Intra-Household Dynamics of Non-communicable Diseases

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September 30, 2025

Abstract

Non-communicable diseases (NCDs) are the primary driver of the rising global disease burden, a trend largely propelled by an aging population that disproportionately affects older adults. Leveraging the random timing of two major NCDs, heart attacks and strokes that do not kill, I estimate an event study model to examine NCDs' impacts on individuals' labor market outcomes, as well as intra-household spillover effects on spouses' employment outcomes and household consumption across categories. To contextualize the indirect effects of these health shocks, the paper also quantifies the impact of NCDs by analyzing healthcare utilization, medical expenses, and related health outcomes. The findings show that individuals' employment probability and weekly working hours decrease by 6.8% and 9.4% in the 2 years following a shock, which leads to a 7.3% decrease in earned income over the same period. The overall spillover effects on spouses' employment outcomes are imprecisely estimated. However, there is gender heterogeneity: wives experience a 7.8% increase in earned income following their husbands' health shocks, while husbands show no response to their wives' shocks. Additionally, affected households decrease non-medical spending by 26.8% in the 2-4 years post-shock in response to the substantial rise in out-of-pocket medical expenditures incurred during the initial post-shock period. This decrease comes entirely from less essential, non-food expenses, demonstrating the trade-offs households make to manage increased health care spending.

JEL Classification: I12, J22, E21

Keywords: health shocks, labor supply, consumption, health care expenditure, intra-household spillovers

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I. Introduction

According to the Institute for Health Metrics and Evaluation, non-communicable diseases (NCDs) accounted for 1.73 billion disability-adjusted life years (DALYs) in 2021, which represents 67.6% of total DALYs caused by diseases. This is a marked shift since 1990 when communicable, maternal, neonatal, and nutritional (CMNN) diseases accounted for 50.9% of total disease-related DALYs (GBD 2016 DALYs and HALE Collaborators, 2017). One major factor contributing to this change in disease burden is the rapidly aging population that is disproportionately affected by NCDs (United Nations, 2012). Beyond directly impacting older adults by increasing mortality, deteriorating the health of survivors, and increasing their medical spending, NCDs may also affect older adults and their families through indirect, secondary channels such as altering labor market decisions, influencing consumption behaviors, and creating intra-household spillovers. According to the World Health Organization (WHO), health care costs for NCDs rapidly deplete household resources in low-resource settings, pushing millions into poverty each year (World Health Organization, 2024). Therefore, it is crucial to explore the channels through which NCDs affect individuals and their families in low- and middle-income countries with relatively limited resources to quantify these impacts. Such efforts can aid policymakers in designing evidence-based policies to mitigate the adverse effects of NCDs effectively.[0]

This paper examines the impacts of NCDs on households' labor supply and consumption among older adults in China by analyzing the onset of two conditions—heart attack and stroke. The rationale for focusing on these diseases is two-fold. First, the 2019 Global Burden of Disease (GBD) study identifies cardiovascular diseases as the leading cause of disease burden among individuals aged 50 and above, and they are listed among the ten most significant contributors to the rising disease burden (GBD 2019 Diseases and Injuries Collaborators, 2020). Second, both heart attacks and strokes generally manifest acutely

0 An example of a policy measure addressing these complexities is the legislative guarantee of paid sick leave, which is implemented in most countries. However, the specific provisions of this benefit, including eligibility criteria, duration, and wage replacement rates, vary considerably across countries.

and arise at unpredictable times (Chandra and Staiger, 2007; Doyle, 2011; World Health Organization, 2021). This sudden and unpredictable onset is a defining characteristic that significantly differentiates them from chronic diseases such as diabetes or chronic obstructive pulmonary disease, which typically evolve over years and often allow for some degree of prediction and management. The abrupt nature of these events serves as a source of exogenous variation, which makes them particularly suitable for empirical analyses that require clear delineation between cause and effect. To reinforce the validity of using these events for the robust estimation of causal effects, I provide evidence in my analysis to demonstrate the unpredictability of the timing of these health shocks.

In my analysis, I use an event study model. I define the event time for each health shock as when a doctor first makes a formal diagnosis confirming the presence of at least one of the two conditions. In cases where individuals experience multiple health shocks across different survey waves, the event time is defined as the diagnosis date of the initial health shock, and these individuals are considered "treated" from that point onward. This approach mitigates concerns that individuals with a prior health shock might anticipate subsequent shocks and respond differently. Individuals from households that did not experience any health shocks during the study period are used to provide a baseline for comparing changes in outcomes due to health shocks. To estimate the event study model, I adopt the estimation method proposed by Callaway and Sant'Anna (2021). This approach overcomes the limitations of traditional two-way fixed-effects (TWFE) regression models with leads and lags that may introduce bias in staggered settings where treatment effect dynamics may be heterogeneous across treatment groups.

The data source for my analysis is the China Health and Retirement Longitudinal Study (CHARLS). There are four sets of outcomes. First, to contextualize the eventual focus of the paper, the indirect effects of health shocks, I examine the magnitude and severity of the health shocks by examining health outcomes, healthcare utilization, and medical expenditure for the patients themselves. Second, I examine changes in individuals' labor supply and earned income following a health shock. Third, I examine changes in individuals' labor supply and earned income following a spouse's health shock to quantify intra-spousal spillover effects. Last, I examine changes in household consumption per capita across various spending categories following a health shock.

My findings show that experiencing a health shock leads to a statistically significant decline in physical health but not in mental health 0-2 years post-shock. Specifically, individuals' Activities of Daily Living (ADL) score, which measures the number of daily activities individuals need assistance with and ranges from 0 to 6, increases by 0.18 points, representing a 32.5% rise from the treatment group's baseline mean. In addition, individuals' self-rated health, measured on a scale from 1 to 5 where 1 indicates excellent health and 5 indicates very poor health, increases by 0.18 points, which represents a 5.5% decline. In contrast, affected individuals experience a statistically insignificant 2.9% increase in the probability of having depression, suggesting the shocks' minimal impact on mental health. My findings also show a significant increase in both healthcare utilization and medical spending 0-2 years post-shock. The probabilities of utilizing any inpatient and outpatient care increase by 10.5 and 2.8 percentage points, respectively, representing increases of 61.0% and 11.9% from baseline levels. Additionally, the number of inpatient care episodes, nights spent in the hospital, and outpatient care episodes increase by 0.20, 1.47, and 0.10, respectively, representing increases of 77.7%, 74.7%, and 19.5%. In line with the increased health care utilization, total and out-of-pocket (OOP) medical spending increases by 4,554 RMB and 2,756 RMB, respectively, representing increases of 97.0% and 97.5%.[1] These estimates indicate that the health shocks analyzed lead to a substantial increase in medical expenditure and a marked decline in physical health. In contrast to the statistically significant direct effects, my findings indicate that intra-spousal spillover effects on health outcomes, healthcare utilization, and medical expenditure are statistically insignificant.

My findings also show that experiencing a health shock affects individuals' labor market

1 All monetary values are adjusted to 2010 RMB using the Consumer Price Index (CPI).

outcomes 0-2 years post-shock. At the extensive margin, individuals are 4.0 percentage points less likely to be employed, representing a 6.8% decrease from the baseline mean. At the intensive margin, individuals work 2.3 fewer hours per week, representing a 9.4% decrease. These changes in labor supply lead to a 382 RMB decrease in individuals' earned income over the same period, representing a 5.6% decrease. Heterogeneity analysis shows that the effects of experiencing a health shock on labor supply are similar for women and men, with men exhibiting slightly greater responsiveness to the shocks. Specifically, males face a 7.1% and 11.3% decrease in labor market participation on the extensive and intensive margins, respectively, which leads to a 9.3% decrease in earned income. In comparison, females experience a 6.4% and 7.5% decrease at the extensive and intensive margins, respectively, and a statistically insignificant 1.6% decrease in earned income.

In addition, my findings show a small and statistically insignificant change in individuals' labor supply and earned income following a spouse's health shock. However, the evidence suggests heterogeneity by gender. Specifically, wives' earned income increases by 496 RMB, or approximately 7.8%, 0–2 years following their husbands' health shocks. The mechanism behind this increase remains unclear. One possibility is that it results from gains at both the extensive and intensive margins of labor supply, although the estimates are noisy and not individually statistically significant. Another possibility is that wives may switch to higher-paying jobs. In contrast, husbands' labor market participation and earned income exhibit no statistically significant changes following their wives' health shocks.

Another set of findings shows that health shocks also lead to changes in households' consumption patterns. Specifically, households' per capita OOP medical expenditure increases on average by 1,710 RMB 0-2 years post-shock, which represents a 101.1% increase from the baseline mean. There is no statistically significant change in per capita non-medical, non-food expenditure over the same period. However, it decreases by 1,787 RMB 2-4 years post-shock, which is likely a subsequent response to the earlier increase in OOP medical expenditure. In contrast, per capita food expenditure shows no significant change after a health shock, suggesting limited flexibility in reducing essential spending.

My work relates to the literature examining the impact of health shocks on individuals' labor market outcomes. The majority of studies report a decline in labor market participation following health shocks, though the magnitude of of the estimated effects varies widely. Using data from Taiwan, Mete and Schultz (2002) showed that individuals who suffered a stroke reduced their labor market participation by 72.8%, while those who experienced a heart disease saw a reduction of 27.3%. Rocco et al. (2011) showed that self-reported long-term health problems led to a 42.7% decrease in employment probability using data from Egypt. Another study by García-Gómez (2011) explored how low self-rated health affects labor market participation in nine European countries. The study found that in Ireland, low self-rated health led to a 30.4% decrease in employment probability, whereas in France, there was a statistically insignificant 3.1% increase in employment probability. Several other studies found weaker effects. For example, Rees and Sabia (2015) showed that migraines resulted in a statistically insignificant 10.6% decrease in employment probability and a 28.8% decrease in earned income using data from the U.S. Similarly, using data from the U.K., Jones et al. (2020) found that cancer, stroke, or myocardial infarction led to a 7.2% decrease in employment probability and a 5.5% decrease in earned income. Additionally, Kumara and Samaratunge (2018) found that NCDs led to a 9.5% decrease in employment probability and a 47.9% decrease in earned income using data from Sri Lanka.

My work also relates to the literature on intra-household spillover effects of health shocks. García-Gómez et al. (2013) estimated that individuals reduced their labor force participation by 0.9 percentage points in response to their spouses' acute hospital admission using data from the Netherlands. Jeon and Pohl (2017) found that husbands' employment probability and annual earnings decreased by 2.5% and 3.6%, respectively, following their wives' cancer diagnosis using data from Canada. The authors also found slightly larger declines for wives, with employment probability and annual earnings decreasing by 3.1% and 5.9%, respectively, following their husbands' cancer diagnosis. Another study by Fadlon and Nielsen

(2021) showed that spouses' severe nonfatal health events resulted in a decrease in individuals' labor force participation and annual earnings, whereas fatal health events led to an increase in labor force participation and annual earnings among widows and widowers using data from Denmark. In contrast, some studies found weaker or insignificant effects. For instance, Mahal et al. (2013), Kim et al. (2018), and Jolly and Theodoropoulos (2023) found positive but statistically insignificant spousal spillover effects. Other studies have focused on examining the impact of health shocks on household consumption (Gertler and Gruber, 2002; Asfaw and Braun, 2004; Powell-Jackson and Hoque, 2012). These studies primarily observed negative estimates for changes in household non-medical consumption following a health shock. However, the results present a mixture of statistically significant and insignificant findings.

My paper contributes to the literature in two ways. First, given that the majority of studies on the effects of health shocks on labor market outcomes focus on high-income countries, my paper contributes to the literature by extending the analysis to a major middle-income country. The economic, institutional, and family structure differences between high-income and low- or middle-income settings are significant, which may influence how individuals and households respond to health shocks. For example, Lokshin and Yemtsov (2001) found that households' responses to economic strain were heavily influenced by their levels of human capital, with those having higher human capital more likely to engage in active coping strategies. Second, my analysis specifically targets abrupt, unpredictable health shocks that are less prone to endogeneity concerns and utilizes an event study model to assess the immediate effects following the event.

The remainder of this paper is organized as follows: Section II provides an overview of the public health insurance system in China. Section III describes the data. Section IV outlines the empirical framework. Section V presents the results. Section VI concludes.

II. Background

Public health insurance in China serves as the primary safeguard against high healthcare expenditures for most households. Historically, this system included three major programs: the Urban Employee Basic Medical Insurance (UEBMI), the Urban Resident Basic Medical Insurance (URBMI), and the New Rural Cooperative Medical Scheme (NRCMS). By 2011, these programs had collectively approached nearly universal coverage, with more than 95% of the population insured under these schemes. In 2016, URBMI and NRCMS were merged to form the Urban and Rural Residents Basic Medical Insurance (URRBMI), a move aimed at standardizing health insurance across urban and rural areas and enhancing healthcare access and equity. The UEBMI, initiated in the late 1990s, was specifically designed for urban employees. This program aims to provide comprehensive medical coverage to this segment of the population, including both current workers and retirees. The UEBMI is primarily funded through employer and employee contributions, and funds are collected and managed at municipal or provincial levels. This program covers a wide range of medical services, including inpatient care, outpatient care, maternity services, and serious disease treatment, and generally offers higher reimbursement levels than its counterpart, URRBMI. The URRBMI, emerging from the merger of URBMI and NRCMS, serves previously uncovered urban residents and rural populations. This program is funded through individual premiums and government subsidies. The URRBMI provides essential medical services, though with more limited coverage compared to UEBMI. This program plays a crucial role in ensuring that non-employed individuals, including retirees from the non-formal sectors, have access to healthcare.

