years for the partner if the shocked individual. The effects are shown separately by parental status of the couple in $t = -3$. We classify couples as with children if there are any individuals under 18 years old living in the same household. Coefficients for $t = -5$ to -1 are zero by construction due to our sample restrictions. Standard errors are clustered at the individual level. This figure is referenced in Section III.B.

Figure A9: Hospital Visits and Survival Rates By Shock Type



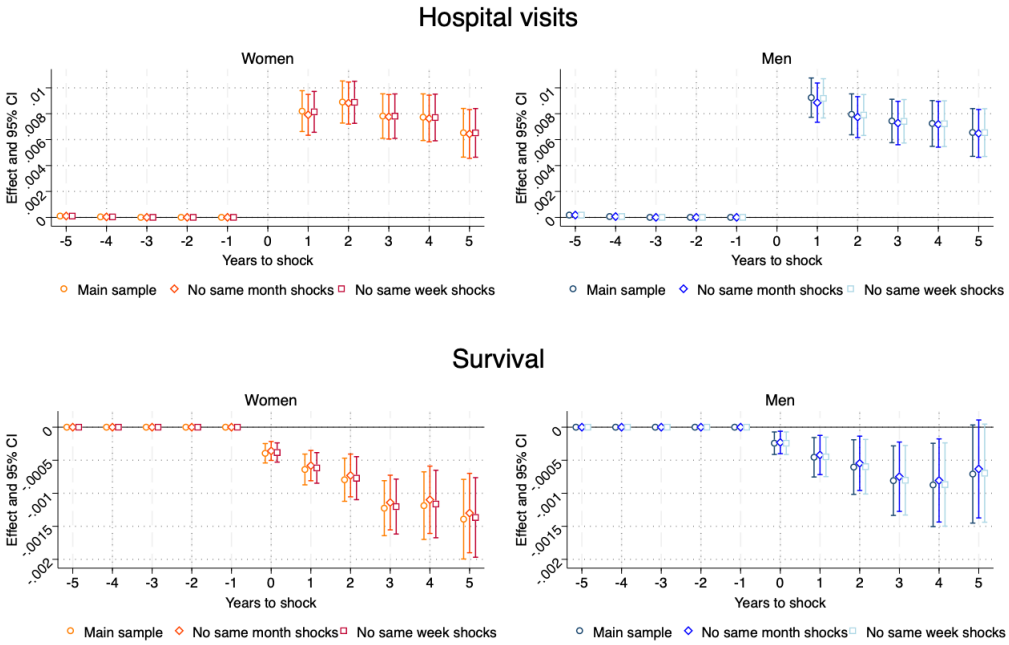
Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on hospital visits and survival in the subsequent 5 years for the partner of the shocked individual. The effects are shown separately for two different subsets of initial shocks: shocks followed by a hospitalization of at least 3 nights, urgent shocks followed by a hospitalization of at least 3 nights. We define as urgent, shocks for which the hospital visit starts at the Emergency Room or that have an urgent code from the referring physician. Coefficients for $t = -5$ to -1 are zero by construction due to our sample restrictions. For hospital visits, coefficients in $t = 0$ cannot be interpreted meaningfully given the different sample restrictions imposed on partners in the treated and control groups. In particular, we match treated and control couples at the yearly level due to computational feasibility. This implies that we need to impose the restriction of no previous hospital visits until the year of the shock for partners in the control sample, while the restriction is imposed until the precise date of the shock for partners in the treated sample. Standard errors are clustered at the individual level. This figure is referenced in Section IV.

Figure A10: Health Spillover Effects: Behavior Changes



Notes: This figure show our estimates for the coefficients γ_t from a specification analogous to Eq. 1, where we control for calendar year and we do not include individual FE. Specifically, the figure shows the effect of a health shock in $t = 0$ on the prescription of sleping medication (ATC codes N05B and N05) in the subsequent 5 years for the partner of the shocked individual. The indicators for are equal to 1 if the individual filled any prescription for a drug in this category during the year. This figure is referenced in Section III.C.

Figure A11: Hospital Visits and Survival Rates Excluding Same Week or Same Month Shocks



Notes: This figure shows our estimates for the coefficients γ_t from Eq. 1. Specifically, it shows the effect of a health shock in $t = 0$ on hospital visits and survival in the subsequent 5 years for the partner of the shocked individual. The effects are shown separately for the main sample and for the subset of couples in which the partner of the shocked individual did not experience a shock within a month or a week of their partner's initial shock in $t = 0$. Coefficients for $t = -5$ to -1 are zero by construction due to our sample restrictions. For hospital visits, coefficients in $t = 0$ cannot be interpreted meaningfully given the different sample restrictions imposed on partners in the treated and control groups. In particular, we match treated and control couples at the yearly level due to computational feasibility. This implies that we need to impose the restriction of no previous hospital visits until the year of the shock for partners in the control sample, while the restriction is imposed until the precise date of the shock for partners in the treated sample. Standard errors are clustered at the individual level. This figure is referenced in Section IV.