III. Data

The primary data for this analysis is the China Health and Retirement Longitudinal Study (CHARLS). CHARLS provides a nationally representative dataset of individuals aged

45 and above and captures detailed information on individual-level outcomes, including health conditions, healthcare utilization, insurance coverage, and employment history, and household-level outcomes such as consumption, wealth, and family structure. It also includes data on demographics and community-level characteristics. The baseline survey was conducted in 2011. Follow-up surveys were conducted biennially except for the fourth wave where there was a three-year gap between the third and fourth waves. In my analysis, I use data from the 2011-2018 survey waves.

To examine the impacts of NCDs, my analysis focuses on two conditions: heart attacks and strokes because of their prevalence and acute, unpredictable onset. To identify the timing of the onset of either of the two conditions for an individual, I use the individual's response to the question asking whether a doctor has ever told them they have had a specific condition in each survey wave. An individual's treatment status changes from untreated to treated in the first survey wave they answer "yes" to the question, and the individual remains treated in all subsequent survey waves. For individuals who are diagnosed with more than one condition across survey waves, only the time of onset of the earliest diagnosed condition is used to determine when they become treated. Since the Callaway and Sant'Anna (2021) event study estimation method requires all observations to be untreated at baseline, I exclude households that reported having experienced a heart attack or stroke before the 2011 baseline interview from my sample. In addition, for inclusion in the sample, individuals are required to appear in two consecutive survey waves. Furthermore, to accurately quantify the relative changes in the outcomes of interest post-shock, it is essential for individuals who experienced a health shock during the study period to have been present in the survey wave immediately preceding the shock.

In addressing the effects of health shocks on labor market outcomes and household consumption, it is crucial to ensure that the estimated effects apply specifically to survivors of these shocks. However, the CHARLS data presents challenges in precisely determining survival status due to the absence of exact death dates and the extended interval between survey waves. Given these constraints, I adopt hospital discharge as a proxy for survival post-shock. This approach is based on the assumption that the majority of heart attack and stroke patients who seek medical care are hospitalized, and thus discharge can reasonably be taken as evidence of survival at least until that point. Since CHARLS only surveys individuals who are living at home during the interviews, their participation in the survey wave following a health shock strongly suggests that they survived beyond the initial impact of the shock. Although this approach does not capture the exact survival duration, it is the most feasible method given the data limitations, and it is consistent with epidemiological studies that rely on hospital records to infer short-term survival outcomes.

The analysis categorizes outcomes into four sets. The first set focuses on changes in individuals' health, healthcare utilization, and medical expenditure following a health shock. The second set focuses on changes in individuals' labor supply at the extensive and intensive margins as well as earned income following a health shock. The third set focuses on changes in those outcomes following a spouse's health shock. The last set focuses on changes in household consumption per capita across various spending categories, including medical, food, and non-medical, non-food expenditures, following a health shock.[2] These outcomes are derived from a series of questions asked in each survey wave. Individual-level outcomes are reported directly by each participant, while household-level outcomes are provided by the designated head of each participating household. Besides health status, which reflects the current health condition of individuals, the time frames for all other variables in the analysis range from the past week or past month to the past year.

Table 1 presents the summary statistics of individual and household characteristics at the 2011 baseline interview. Column (1) in Panel A shows the mean characteristics for individuals who did not experience any health shocks between the 2011 and 2018 interviews. I excluded individuals whose spouses experienced a health shock from this group because

2 In the analysis, non-medical, non-food expenditures include those incurred on clothing and bedding, long-distance travel, central heating, furniture and durable goods, education and training, fitness activities, beauty services, transportation and communication devices, automobiles, electronics, property management fees, and societal donations.

these individuals may be indirectly affected by their spouses' health shocks through spillover effects, making them unsuitable as a comparison group for the treatment group. This sample serves as the control group in the analysis of individual-level outcomes. Column (2) in Panel A shows the mean characteristics for individuals who experienced at least one health shock between the 2011 and 2018 interviews. In households where both individuals experienced a health shock, I excluded those who had a later shock from this treatment group to prevent endogenous behavioral responses to a spouse's health shock. This sample serves as the treatment group in the analysis of outcomes for individuals who experienced a health shock. The sample size of this treatment group is 1,720. Out of these health shocks, approximately 14% occurred during the 2013 survey wave, 31% during the 2015 survey wave, and 55% during the 2018 survey wave. Column (3) in Panel A shows the mean characteristics for individuals who did not experience any health shocks but whose spouses experienced at least one health shock between the 2011 and 2018 interviews. This sample serves as the treatment group in the examination of intra-spousal spillover effects.

Comparing the individual characteristics across Columns (1)-(3) of Table 1 shows that the control group is the youngest, while the "health shock" group is the oldest among the three groups. In addition, females are more likely to experience a health shock than males. The three groups have similar distributions of education levels, with approximately 90% having education levels below high school. In both the control group and the "spouses of affected individuals" group, 74% of individuals were employed in the year prior to the interview, whereas only 63% of individuals in the "health shock" group were employed. This difference in employment rates results in the former two groups having higher earned income than the latter group. The summary statistics also indicate that over 80% of the sample have a rural Hukou.[3] Over 90% and 2% of the sample are enrolled in public and private health insurance, respectively. Additionally, individuals in the "health shock" group on average reported worse

3 "Hukou" is a household registration system used in China that officially identifies a person as a resident of an area. It is a critical element in determining access to various public services, including education, healthcare, and housing.

self-rated health than those in the other two groups at the baseline interview. Specifically, approximately 35% of the "health shock" group rate their health as either poor or very poor, compared to only 20% of the control group and 22% of the "spouses of affected individuals" group.

Panel B of Table 1 presents the summary statistics of household characteristics at the 2011 baseline interview. Column (1) shows the mean characteristics for households that did not experience any health shocks between the 2011 and 2018 interviews. For household-level analysis, the control group consists of households in which no members experienced any health shocks during the study period. Column (2) shows the mean characteristics for households in which at least one member surveyed experienced a health shock during the study period. The entries show that the majority of households in both groups are married and have children. In addition, 68% of households in the control group live in rural areas, compared to 65% for the control group. In addition, households in the treatment group have less per-capita wealth on average than those in the control group.

IV. Empirical Framework

The traditional approach to estimating the treatment effect dynamics involves using a TWFE regression model with leads and lags. In the context of this analysis, the model can be expressed as follows:

$$Y_{it} = \beta_0 + \sum_{\substack{s=-3 \\ s\neq -1}}^{s=2} \tau_s \mathbf{1}(K_{it} = s) + \beta_1 \boldsymbol{X}_{it} + \boldsymbol{\lambda_i} + \boldsymbol{\lambda_t} + \epsilon_{it} \tag{1}$$

For the individual-level analysis, the outcomes of interest Y_{it} include individual i's health outcomes, health care utilization, health care expenditure, and labor market outcomes in survey wave t. For the household-level analysis, the outcomes of interest Y_{it} include per capita total expenditure, OOP medical expenditure, food expenditure, and non-medical, non-food expenditure in survey wave t. The variable K_{it} denotes the number of survey waves since the health shock. For example, if the health shock occurs between the 2011 and 2013 interviews, then for individual i, the observation for the 2013 interview is assigned a value of 0, the observation for the 2015 interview is assigned a value of 1, and so on. The indicator variable $\mathbf{1}(K_{it} = s)$ equals one when K_{it} equals s. The survey wave immediately preceding the health shock is used as the base period and is therefore excluded from the regression. Since four survey waves are used in the analysis and the "always treated" group is excluded from the sample, the value of s ranges from -3 to 2, excluding -1. The vector $\boldsymbol{X}_{it}$ is a set of time-variant individual or household characteristics. The vector $\boldsymbol{\lambda_i}$ is a set of individual or household fixed effects. The vector $\boldsymbol{\lambda_t}$ is a set of survey wave fixed effects.

Typically, researchers interpret τ_s for non-negative values of s as the causal effect of the treatment on the outcome of interest s survey waves from the shock. However, when treatment effect dynamics are heterogeneous across treatment cohorts, TWFE models can be biased due to problematic properties of some of the weights. This issue is particularly concerning in the presence of substantial treatment heterogeneity that increases the sensitivity of estimates to the weighting schemes employed (Callaway and Sant'Anna, 2021). In addition, interpreting τ_s for negative values of s as a measure of pre-trend can be problematic because pre-trends can emerge purely as a result of heterogeneity in treatment effects (Sun and Abraham, 2021). Furthermore, the weighting schemes used are determined implicitly by the underlying estimation method and suffer from the issue of non-transparency. To account for these potential issues of the traditional approach, I estimate Equation 1 using the methodology developed by Callaway and Sant'Anna (2021). In addition, standard errors are clustered at the household level to account for within-household correlations across years.

The identification of the group-time average treatment effects on the treated, $ATT(g, t)'s$, relies on two key assumptions: "conditional parallel trends" and "limited treatment anticipation". To assess the plausibility of the former assumption, I examine the chi-square statistic for the null hypothesis that all pretreatment $ATT(g, t)'s$ are equal to zero and visually inspect the event study graphs. However, it is important to note that these diagnostics do not definitively test the assumption of conditional parallel trends. To assess the plausibility of the latter assumption, I estimate two Probit models to examine the randomness of the health shocks and their timing. The first model examines the randomness of the health shocks using the full sample. The dependent variable is an indicator that equals one if an individual experienced a health shock during the study period. A strict test of whether the shock is random is whether the covariates in the model are jointly zero. As heart attacks and strokes have a large behavioral component, and behaviors are typically correlated with measures of socioeconomic status, this test is likely to fail. The second model focuses exclusively on individuals who had a health shock during the study period and examines the non-predictiveness of the timing of the shocks. The dependent variable is an indicator that equals one if an individual had a health shock in a later rather than an earlier survey wave. Here, I define a later survey wave as the 2018 survey wave and an earlier survey wave as either the 2013 or the 2015 survey wave. Both indicators are regressed against a set of individual characteristics from the 2011 baseline interview to examine the statistical significance of the coefficients.

V. Results

V.A. The Non-Predictiveness of Shock Timing

Table 2 presents the estimates from two Probit models that examine the randomness of the health shocks and their timing, respectively. Column (1) shows the probability of experiencing a health shock as a function of various individual characteristics at the 2011 baseline interview. Column (2) shows the corresponding average marginal effects. The entries show that half of the baseline individual characteristics are statistically significantly associated with the probability of experiencing a health shock during the study period. Specifically, older age, being female, higher education, urban Hukou, public health insurance, and poorer physical and mental health are all associated with a greater likelihood of experiencing a health shock. In particular, self-rated health exhibits strong predictive power. The table also reports the p-value for a Wald test of the hypothesis that all the coefficients in the model are jointly zero. For both the Probit model and the corresponding average marginal effects, the p-values are statistically significant at the 1% level, which indicates the non-randomness of the effects of the baseline individual characteristics on the probability of experiencing a health shock.

Column (3) of Table 2 shows the probability of experiencing a health shock in the 2018 survey wave instead of the 2013 and 2015 survey waves as a function of various individual characteristics at the 2011 baseline interview. Column (4) shows the corresponding average marginal effects. In contrast to the estimates in Column (2), all but one estimate in Column (4) are statistically insignificant. The only individual characteristic statistically significantly associated with the probability of experiencing a later shock is an individual's earned income in the past year, and the effect is very small. A 1,000 RMB increase in earned income corresponds to only a 0.04-percentage-point decrease in the probability of having a later shock. This negative correlation may be explained by higher-income individuals having better access to preventive care such as regular health check-ups and early screenings that allow them to manage health risks more proactively. For both the Probit model and the corresponding average marginal effects, the p-values for the Wald test are statistically significant. However, they are only marginally significant at the 10% level, which suggests that the baseline individual characteristics do not strongly influence the timing of the health shocks. Taken together, the findings from the two Probit models indicate that while the occurrence of a health shock is not entirely random, its timing appears largely unpredictable. This unpredictability reinforces the validity of using the diagnosis of a heart attack or a stroke in the event study model, as it mitigates concerns about anticipatory behavior and enhances the plausibility of the parallel trends assumption.