B Additional Tables

Table B1: Most Common Diagnostic Groups: Women

Main Diagnosis Categories in t=0	**Total Number of Diagnoses**	**Share of Total Diagnoses**	**Share of Totall Diagnoses in Control**	**Avg Age at Diagnosis in Control**	**Avg Nights in Hospital in Control**	**Avg Num Hosp. Visits Next Years in Control**	**5-Year Survival Probability in Control**
Neoplasms	65,857	38.0%	18%	46.1	1.8	2.1	76.5%
Injury	26,196	15.1%	4.3%	43.6	2.8	0.4	96.1%
Digestive	19,266	11.1%	10.0%	42.8	2.0	0.6	96.9%
Genitourinary	16,542	9.5%	11.8%	41.5	1.2	0.3	98.2%
Circulatory	16,313	9.4%	6.7%	45.4	2.5	0.4	95.5%
Nervous	11,090	6.4%	6.3%	45.1	0.8	0.9	97.7%
Musculoskeletal	5,095	2.9%	11.3%	44.7	1.0	0.6	98.5%
Respiratory	4,896	2.8%	3.3%	41.2	2.5	0.6	95.1%
Infections	2,870	1.7%	0.7%	42.5	4.0	0.8	92.7%
Skin	2,269	1.3%	1.6%	42.8	1.0	2.2	98.1%
Symptoms	1,488	0.9%	8.7%	43.3	1.1	0.6	94.3%
Supplementary	942	0.5%	12.9%	44.0	0.6	2.0	88.8%
Mental	33	0.0%	0.7%	42.7	20.0	1.0	94.5%
Endocrine	16	0.0%	1.7%	42.9	2.1	1.0	95.6%
Average in control				**39.8**	**0.0**	**0.1**	**98.2%**

Notes: The Table reports the most common diagnostic groups for the diagnoses that we classify as health shocks - i.e. hospital visits whose onset is exogenous and cannot be medically predicted, excluding visits related to pregnancy and childbirth - for the sick women in our main sample. For each diagnostic group we report the total number of $t = 0$ shocks in the sample of sick individual and their share of total shocks. We also report a set of statistics based on the full sample of possible controls - i.e. the control sample which passes our sample restrictions, but that is not necessarily matched to a treated couple. Specifically, for each diagnostic group we report the share of total shock diagnoses, the average age at diagnosis, the average number of nights spent in the hospital immediately following a diagnosis in this group, the average number of hospital visits one year after a diagnosis, and the 5-year survival probability. The bottom line in the table reports these statistics for the full control sample. This Table is referenced in Section B..1

Table B2: Most Common Diagnostic Groups: Men

Main Diagnosis Categories in t=0	**Total Number of Diagnoses**	**Share of Total Diagnoses**	**Share of Totall Diagnoses in Control**	**Avg Age at Diagnosis in Control**	**Avg Nights in Hospital in Control**	**Avg Num Hosp. Visits Next Years in Control**	**5-Year Survival Probability in Control**
Injury	43,265	25.9%	6.9%	44.6	3.0	0.3	96.0%
Circulatory	39,071	23.4%	13.4%	49.3	3.1	0.5	94.8%
Neoplasms	29,686	17.8%	11.1%	49.2	2.5	2.2	59.7%
Digestive	20,673	12.4%	12.8%	46.1	1.7	0.5	95.8%
Nervous	6,515	3.9%	5.4%	47.4	1.1	0.7	96.2%
Respiratory	6,119	3.7%	4.4%	44.0	2.4	0.5	94.6%
Musculoskeletal	5,126	3.1%	15.4%	45.4	0.9	0.4	98.2%
Skin	4,800	2.9%	2.2%	44.4	1.0	3.3	97.5%
Symptoms	4,210	2.5%	11.4%	46.7	1.0	0.6	93.7%
Infections	4,020	2.4%	1.1%	45.0	4.0	0.8	92.9%
Genitourinary	2,292	1.4%	3.9%	46.5	1.5	0.5	96.4%
Supplementary	336	0.2%	9.%	47.5	0.9	1.5	86.0%
Mental	12	0.0%	0.5%	45.4	14.7	0.8	91.9%
Average in control				**39.8**	**0.0**	**0.1**	**98.2%**