V.B. Main Results

Table 3 presents the event study estimates for the direct impacts of health shocks on individuals' health, healthcare utilization, and medical expenditure 0-2 years post-shock. These estimates provide context for understanding the indirect impacts of health shocks on household labor supply and consumption. Column (1) presents the mean values of the outcome variables during the reference period, defined as the survey wave immediately preceding the wave in which the health shock occurs. These baseline means serve as a reference for calculating relative changes in the estimates. Column (2) reports the estimated changes in the outcomes in the survey wave during which the health shock occurs. Since the survey waves are generally two years apart, these estimates should be interpreted as the impacts of experiencing a health shock on the outcomes of interest 0–2 years after the shock.

Panel A of Table 3 presents the changes in individuals' health. The ADL score, which ranges from 0 to 6, measures the number of daily activities individuals have difficulty performing independently. Self-rated health is assessed on a scale from 1 to 5, where 1 indicates excellent health and 5 indicates very poor health. The entries show that individuals' ADL score increases by 0.18 points or 32.5% post-shock. In addition, the score for self-rated health increases by 0.18 points or 5.5% following a health shock, as expected. Unlike the deterioration in physical health, the change in the likelihood of depression following a health shock is statistically insignificant.

Panel B of Table 3 presents the changes in healthcare utilization.[4] The estimates indicate that individuals are 10.5 percentage points more likely to utilize inpatient care following a health shock, representing an increase of 61.0%. In addition, individuals who experienced a health shock demand 0.2 more episodes of inpatient care, representing an increase of 77.7%. Similarly, individuals stay 1.5 more nights in hospital following a health shock, representing

4 Since the survey collects information on inpatient healthcare utilization over the past year and outpatient healthcare utilization over the past month at each interview, the estimates reflect changes in healthcare utilization between the year or month prior to the interview in the survey wave when the shock occurs and the year or month prior to the interview in the previous survey wave.

an increase of 74.7%. For outpatient care utilization, the estimates indicate that individuals are 2.8 percentage points more likely to utilize outpatient services following a health shock, which represents an 11.9% increase. Additionally, the number of outpatient care episodes per individual increases by 0.1 following a health shock, representing a 19.5% increase.

Panel C of Table 3 presents the corresponding changes in medical expenditure. The estimates indicate that individuals' annual total inpatient expenditure increases by 1,782 RMB following a health shock, representing an increase of 101.1%, while annual OOP inpatient expenditure increases by 1,088 RMB or 125.1%. Additionally, monthly total outpatient expenditure increases by 231 RMB, representing an increase of 89.5%, while monthly OOP outpatient expenditure rises by 139 RMB or 85.3%. Taken together, the magnitude of these effects highlights the substantial burden of health shocks, particularly in terms of worsened physical health and increased healthcare demands and costs.[5]

Figure 1 to Figure 5 display the event study graphs corresponding to the outcomes of interest presented in Table 3. There are two key observations that are critical for understanding the temporal dynamics of health shocks. First, the pre-shock ATT values and corresponding confidence intervals indicate pre-trends are absent. This suggests that there are no underlying trends in the outcomes of interest affecting individuals prior to the onset of a health shock, which reinforces the assumption that subsequent changes in the outcomes of interest can be attributed directly to the shock itself. Second, the impact of a health shock on several outcomes, including physical health and selective measures of inpatient care utilization and expenditure, lasts through 2-4 years post-shock. Specifically, there is a continuous deterioration in individuals' physical health 2-4 years post-shock. Meanwhile, the magnitude of the effects on specific measures of inpatient care utilization and expenditure, although diminished, remains statistically significant over the same period. The persistence of these effects underscores the severity and enduring nature of the shocks, suggesting that

5 Based on the baseline average annual earned income of individuals who experienced a health shock between the 2011 and 2018 interviews, as presented in Table 1, the increase in healthcare costs 0-2 years post-shock accounts for 38.2% of their annual earned income.

their repercussions are not confined to the immediate aftermath but continue to affect health status and healthcare demand over a medium-term horizon.

Table 4 presents the event study estimates for the indirect impacts of health shocks on individuals' health, healthcare utilization, and medical expenditure 0-2 years following a spouse's health shock. None of the outcome variables demonstrates statistically significant changes. For example, the statistically insignificant increase in ADL score is accompanied by a confidence interval of $[-0.017, 0.093]$. While this interval includes zero, the upper bound of this interval suggests a possible increase of up to 40.8% relative to the baseline mean, and the lower bound indicates a possible decrease of up to 7.5%. This wide range suggests substantial uncertainty regarding the true effect of the treatment on the ADL score. In addition, the statistically insignificant decrease in the probability of depression is accompanied by a confidence interval of $[-0.036, 0.033]$. This interval indicates moderate uncertainty regarding the effect of the treatment on the probability of depression. The upper bound of this interval suggests a potential increase by up to 11.5% relative to the baseline mean, while the lower bound indicates a potential decrease by up to 12.6%.

The changes in healthcare utilization following a spouse's health shock are also inconclusive. For instance, the increase of 0.5 percentage points in the probability of using inpatient care is accompanied by a confidence interval of $[-2.3, 3.3]$, which suggests a possible increase of up to 32.3% relative to the baseline mean and a possible decrease of up to 22.5%. The financial implications, as reflected in medical expenditure, are more inconclusive due to the broader confidence intervals. The estimated change in total inpatient expenditure is 229 RMB. The associated confidence interval of $[-261, 720]$ indicates that while there might be a decrease, substantial increases are also within the realm of possibility, which precludes definitive conclusions. Similarly, the confidence interval of $[-168, 934]$ associated with the total outpatient expenditure of 383 RMB reflects uncertainty in estimating the true economic impact on households following a spouse's health shock. Figure 6 to Figure 10 display the event study graphs corresponding to the outcomes of interest presented in Table 4.

Table 5 presents the event study estimates for the impacts of health shocks on the labor supply and earned income for individuals 0-2 years following both their own and their spouses' health shocks. These estimates help illuminate the broader economic consequences of health shocks beyond medical expenditure. Panel A presents the estimated changes in labor market outcomes for individuals who experienced a health shock. Column (1) presents the mean values of the outcome variables during the reference period. Column (2) shows the event study estimates for the full sample. The estimates in Column (2) show that individuals' labor supply decreases at both the extensive and intensive margins following a health shock. Specifically, at the extensive margin, the likelihood of individuals working decreases by 4.0 percentage points following a shock, which corresponds to a 6.8% reduction from the baseline mean. At the intensive margin, individuals work an average of 2.3 fewer hours per week following a shock, which represents a 9.4% decrease from the baseline mean. The reduction in labor supply results in a decrease in annual earned income by 382 RMB, which represents a 5.6% decline.

Columns (3)-(6) of Table 5 delve into the results from a heterogeneity analysis by gender. The estimates indicate that both females and males exhibit similar responses to a health shock, with males showing a slightly greater response. Specifically, the likelihood of females working decreases by 3.4 percentage points following a shock, which represents a 6.4% reduction from the baseline mean, while the likelihood of males working decreases by 4.8 percentage points, which represents a 7.1% reduction. In addition, females work an average of 1.6 fewer hours per week following a shock, which represents a 7.6% decrease. However, this estimate is only marginally significant. For males, there is a reduction of 3.3 hours in weekly working hours following a shock, representing an 11.3% decrease. For females, the reduction in labor supply results in a corresponding decrease in annual earned income by 91 RMB or 1.6%. However, this estimate is statistically insignificant. For males, the reduction in labor supply results in a corresponding decrease in annual earned income by 788 RMB or 9.3%.

Panel B of Table 5 presents changes in individuals' labor market supply and earned income 0-2 years following a spouse's health shock. The estimates in Column (2) indicate that there are no statistically significant changes in labor supply at either the extensive or intensive margins. At the extensive margin, there is a statistically insignificant decrease in the likelihood of working by 1.0 percentage point. At the intensive margin, there is a statistically insignificant increase of 0.2 hours in weekly working hours. These changes in labor supply result in a statistically insignificant increase in annual earned income of 147 RMB. Heterogeneity analysis by gender shows a statistically insignificant increase of 1.0 percentage point in the likelihood of wives working and a statistically insignificant increase of 0.9 hours in their weekly working hours following their husbands' health shocks. Despite the imprecisely estimated changes in labor supply, wives' earned income increases by 496 RMB following their husbands' health shocks. This increase could potentially be explained by a true positive effect on labor market participation or productivity that is masked by statistical noise or sample limitations, or by shifts toward higher-paying jobs. For males, there is a statistically insignificant decrease of 2.5 percentage points in the likelihood of working and a statistically insignificant decrease of 3.7 hours in weekly working hours following their wives' health shocks, resulting in a statistically insignificant decrease of 173 RMB in earned income.

Figure 11 to Figure 16 display the event study graphs corresponding to the outcomes of interest presented in Table 5. These graphs indicate the absence of pre-trends, thereby supporting the interpretation that the observed effects following a health shock can indeed be attributed to the shock itself rather than to pre-existing trends. In addition, the graphs show that for the outcomes in Table 5 that are affected by a health shock, the effects generally dissipate after the survey wave in which the shock occurred. The only exceptions are the likelihood of males working after experiencing a health shock and wives' earned income after their husbands experienced a health shock. For these two outcomes, the effects not only persist into the second post-shock wave but also intensify in the second wave compared to the first.

Table 6 presents the event study estimates of changes in per capita household consumption across various spending categories. Per capita household consumption instead of aggregate household consumption is used to ensure equitable and accurate comparisons across households of varying sizes and compositions. Column (1) presents the mean values of the outcome variables during the reference period. Column (2) presents the event study estimates. The estimates show that per capita OOP medical expenditure increases by 1,710 RMB, which represents a more than 100% increase from the baseline mean. In addition, per capita food expenditure decreases by 42 RMB, and per capita non-medical, non-food expenditure decreases by 826 RMB, although both estimates are statistically insignificant. These changes contribute to a marginally significant overall increase in per capita total expenditure by 847 RMB, which represents a 9.8% rise from the baseline mean.

Figure 17 displays the event study graphs corresponding to the outcomes of interest presented in Table 6. Figure 17(a) shows that the effect of a health shock on per capita medical expenditure dissipates after the survey wave in which the shock occurred. Figure 17(c) indicates that while there is no change in per capita non-medical, non-food expenditure during the survey wave in which the shock occurred, a statistically significant reduction of 1,787 RMB is observed in this category in the subsequent survey wave, 2-4 years post-shock. This pattern may reflect households' consumption smoothing behavior where they curtail less essential spending to offset the increased costs incurred from earlier medical expenditure.

V.C. Results From a TWFE Regression Model

Table 7 to Table 10 report the event study estimates obtained from a traditional TWFE regression model with leads and lags. Comparing these estimates to those derived from the Callaway and Sant'Anna (2021) estimation method, which accounts for potential biases that may arise in the presence of heterogeneous treatment effects and staggered adoption, shows that while there are some differences in point estimates and standard errors between the two approaches, the overall patterns in the results remain largely consistent. The estimated effects follow a similar trajectory over time, and statistical significance is mostly unchanged across the two methods, with only three outcomes exhibiting differences in significance levels. Specifically, under the main specification, the change in total outpatient expenditure for individuals who experienced a health shock is statistically significant at the 10% level, whereas the traditional TWFE model estimates it to be statistically significant at the 5% level. Similarly, the change in per capita total expenditure is statistically significant at the 10% level under the main specification, compared to the 5% level under the traditional TWFE model. Additionally, for females, the change in the likelihood of being employed is statistically significant at the 5% level under the main specification, compared to the 10% level under the traditional TWFE model. These minor differences suggest that while the alternative estimation approach refines the precision of certain estimates, it does not fundamentally alter the key conclusions drawn from the analysis. This consistency across methods reinforces the robustness of the findings and indicates that the observed effects are not merely artifacts of the estimation technique but rather reflect true underlying relationships.

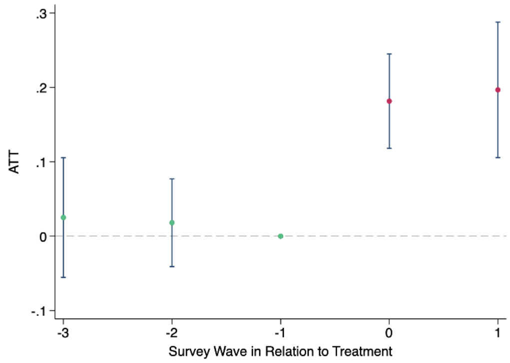
VI. Conclusion

This paper has systematically explored the multifaceted impacts of health shocks on individuals and their households in China, particularly focusing on labor market outcomes and household consumption patterns. The findings demonstrate that health shocks, specifically heart attacks and strokes which have an acute onset, substantially diminish physical health and increase healthcare utilization and medical expenditures significantly, which underscores the severe nature of these conditions. Despite these significant direct effects on the individuals experiencing a shock, the spillover effects on spouses' health outcomes, healthcare utilization, and medical expenditures are statistically insignificant, with large confidence intervals indicating uncertainty about the magnitude of these effects.