Notes: The Table reports the most common diagnostic groups for the diagnoses that we classify as health shocks - i.e. hospital visits whose onset is exogenous and cannot be medically predicted, excluding visits related to pregnancy and childbirth - for the sick men in our main sample. For each diagnostic group we report the total number of $t = 0$ shocks in the sample of sick individual and their share of total shocks. We also report a set of statistics based on the full sample of possible controls - i.e. the control sample which passes our sample restrictions, but that is not necessarily matched to a treated couple. Specifically, for each diagnostic group we report the share of total shock diagnoses, the average age at diagnosis, the average number of nights spent in the hospital immediately following a diagnosis in this group, the average number of hospital visits one year after a diagnosis, and the 5-year survival probability. The bottom line in the table reports these statistics for the full control sample. This Table is referenced in Section B..1

Table B3: Summary Statistics by Group: Income

Variable	**Low Family Income in t=-3**		**Medium Family Income in t=-3**		**High Family Income in t=-3**	
	Women	*Men*	*Women*	*Men*	*Women*	*Men*
Age	42.60	44.80	42.00	44.10	43.70	45.70
Age of partner	44.60	42.40	43.90	41.80	45.50	43.60
Employment income	8,516	16,147	16,425	35,116	27,056	60,688
Employment income of partner	16,334	8,801	35,562	16,796	61,420	27,653
Employed	0.58	0.61	0.86	0.96	0.89	0.97
Employed partner	0.61	0.59	0.96	0.87	0.97	0.90
Total hours per week	11	19	18	32	21	33
Total hours per week of partner	19	11	32	19	33	21
Family size	3.40	3.40	3.40	3.40	3.40	3.40
Main earner in the household	0.34	0.64	0.15	0.84	0.16	0.83
Observations	28,905	30,476	29,257	29,853	29,465	29,476

Notes: The Table reports summary statistics by gender and couple employment income tercile in $t = -3$, for the final sample of sick individuals in the year preceding the health shock, $t = -1$. Employment is only defined for years 2006 onwards, as we do not have data on the universe of jobs for the previous years. Total hours worked per week and employment income are conditional on the individual being employed; these variables are defined for the entire period. The variable main earner in the household is constructed as an indicator which is equal to one if the individual is employed and earns more than their spouse. This Table is referenced in Section III.B.

Table 4: Summary Statistics by Group: Shock Severity

Variable	**Severe Shock**		**Non Severe Shock**	
	Women	*Men*	*Women*	*Men*
Age	43.5	46.4	42.1	42.9
Age of partner	45.3	44.0	44.1	40.7
Employment income	16,301	36,518	17,438	37,218
Employment income of partner	24,152	10,383	23,307	11,258
Employed	0.75	0.83	0.78	0.85
Employed partner	0.68	0.5	0.67	0.62
Total hours per week	15.80	27.10	16.80	28.00
Total hours per week of partner	22.1	12.4	21.7	13.5
Family size	3.3	3.3	3.3	3.4
Main earner in the household	0.2	0.8	0.2	0.8
Observations	**63,603**	**76,289**	**106,046**	**82,160**

Notes: The Table reports summary statistics by gender and severity of the initial shock, for the final sample of sick individuals in the year preceding the health shock, $t = -1$. We classify shocks as severe if the mortality risk associated with the diagnosed condition for the control group is above the median. Employment is only defined for years 2006 onwards, as we do not have data on the universe of jobs for the previous years. Total hours worked per week and employment income are conditional on the individual being employed; these variables are defined for the entire period. The variable main earner in the household is constructed as an indicator which is equal to one if the individual is employed and earns more than their spouse. This Table is referenced in Section III.B.

Table 5: Summary Statistics by Group: Parental Status

Variable	**Children in t=-3**		**No Children in t=-3**	
	Women	*Men*	*Women*	*Men*
Age	43.6	45.6	40.1	42.1
Age of partner	45.6	43.4	42.1	39.8
Employment income	15,299	38,624	21,456	32,226
Employment income of partner	25,357	10,312	20,337	13,424
Employed	0.75	0.84	0.82	0.85
Employed partner	0.68	0.60	0.66	0.65
Total hours per week	14.70	27.70	21.10	27.40
Total hours per week of partner	22.3	11.7	21.3	16.8
Family size	3.8	3.9	2.1	2.1
Main earner in the household	0.2	0.8	0.3	0.7
Observations	**122,904**	**119,034**	**50,325**	**48,057**

Notes: The Table reports summary statistics by gender and parental status of the couple in $t = -3$, for the final sample of sick individuals in the year preceding the health shock, $t = -1$. We classify couples as with children if there are any individuals under 18 years old living in the same household. Employment is only defined for years 2006 onwards, as we do not have data on the universe of jobs for the previous years. Total hours worked per week and employment income are conditional on the individual being employed; these variables are defined for the entire period. The variable main earner in the household is constructed as an indicator which is equal to one if the individual is employed and earns more than their spouse. This Table is referenced in Section III.B.