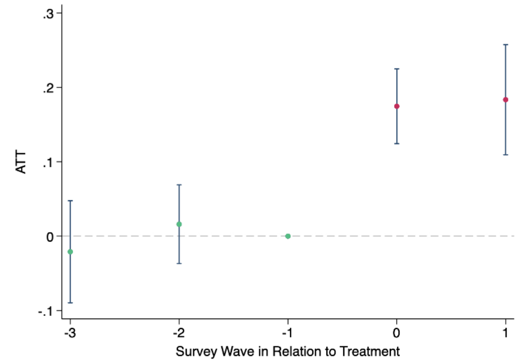
In the labor market, health shocks lead to a notable reduction in employment likelihood and working hours, with corresponding declines in earned income. The effects are similar across genders, with a slightly more pronounced impact on males. These outcomes align with existing literature, reinforcing the impact of poor health on economic productivity and labor participation. When examining the spousal effects of these shocks, the data consistently show no statistically significant impact for the full sample. This pattern holds true for husbands as well where no notable changes are observed following their wives' health shocks. In contrast, wives' earned income increases following their husbands' health shocks, suggesting a potential compensatory dynamic in response to the financial strain caused by the health shock. However, the evidence does not clearly establish the underlying mechanism driving this increase. Additionally, this paper illustrates the resilience of food expenditure against the financial strains imposed by health shocks, while non-essential spending is notably reduced, suggesting a strategic reallocation of household budgets in times of health-induced economic stress.

This paper contributes to the existing literature by offering a fresh perspective on the economic ramifications of health deteriorations in a major middle-income country where economic structures, labor market dynamics, and social safety nets differ significantly from those in high-income settings. Furthermore, by focusing on abrupt and unpredictable health shocks, this study minimizes endogeneity concerns and enables a more precise identification of their short-term causal effects. Future research could build on these findings by exploring longer-term impacts of health shocks on households and by examining the role of social protection programs in mitigating these effects. Moreover, comparative studies across different regions within China or between countries could provide deeper insights into the global applicability of these findings and the effectiveness of various policy interventions. By continuing to refine our understanding of these dynamics, policymakers can better design and implement strategies that not only address the immediate health needs but also bolster economic stability in the face of health adversities.

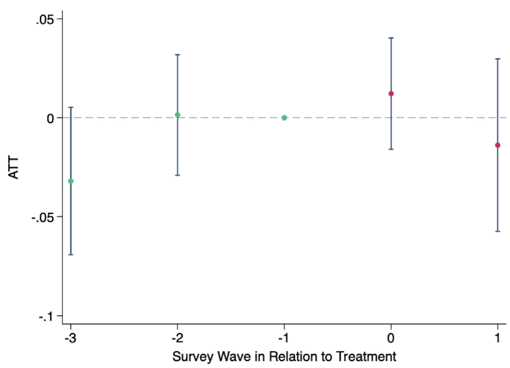
VII. Figures and Tables



(a) ADL Score

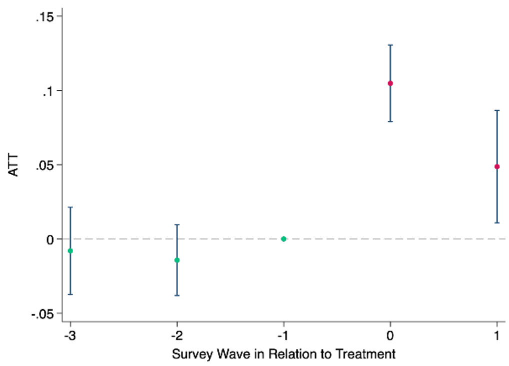


(b) Self-Rated Health

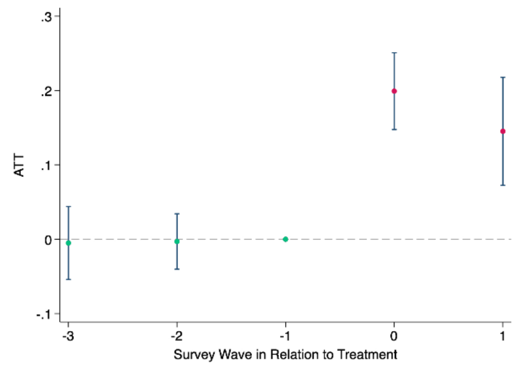


(c) Probability of Depression

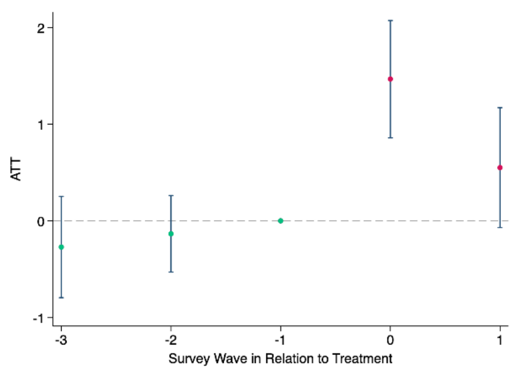
Figure 1: Event Study Estimates of Changes in Health Outcomes Following a Health Shock. The ADL score, which ranges from 0 to 6, is a measure used to assess the degree of assistance an individual requires with daily activities. Higher scores on this scale indicate that an individual requires assistance with a greater number of daily activities, signifying more severe functional impairment. Individuals' self-rated health is measured on a scale from 1 to 5 where 1 indicates excellent health and 5 indicates very poor health. The treatment group comprises individuals diagnosed with a heart attack or stroke between the 2011 and 2018 interviews, excluding those whose spouses experienced a health shock prior to their own diagnosis. The control group consists of individuals from households that did not report any health shocks during the same period. The error bars represent 95% confidence intervals.



(a) Probability of Receiving Inpatient Care

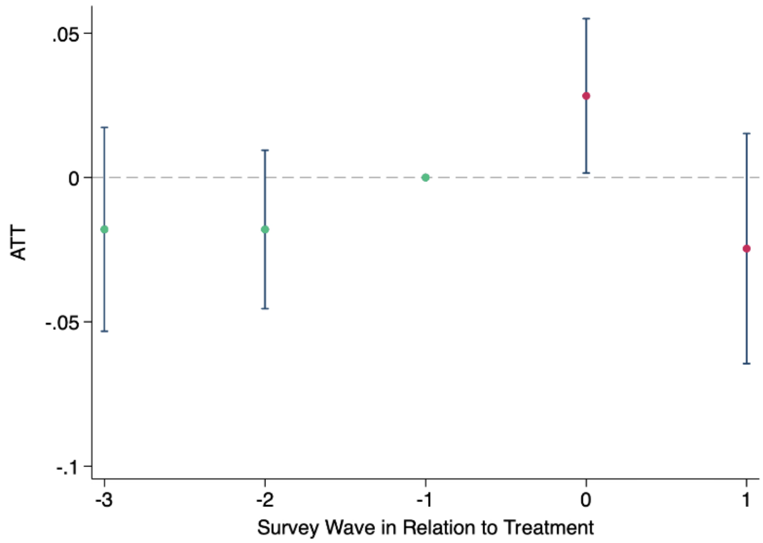


(b) Number of Inpatient Care Episodes

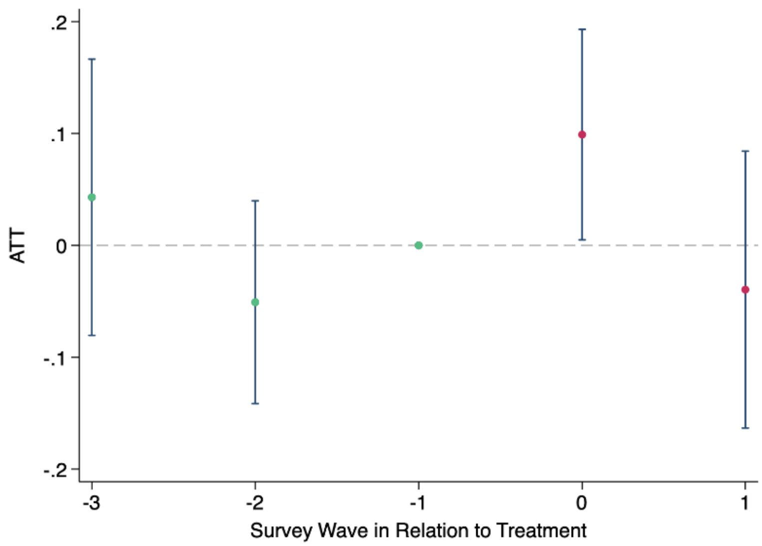


(c) Number of Nights Hospitalized During the Most Recent Inpatient Care Episode

Figure 2: Event Study Estimates of Changes in Inpatient Care Utilization Following a Health Shock. The treatment group comprises individuals diagnosed with a heart attack or stroke between the 2011 and 2018 interviews, excluding those whose spouses experienced a health shock prior to their own diagnosis. The control group consists of individuals from households that did not report any health shocks during the same period. The error bars represent 95% confidence intervals.

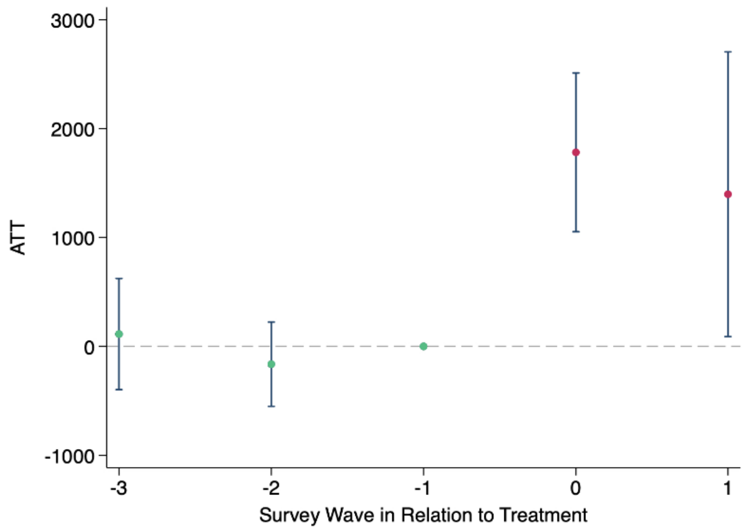


(a) Probability of Receiving Outpatient Care

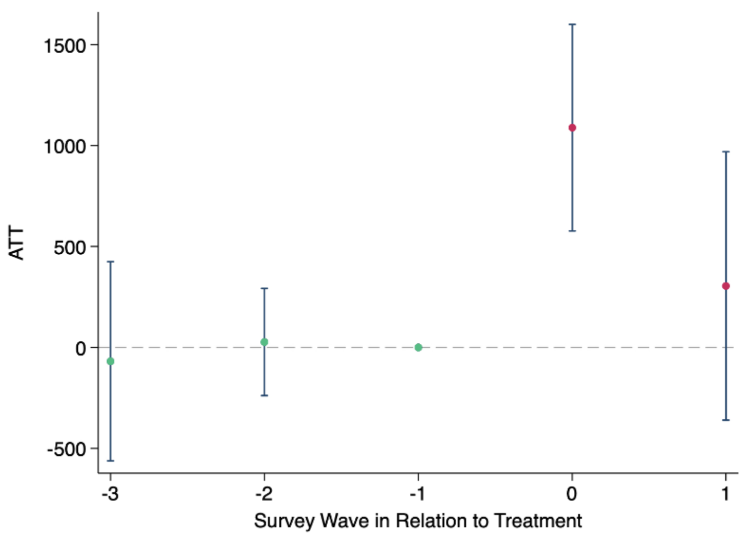


(b) Number of Outpatient Care Episodes

Figure 3: Event Study Estimates of Changes in Outpatient Care Utilization Following a Health Shock. The treatment group comprises individuals diagnosed with a heart attack or stroke between the 2011 and 2018 interviews, excluding those whose spouses experienced a health shock prior to their own diagnosis. The control group consists of individuals from households that did not report any health shocks during the same period. The error bars represent 95% confidence intervals.

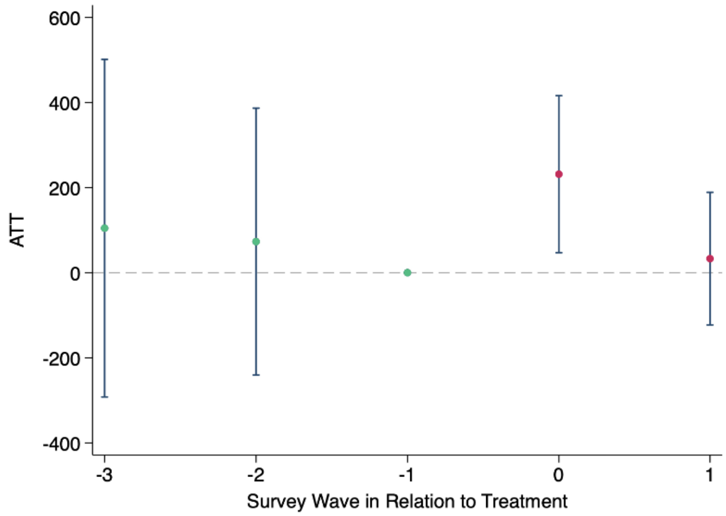


(a) Total Inpatient Expenditure

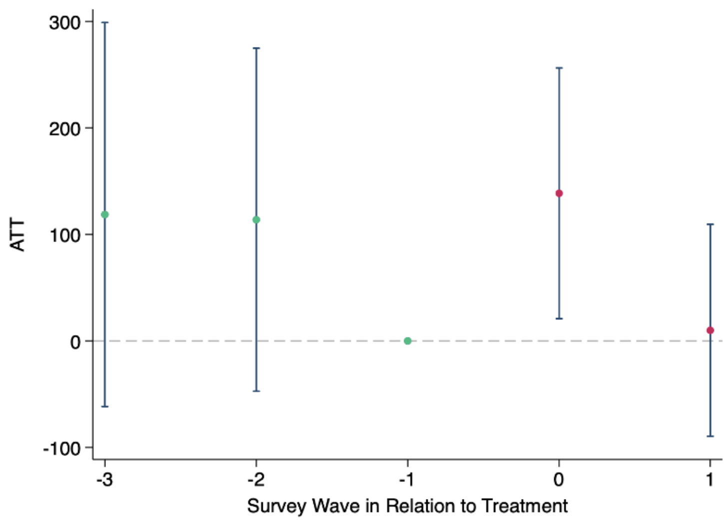


(b) OOP Inpatient Expenditure

Figure 4: Event Study Estimates of Changes in Inpatient Expenditure Following a Health Shock. The treatment group comprises individuals diagnosed with a heart attack or stroke between the 2011 and 2018 interviews, excluding those whose spouses experienced a health shock prior to their own diagnosis. The control group consists of individuals from households that did not report any health shocks during the same period. The error bars represent 95% confidence intervals.

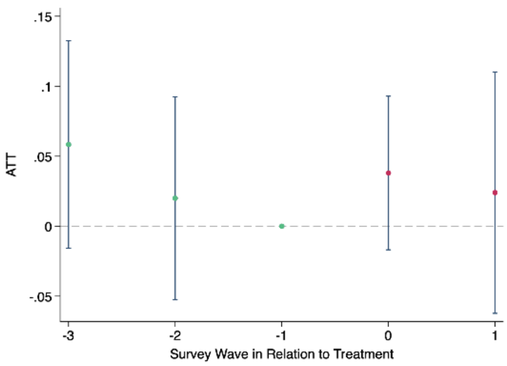


(a) Total Outpatient Expenditure

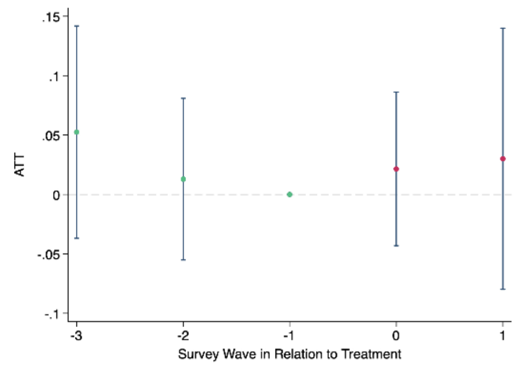


(b) OOP Outpatient Expenditure

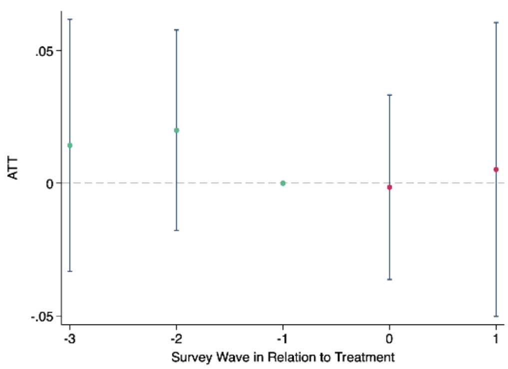
Figure 5: Event Study Estimates of Changes in Outpatient Expenditure Following a Health Shock. The treatment group comprises individuals diagnosed with a heart attack or stroke between the 2011 and 2018 interviews, excluding those whose spouses experienced a health shock prior to their own diagnosis. The control group consists of individuals from households that did not report any health shocks during the same period. The error bars represent 95% confidence intervals.



(a) ADL Score

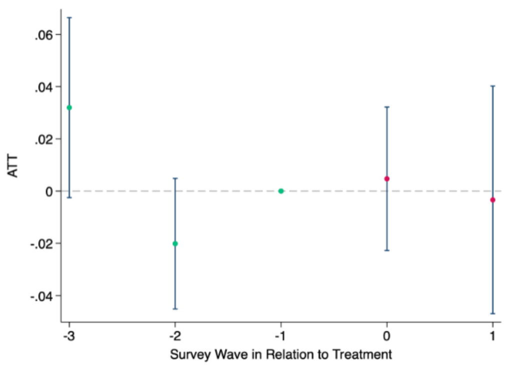


(b) Self-Rated Health

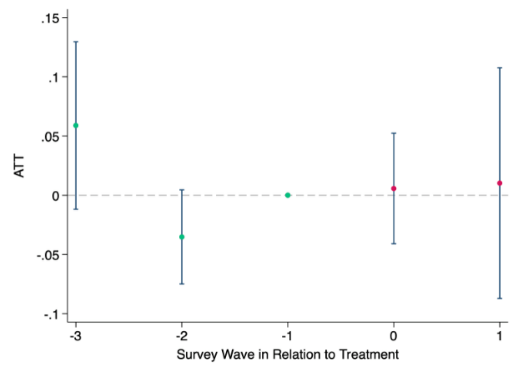


(c) Probability of Depression

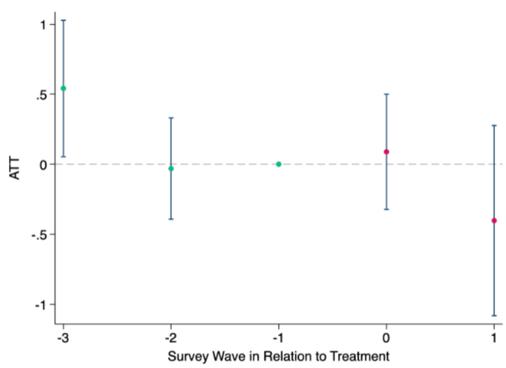
Figure 6: Event Study Estimates of Changes in Health Outcomes Following a Spouse's Health Shock. The ADL score, which ranges from 0 to 6, is a measure used to assess the degree of assistance an individual requires with daily activities. Higher scores on this scale indicate that an individual requires assistance with a greater number of daily activities, signifying more severe functional impairment. Individuals' self-rated health is measured on a scale from 1 to 5 where 1 indicates excellent health and 5 indicates very poor health. The treatment group consists of individuals who were not diagnosed with a heart attack or stroke but whose spouses were diagnosed with one of these conditions during the 2011 and 2018 interviews. The control group consists of individuals from households that did not report any health shocks during the same period. The error bars represent 95% confidence intervals.



(a) Probability of Receiving Inpatient Care

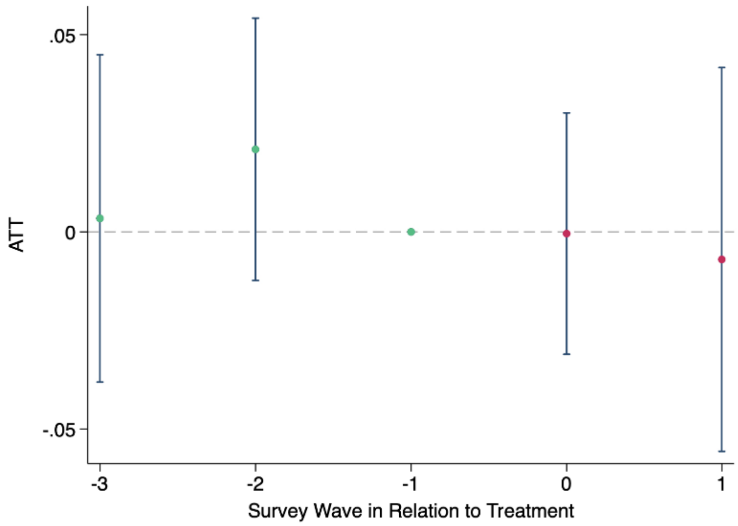


(b) Number of Inpatient Care Episodes

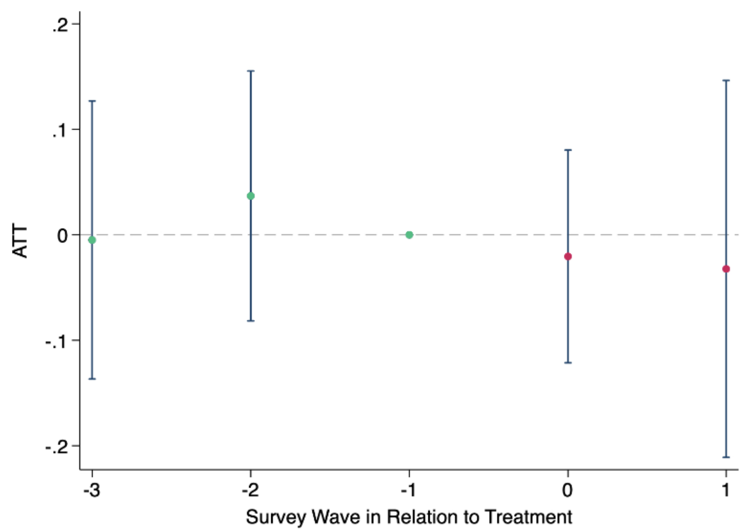


(c) Number of Nights Hospitalized During the Most Recent Inpatient Care Episode

Figure 7: Event Study Estimates of Changes in Inpatient Care Utilization Following a Spouse's Health Shock. The treatment group consists of individuals who were not diagnosed with a heart attack or stroke but whose spouses were diagnosed with one of these conditions during the 2011 and 2018 interviews. The control group consists of individuals from households that did not report any health shocks during the same period. The error bars represent 95% confidence intervals.

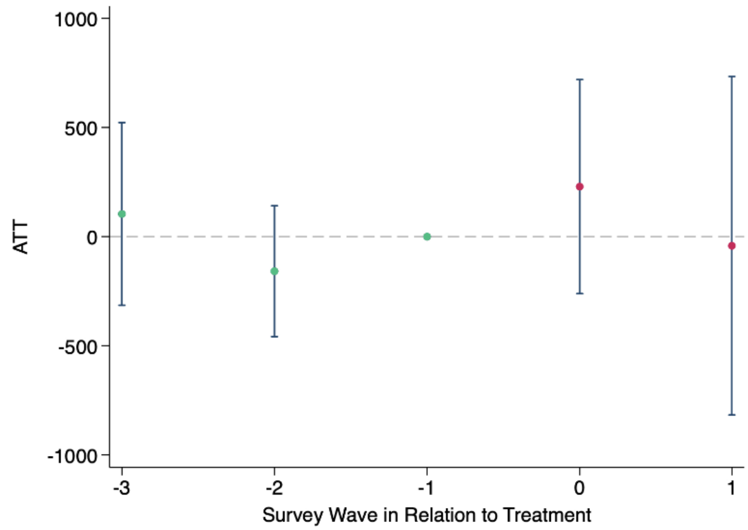


(a) Probability of Receiving Outpatient Care

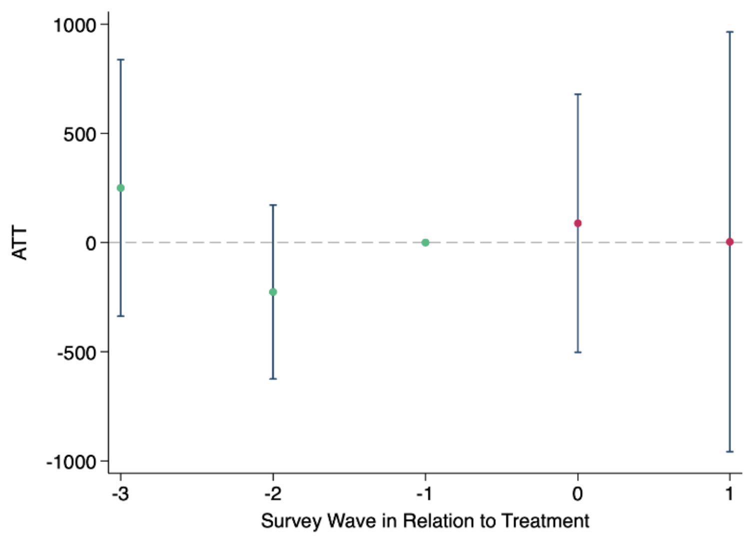


(b) Number of Outpatient Care Episodes

Figure 8: Event Study Estimates of Changes in Outpatient Care Utilization Following a Spouse's Health Shock. The treatment group consists of individuals who were not diagnosed with a heart attack or stroke but whose spouses were diagnosed with one of these conditions during the 2011 and 2018 interviews. The control group consists of individuals from households that did not report any health shocks during the same period. The error bars represent 95% confidence intervals.

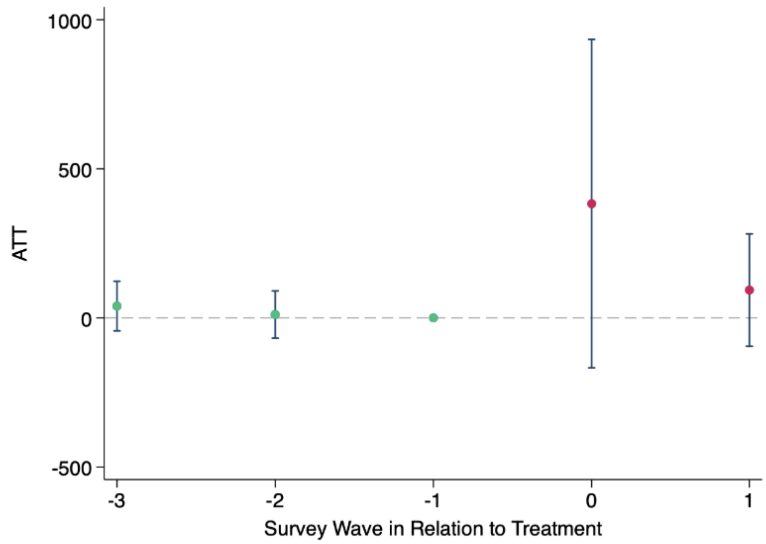


(a) Total Inpatient Expenditure

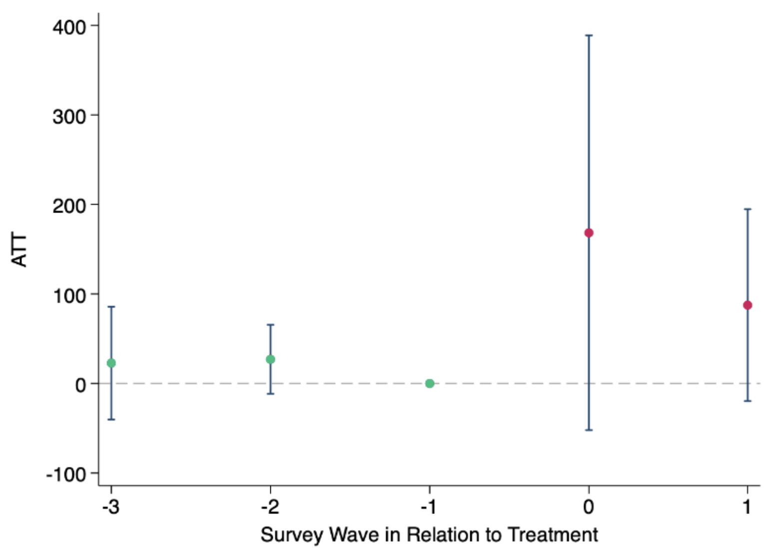


(b) OOP Inpatient Expenditure

Figure 9: Event Study Estimates of Changes in Inpatient Expenditure Following a Spouse's Health Shock. The treatment group consists of individuals who were not diagnosed with a heart attack or stroke but whose spouses were diagnosed with one of these conditions during the 2011 and 2018 interviews. The control group consists of individuals from households that did not report any health shocks during the same period. The error bars represent 95% confidence intervals.

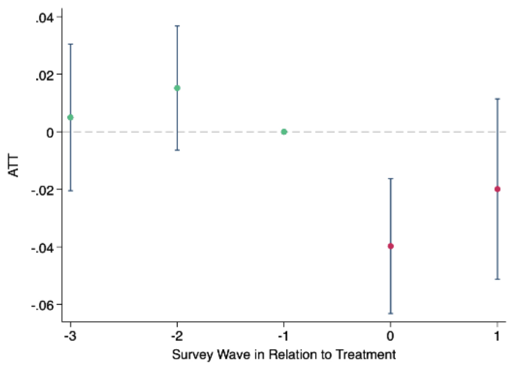


(a) Total Outpatient Expenditure

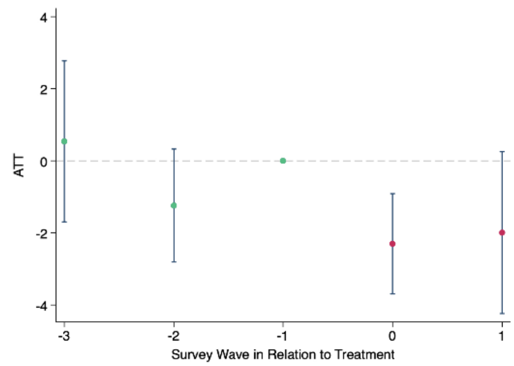


(b) OOP Outpatient Expenditure

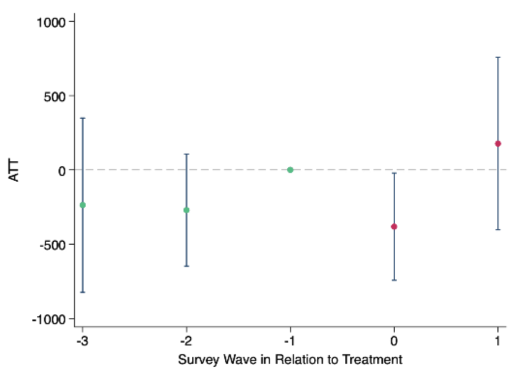
Figure 10: Event Study Estimates of Changes in Outpatient Expenditure Following a Spouse's Health Shock. The treatment group consists of individuals who were not diagnosed with a heart attack or stroke but whose spouses were diagnosed with one of these conditions during the 2011 and 2018 interviews. The control group consists of individuals from households that did not report any health shocks during the same period. The error bars represent 95% confidence intervals.



(a) Employment Probability

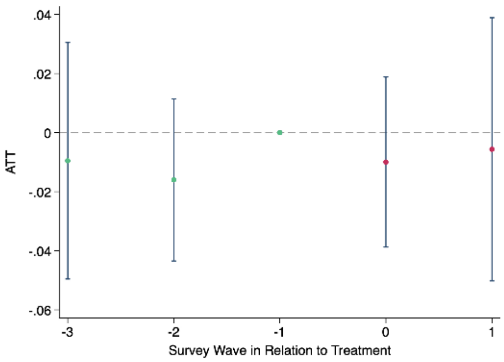


(b) Weekly Working Hours

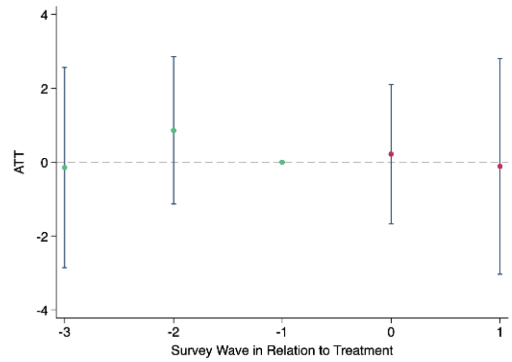


(c) Earned Income

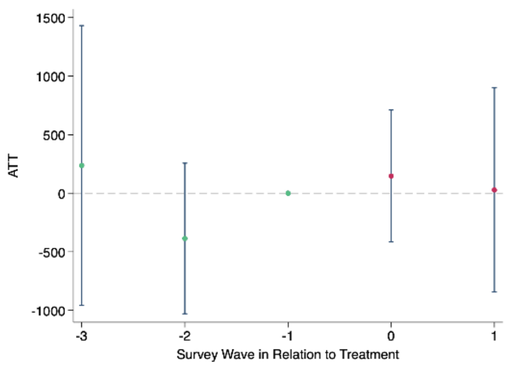
Figure 11: Event Study Estimates of Changes in Labor Market Outcomes Following a Health Shock. The treatment group comprises individuals diagnosed with a heart attack or stroke between the 2011 and 2018 interviews, excluding those whose spouses experienced a health shock prior to their own diagnosis. The control group consists of individuals from households that did not report any health shocks during the same period. The error bars represent 95% confidence intervals.



(a) Employment Probability

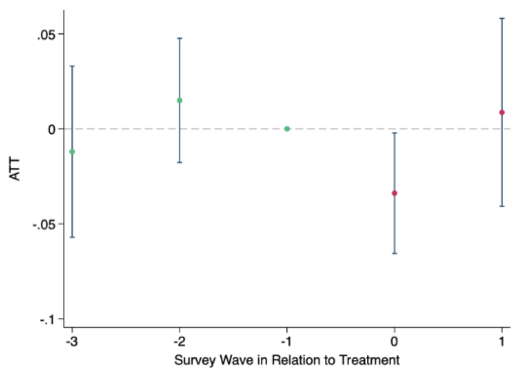


(b) Weekly Working Hours

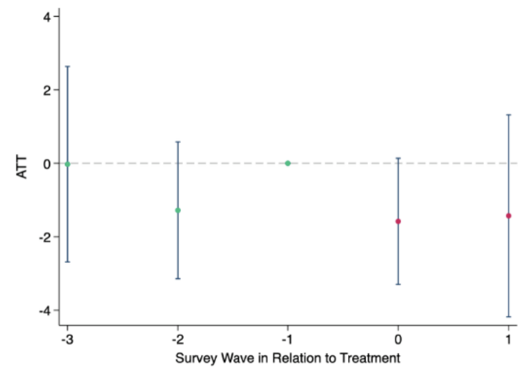


(c) Earned Income

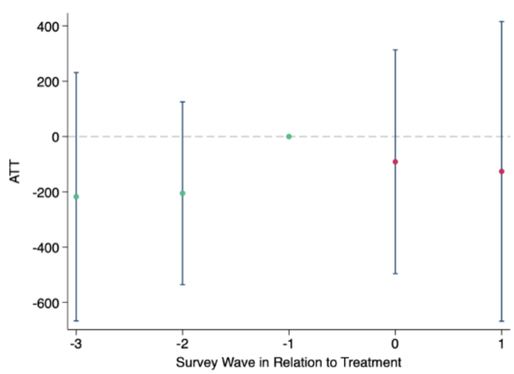
Figure 12: Event Study Estimates of Changes in Labor Market Outcomes Following a Spouse's Health Shock. The treatment group consists of individuals who were not diagnosed with a heart attack or stroke but whose spouses were diagnosed with one of these conditions during the 2011 and 2018 interviews. The control group consists of individuals from households that did not report any health shocks during the same period. The error bars represent 95% confidence intervals.



(a) Employment Probability

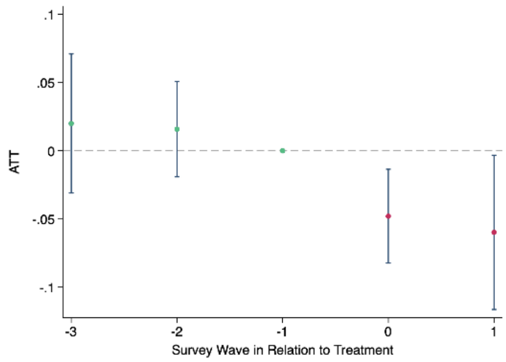


(b) Weekly Working Hours



(c) Earned Income

Figure 13: Heterogeneity Analysis: Event Study Estimates of Changes in Females' Labor Market Outcomes Following a Health Shock. The treatment group comprises females diagnosed with a heart attack or stroke between the 2011 and 2018 interviews, excluding those whose spouses experienced a health shock prior to their own diagnosis. The control group consists of females from households that did not report any health shocks during the same period. The error bars represent 95% confidence intervals.



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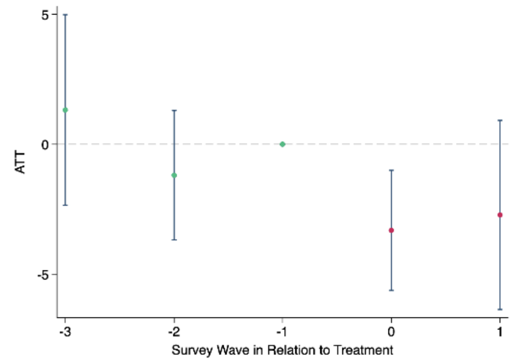

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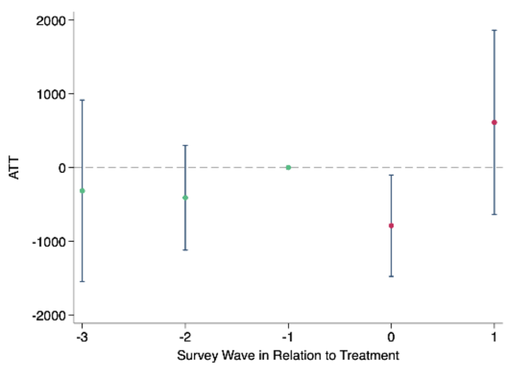
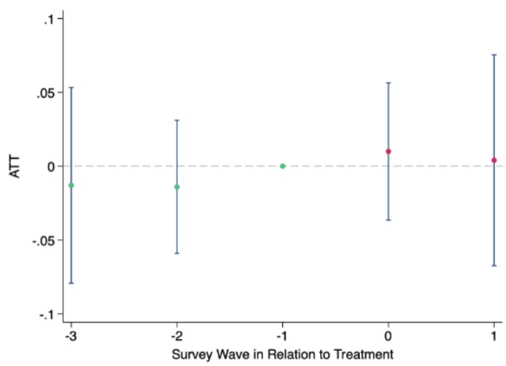
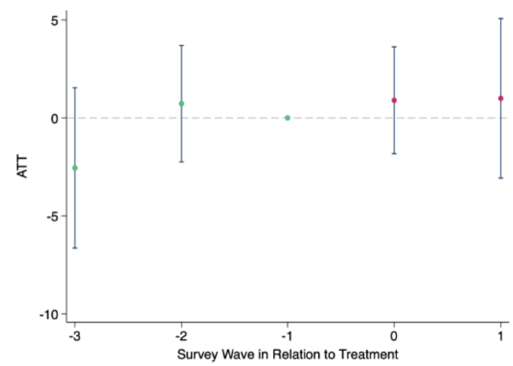


(c) Earned Income

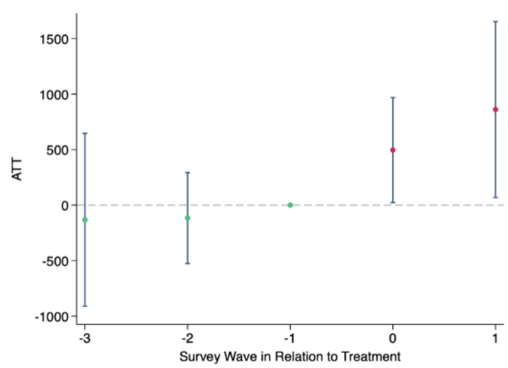
Figure 14: Heterogeneity Analysis: Event Study Estimates of Changes in Males' Labor Market Outcomes Following a Health Shock. The treatment group comprises males diagnosed with a heart attack or stroke between the 2011 and 2018 interviews, excluding those whose spouses experienced a health shock prior to their own diagnosis. The control group consists of males from households that did not report any health shocks during the same period. The error bars represent 95% confidence intervals.



(a) Employment Probability

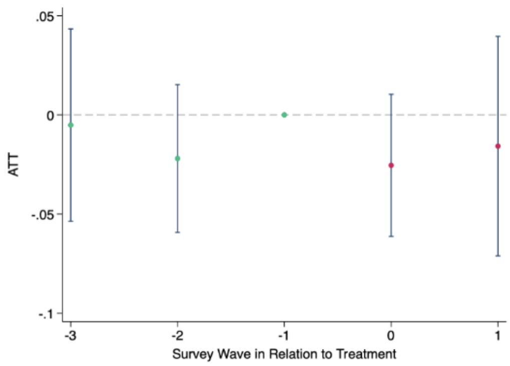


(b) Weekly Working Hours

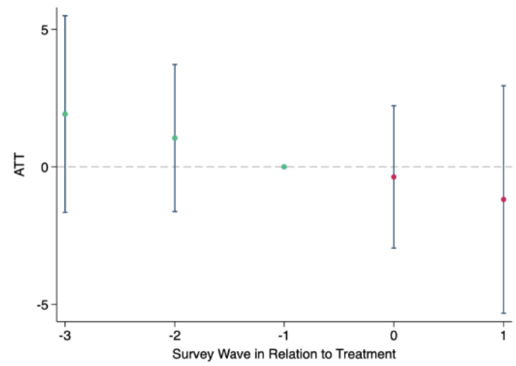


(c) Earned Income

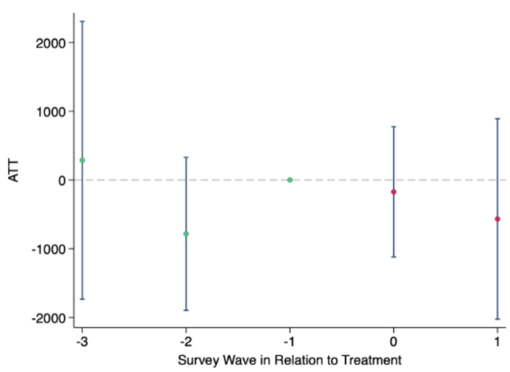
Figure 15: Heterogeneity Analysis: Event Study Estimates of Changes in Females' Labor Market Outcomes Following a Spouse's Health Shock. The treatment group consists of females who were not diagnosed with a heart attack or stroke but whose spouses were diagnosed with one of these conditions during the 2011 and 2018 interviews. The control group consists of females from households that did not report any health shocks during the same period. The error bars represent 95% confidence intervals.



(a) Employment Probability

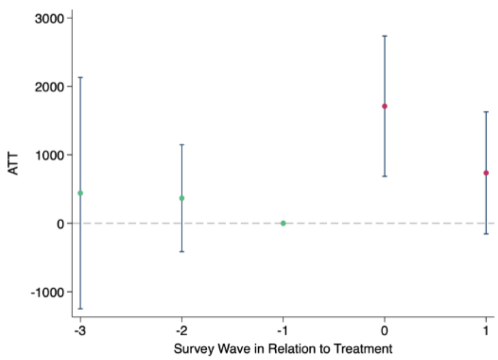


(b) Weekly Working Hours

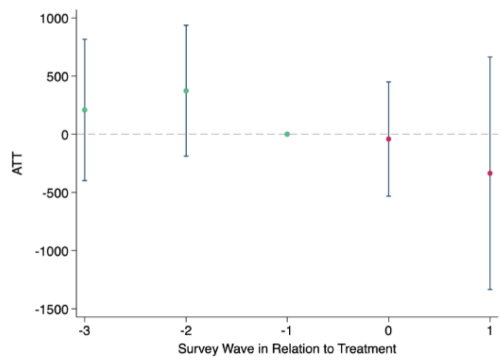


(c) Earned Income

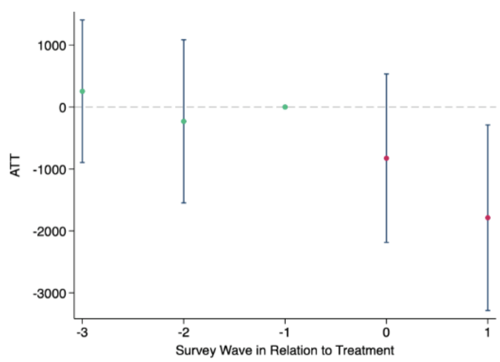
Figure 16: Heterogeneity Analysis: Event Study Estimates of Changes in Males' Labor Market Outcomes Following a Spouse's Health Shock. The treatment group consists of males who were not diagnosed with a heart attack or stroke but whose spouses were diagnosed with one of these conditions during the 2011 and 2018 interviews. The control group consists of males from households that did not report any health shocks during the same period. The error bars represent 95% confidence intervals.



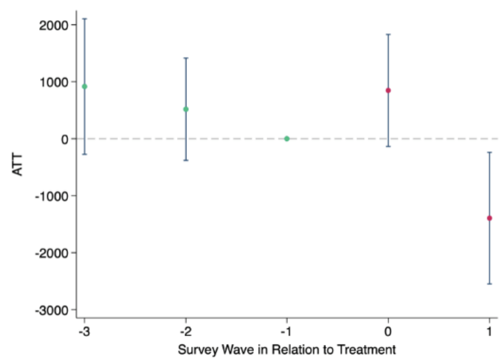
(a) Per Capita OOP Medical Expenditure



(b) Per Capita Food Expenditure



(c) Per Capita Non-Medical, Non-Food Expenditure



(d) Per Capita Total Expenditure

Figure 17: Event Study Estimates of Changes in Per Capita Household Consumption Across Spending Categories Following a Member's Health Shock. The treatment group consists of households in which at least one member was diagnosed with a heart attack or stroke between the 2011 and 2018 interviews. The control group consists of households that reported no health shocks during the same period. The error bars represent 95% confidence intervals.

Table 1: Summary Statistics At the Baseline Interview

	Sample Without Health Shocks (1)	Sample With Health Shocks (2)	Spouses of Individuals With Health Shocks (3)
A. Individual Characteristics			
Age	56.51	59.47	57.34
Female	0.54	0.59	0.45
Education			
No Formal Education	47.45	49.67	42.74
Below High School	42.15	39.18	45.93
High School	9.31	9.78	10.09
Above High School	1.09	1.37	1.24
Worked In the Past Year	0.74	0.63	0.74
Annual Earned Income	10,212	7,209	8,741
Rural Hukou	0.86	0.81	0.82
Public Insurance	0.93	0.93	0.95
Private Insurance	0.02	0.02	0.03
Self-Rated Health			
Excellent	7.75	4.33	6.39
Good	20.80	12.61	18.66
Fair	51.03	48.36	52.78
Poor	17.82	29.59	18.45
Very Poor	2.60	5.11	3.72
Observations	10,512	1,720	1,094
B. Household Characteristics			
Married	0.81	0.84	-
Rural	0.68	0.65	-
Whether Have Children	0.97	0.97	-
Co-residence With Children	0.63	0.59	-
Per Capita Wealth	110,649	77,146	-
Observations	5,809	1,720	-

Note: This table presents the summary statistics of individual and household characteristics at the 2011 baseline interview. All individuals are untreated at the baseline. Column (1) in Panel A reports the mean characteristics of individuals who did not experience any health shock. Individuals whose spouses experienced a health shock are excluded to avoid potential spousal spillover effects. Column (2) in Panel A reports the mean characteristics of individuals who experienced a health shock. Individuals whose spouses have previously experienced a health shock are excluded to avoid potential spousal spillover effects. Column (3) reports the mean characteristics of individuals who did not experience any health shocks but whose spouses experienced a health shock. Column (1) in Panel B reports the mean characteristics for households that did not experience any health shocks. Column (2) in Panel B reports the mean characteristics for households that experienced at least one health shock.

Table 2: Randomness of Health Shocks and Their Timing

	Health Shocks (1)	Average Marginal Effect (2)	Timing of Health Shocks (3)	Average Marginal Effect (4)
Age	0.018***	0.005***	0.000	0.000
	(0.002)	(0.001)	(0.004)	(0.002)
Female	0.118***	0.033***	−0.033	−0.013
	(0.043)	(0.012)	(0.082)	(0.032)
Education				
Elementary or Middle School	0.091**	0.025***	0.044	0.017
	(0.039)	(0.011)	(0.074)	(0.029)
High School	0.212***	0.061***	−0.126	−0.050
	(0.067)	(0.020)	(0.125)	(0.049)
Above High School	0.150	0.042	-0.135	−0.053
	(0.164)	(0.048)	(0.299)	(0.118)
Employment Status	−0.059	−0.017	0.050	0.020
	(0.041)	(0.012)	(0.075)	(0.029)
Earned Income	-2.160^{-7}	-6.010^{-8}	-1.010^{-6}**	-3.940^{-7}**
	(9.960^{-7})	(2.770^{-7})	(3.980^{-7})	(1.550^{-7})
Rural Hukou	−0.253***	−0.075***	0.091	0.036
	(0.053)	(0.016)	(0.094)	(0.037)
Public Health Insurance	0.085	0.023	0.034	0.013
	(0.073)	(0.019)	(0.136)	(0.053)
Private Health Insurance	−0.051	−0.014	−0.174	−0.068
	(0.114)	(0.032)	(0.224)	(0.087)
Self-Rated Health				
Good	−0.007	−0.001	0.164	0.062
	(0.082)	(0.019)	(0.177)	(0.068)
Fair	0.227***	0.057***	−0.052	−0.020
	(0.083)	(0.017)	(0.159)	(0.062)
Poor	0.512***	0.145***	−0.135	−0.053
	(0.082)	(0.021)	(0.168)	(0.065)
Very Poor	0.541***	0.155***	0.054	0.021
	(0.118)	(0.036)	(0.220)	(0.085)
CESD Score	0.010***	0.003***	−0.003	−0.001
	(0.003)	(0.001)	(0.005)	(0.002)
Inpatient Care Expenditure	4.490^{-6}	1.250^{-6}	-7.800^{-6}	3.040^{-6}
	(4.020^{-6})	(1.120^{-6})	(5.560^{-6})	(2.170^{-6})
Current Smoker	−0.004	−0.001	−0.060	−0.024
	(0.046)	(0.013)	(0.086)	(0.034)
Observations	11,218	11,218	1,561	1,561
P-value (All x's = 0)	0.000	0.000	0.089	0.063

This table presents the estimates from two Probit models that examine the randomness of health shocks and the non-predictiveness of their timing, respectively. The first model examines the probability of getting a shock as a function of various baseline individual characteristics, using the full sample. The results are presented in Column (1). Column (2) presents the corresponding average marginal effects. The second model focuses exclusively on individuals who experienced a health shock during the study period and examines the probability of these individuals experiencing a shock in the 2018 survey wave instead of the 2013 and 2015 survey waves as a function of various baseline individual characteristics. The results are presented in Column (3). Column (4) presents the corresponding average marginal effects. * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$

Table 3: Event Study Estimates For Individuals Who Experienced a Health Shock

	Reference Period Mean (1)	Effect at Shock Wave (2)
A. Health Outcomes		
ADL Score	0.557	0.181***
		(0.032)
Depression	0.420	0.012
		(0.016)
Self-Rated Health	3.183	0.175***
		(0.026)
B. Healthcare Utilization		
Inpatient Care	0.172	0.105***
		(0.013)
Number of Inpatient Care Episodes	0.256	0.199***
		(0.026)
Number of Hospital Nights	1.960	1.465***
		(0.310)
Outpatient Care	0.235	0.028**
		(0.014)
Number of Outpatient Care Episodes	0.507	0.099**
		(0.048)
C. Medical Expenditure		
Total Inpatient Expenditure	1598	1782***
		(372)
OOP Inpatient Expenditure	870	1088***
		(261)
Total Outpatient Expenditure	258	231**
		(94)
OOP Outpatient Expenditure	163	139**
		(60)

Column (1) reports the mean values of the outcome variables from one survey wave prior to the health shock for individuals who experienced a health shock during the 2011 and 2018 interviews. Higher ADL scores and higher scores on self-rated health indicate poorer health. The time frames for inpatient care utilization and inpatient expenditure cover the past year, whereas those for outpatient care utilization and outpatient expenditure cover the past month. Column (2) presents the estimated effects of a health shock during the survey wave in which the shock occurs, specifically 0-2 years post-shock for individuals who experienced a health shock prior to the 2015 interview, and 0-3 years post-shock for those who experienced a health shock between the 2015 and 2018 interviews. These estimates are obtained from the event study model specified in Equation 1, which is estimated using the event study estimation method developed by Callaway and Sant'Anna (2021). * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Table 4: Event Study Estimates for Individuals Whose Spouses Experienced a Health Shock

	Reference Period Mean (1)	Effect at Shock Wave (2)	Confidence Interval (3)
A. Health Outcomes			
ADL Score	0.228	0.038	$[-0.017, 0.093]$
		(0.028)	
Depression	0.286	-0.002	$[-0.036, 0.033]$
		(0.018)	
Self-Rated Health	2.844	0.021	$[-0.043, 0.086]$
		(0.033)	
B. Healthcare Utilization			
Inpatient Care	0.102	0.005	$[-0.023, 0.033]$
		(0.014)	
Number of Inpatient Care Episodes	0.133	0.006	$[-0.041, 0.052]$
		(0.024)	
Number of Hospital Nights	0.985	0.089	$[-0.322, 0.499]$
		(0.210)	
Outpatient Care	0.171	0.000	$[-0.031, 0.030]$
		(0.016)	
Number of Outpatient Care Episodes	0.374	-0.021	$[-0.121, 0.080]$
		(0.051)	
C. Medical Expenditure			
Total Inpatient Expenditure	849	229	$[-261, 720]$
		(250)	
OOP Inpatient Expenditure	512	88	$[-503, 679]$
		(302)	
Total Outpatient Expenditure	123	383	$[-168, 934]$
		(281)	
OOP Outpatient Expenditure	74	168	$[-52, 389]$
		(112)	

Column (1) reports the mean values of the outcome variables from one survey wave prior to the health shock for individuals who did not experience a health shock themselves but whose spouses did during the 2011 and 2018 interviews. Higher ADL scores and higher scores on self-rated health indicate poorer health. The time frames for inpatient care utilization and inpatient expenditure cover the past year, whereas those for outpatient care utilization and outpatient expenditure cover the past month. Column (2) reports the estimated effects of a health shock during the survey wave in which the shock occurs, specifically 0-2 years post-shock for individuals whose spouses experienced a health shock before the 2015 interview, and 0-3 years post-shock for those whose spouses experienced a health shock between the 2015 and 2018 interviews. These estimates are obtained from the event study model specified in Equation 1, which is estimated using the event study estimation method developed by Callaway and Sant'Anna (2021). Column (3) reports the confidence intervals for the estimates in Column (2). * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Table 5: Event Study Estimates of Changes in Labor Market Outcomes

	Reference Period Mean (1)	Full Sample (2)	Reference Period Mean (3)	Females (4)	Reference Period Mean (5)	Males (6)
A. Individuals' Labor Market Outcomes Following a Health Shock						
Employed	0.592	-0.040^{***}	0.535	-0.034^{**}	0.676	-0.048^{***}
		(0.012)		(0.016)		(0.018)
Weekly Working Hours	24.40	-2.30^{***}	21.03	-1.58^{*}	29.28	-3.31^{***}
		(0.71)		(0.88)		(1.18)
Annual Earned Income	6768	-382^{**}	5611	-91	8462	-788^{**}
		(184)		(206)		(351)
A. Individuals' Labor Market Outcomes Following a Spouse's Health Shock						
Employed	0.732	-0.010	0.632	0.010	0.812	-0.025
		(0.015)		(0.024)		(0.018)
Weekly Working Hours	30.19	0.22	24.21	0.90	35.03	-0.37
		(0.96)		(1.39)		(1.32)
Annual Earned Income	8355	147	6378	496^{**}	9925	-173
		(287)		(241)		(484)

This table presents the effects of health shocks on individuals' and their spouses' labor market outcomes. Panel A reports individuals' labor market outcomes following a health shock, while Panel B reports individuals' labor market outcomes following a spouse's health shock. Column (1) reports the mean values of the outcome variables from one survey wave prior to the health shock. Column (2) reports the estimated effects of a health shock during the survey wave in which the shock occurs for individuals who experienced a health shock and for individuals whose spouses experienced a health shock during the study period, respectively. Columns (3)–(6) report the estimates from the heterogeneity analysis by gender. Specifically, Column (4) focuses on females' labor market responses to their own and their spouses' health shocks, while Column (6) focuses on males' responses. These estimates are obtained from the event study model specified in Equation 1, which is estimated using the event study estimation method developed by Callaway and Sant'Anna (2021). * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Table 6: Event Study Estimates of Changes in Household Consumption Per Capita Across Different Spending Categories

	Reference Period Mean (1)	Effect at Shock Wave (2)
Per Capita OOP Medical Expenditure	1691	1710***
		(523)
Per Capita Food Expenditure	4547	−42
		(250)
Per Capita Non-Medical, Non-Food Expenditure	2385	−826
		(694)
Per Capita Total Expenditure	8623	847*
		(501)

Column (1) reports the mean values of the outcome variables from one survey wave prior to the health shock for households with at least one shock during the study period. Column (2) reports the estimated effects of a health shock during the survey wave in which the shock occurs, specifically 0-2 years post-shock for households that reported a health shock before the 2015 interview, and 0-3 years post-shock for those reported experiencing a health shock between the 2015 and 2018 interviews. These estimates are obtained from the event study model specified in Equation 1, which is estimated using the event study estimation method developed by Callaway and Sant'Anna (2021). * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Table 7: Event Study Estimates for Individuals Who Experienced a Health Shock: TWFE Regression Model

	Reference Period Mean (1)	Effect at Shock Wave (2)
A. Health Outcomes		
ADL Score	0.557	0.178***
		(0.032)
Depression	0.420	0.010
		(0.014)
Self-Rated Health	3.183	0.175***
		(0.026)
B. Healthcare Utilization		
Inpatient Care	0.172	0.105***
		(0.013)
Number of Inpatient Care Episodes	0.256	0.196***
		(0.026)
Number of Hospital Nights	1.960	1.390***
		(0.300)
Outpatient Care	0.235	0.029**
		(0.014)
Number of Outpatient Care Episodes	0.507	0.093*
		(0.047)
C. Medical Expenditure		
Total Inpatient Expenditure	1598	1718***
		(363)
OOP Inpatient Expenditure	870	1059***
		(256)
Total Outpatient Expenditure	258	261***
		(96)
OOP Outpatient Expenditure	163	152**
		(62)

Column (1) reports the mean values of the outcome variables from one survey wave prior to the health shock for individuals who experienced a health shock during the 2011 and 2018 interviews. Higher ADL scores and higher scores on self-rated health indicate poorer health. The time frames for inpatient care utilization and inpatient expenditure cover the past year, whereas those for outpatient care utilization and outpatient expenditure cover the past month. Column (2) presents the estimated effects of a health shock during the survey wave in which the shock occurs, specifically 0-2 years post-shock for individuals who experienced a health shock prior to the 2015 interview, and 0-3 years post-shock for those who experienced a health shock between the 2015 and 2018 interviews. These estimates are obtained from a traditional TWFE regression model with leads and lags. * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Table 8: Event Study Estimates for Individuals Whose Spouses Experienced a Health Shock: TWFE Regression Model

	Reference Period Mean (1)	Effect at Shock Wave (2)
A. Health Outcomes		
ADL Score	0.228	0.034
		(0.027)
Depression	0.286	−0.006
		(0.018)
Self-Rated Health	2.844	0.028
		(0.033)
B. Healthcare Utilization		
Inpatient Care	0.102	0.003
		(0.014)
Number of Inpatient Care Episodes	0.133	0.003
		(0.024)
Number of Hospital Nights	0.985	0.055
		(0.206)
Outpatient Care	0.171	0.001
		(0.016)
Number of Outpatient Care Episodes	0.374	−0.020
		(0.051)
C. Medical Expenditure		
Total Inpatient Expenditure	849	229
		(252)
OOP Inpatient Expenditure	512	70
		(293)
Total Outpatient Expenditure	123	369
		(270)
OOP Outpatient Expenditure	74	163
		(108)

Column (1) reports the mean values of the outcome variables from one survey wave prior to the health shock for individuals who did not experience a health shock themselves but whose spouses did during the 2011 and 2018 interviews. Higher ADL scores and higher scores on self-rated health indicate poorer health. The time frames for inpatient care utilization and inpatient expenditure cover the past year, whereas those for outpatient care utilization and outpatient expenditure cover the past month. Column (2) reports the estimated effects of a health shock during the survey wave in which the shock occurs, specifically 0-2 years post-shock for individuals whose spouses experienced a health shock before the 2015 interview, and 0-3 years post-shock for those whose spouses experienced a health shock between the 2015 and 2018 interviews. These estimates are obtained from a traditional TWFE regression model with leads and lags. * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Table 9: Event Study Estimates of Changes in Labor Market Outcomes: TWFE Regression Model

	Reference Period Mean (1)	Full Sample (2)	Reference Period Mean (3)	Females (4)	Reference Period Mean (5)	Males (6)
A. Individuals' Labor Market Outcomes Following Their Health Shocks						
Employed	0.592	-0.037^{***}	0.535	-0.029^{*}	0.676	-0.047^{***}
		(0.012)		(0.016)		(0.018)
Weekly Working Hours	24.40	-2.24^{***}	21.03	-1.50^{*}	29.28	-3.22^{***}
		(0.70)		(0.87)		(1.17)
Annual Earned Income	6768	-375^{**}	5611	-90	8462	-846^{**}
		(186)		(212)		(355)
A. Individuals' Labor Market Outcomes Following a Spouse's Health Shock						
Employed	0.732	-0.009	0.632	0.011	0.812	-0.025
		(0.015)		(0.024)		(0.018)
Weekly Working Hours	30.19	0.26	24.21	1.11	35.03	-0.40
		(0.95)		(1.38)		(1.30)
Annual Earned Income	8355	156	6378	534^{**}	9925	-192
		(286)		(248)		(479)

This table presents the effects of health shocks on individuals' and their spouses' labor market outcomes. Panel A reports individuals' labor market outcomes following a health shock, while Panel B reports individuals' labor market outcomes following a spouse's health shock. Column (1) reports the mean values of the outcome variables from one survey wave prior to the health shock. Column (2) reports the estimated effects of a health shock during the survey wave in which the shock occurs for individuals who experienced a health shock and for individuals whose spouses experienced a health shock during the study period, respectively. Columns (3)–(6) report the estimates from the heterogeneity analysis by gender. Specifically, Column (4) focuses on females' labor market responses to their own and their spouses' health shocks, while Column (6) focuses on males' responses. These estimates are obtained from a traditional TWFE regression model with leads and lags. * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Table 10: Event Study Estimates of Changes in Household Consumption Per Capita Across Different Spending Categories: TWFE Regression Model

	Reference Period Mean (1)	Effect at Shock Wave (2)
Per Capita OOP Medical Expenditure	1691	1716^{***}
		(518)
Per Capita Food Expenditure	4547	-88
		(382)
Per Capita Non-Medical, Non-Food Expenditure	2385	-646
		(587)
Per Capita Total Expenditure	8623	975^{**}
		(492)

Column (1) reports the mean values of the outcome variables from one survey wave prior to the health shock for households with at least one shock during the study period. Column (2) reports the estimated effects of a health shock during the survey wave in which the shock occurs, specifically 0-2 years post-shock for households that reported a health shock before the 2015 interview, and 0-3 years post-shock for those reported experiencing a health shock between the 2015 and 2018 interviews. These estimates are obtained from a traditional TWFE regression model with leads and lags. * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

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