The Effects of Health Shocks on Time Spent in Home Production

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Abstract

In this paper, I examine the causal impact of health shocks on time spent in home production among retirees using the Health and Retirement Study data. On the one hand, an increase in home production can shelter consumption from falling net income due to medical costs increase (income effect). On the other hand, home production requires effort, which may be increasingly difficult after the health shock (impairing effect). To understand these two effects, I evaluate two groups of health shocks, those that result in high medical costs and those that result in activities of daily living limitations. I find strong evidence for impairing effect, i.e, home production decreases and the decline can be as high as 16% of average home production time. I also find that the decrease in home production is not fully offset by an increase in help received or in consumption spending. My findings suggest that when home production is taken into account, health shocks are more damaging than suggested by only monetary costs. Therefore, additional considerations should be given to policies that provide non-pecuniary support to unhealthy people, such as home-and-community-based services.

Keywords: Health shocks; home production; time use; aging

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1 Introduction

Home production—defined as unpaid labor such as meal preparation, house cleaning, laundry, shopping, and yard work—constitutes a substantial portion of daily activity. An average American spends around 12% of their waking hours on home production, with an even higher number for retirees, 17%.[1] If outsourced to market services, the cost of replacing these tasks would consume over a quarter of the median retirement income.[2] A key feature of home production is its dual role: it both contributes to effective consumption and requires effort. This duality implies that changes in health can affect home production through two channels. On the one hand, people can use home production to protect consumption against income changes; on the other hand, they are exposed to additional risk when their ability to exert effort declines. In this paper, I examine these effects by considering the consequences of health shocks on time spent in home production. The analysis focuses on retired individuals, a group particularly suited to this inquiry given their higher exposure to health shocks and greater reliance on home production, while avoiding confounding from labor supply responses.

Within this context, two effects triggered by health shocks warrant particular attention. Firstly, health shocks tend to increase out-of-pocket medical expenditures ([Dobkin et al., 2018]; [Poterba et al., 2017]; [Cheng et al., 2019]). Increased medical expenses impose tighter budget constraints on individuals, potentially causing them to redirect their consumption patterns from market-purchased goods to home-produced goods. While the latter option is more cost-effective, it requires a greater investment of time. I refer to this mechanism as the "income effect". Secondly, health shocks may increase the difficulty of performing physical activity, which can reduce the time spent on home production. I refer to this mechanism as the "impairing effect".

Understanding the importance of the income and impairing effects bears significant policy implications. A common approach to measuring the negative consequences of health shocks is to examine their monetary effects, specifically the decline in income and the increase in medical spending ([Dobkin et al., 2018]). However, considering home production can alter the conclusions based on monetary calculations alone. If the income effect is significant, home production partially insures against health risks, mitigating the losses measured in monetary terms. On the other hand, if the impairing effect is important, health shocks have more detrimental effects than indicated by monetary measures alone. In the latter case, further consideration should be given to policies that offer non-pecuniary support to individuals with poor health, such as home- and community-based care designed to replace home production.

To analyze the impact of health shocks on the time allocation of retired individuals aged 65-85 years, I utilize data from the longitudinal Health and Retirement Study (HRS), drawing from the time-use data in the supplemental Consumption and Activities Mail Survey (CAMS). The examination focuses on both objective and subjective indicators of health shocks. Objective

[1] Source: American Time Use Survey (ATUS) Data

[2] As of 2021, the Bureau of Economic Analysis estimated the wages of the housekeeping cleaners at $12.71 an hour. On average, retirees spend 2.7 hours per day in home production.

measures entail doctor-diagnosed conditions such as psychiatric problems, heart attacks, cancer, high blood pressure, and lung disease. Subjective measures encompass self-reported health status and a depression measure based on the Center for Epidemiological Studies Depression (CES-D) scale.

To gauge the significance of the income and impairing effects on the time spent in home production, a two-step strategy is employed. In the initial step, various health shocks are categorized into three groups. Group 1 comprises health shocks that incur high medical costs but entail less physical impairment compared to other health shocks, hence referred to as "costly shocks." Group 2 encompasses shocks that are not financially burdensome but result in substantial physical impairment, denoted as "impairing shocks." The costliness of the shocks is measured by the increase in out-of-pocket medical expenditures, while the extent of physical impairment is determined by the escalation in limitations in activities of daily living (ADL).[3] As certain health shocks cannot be exclusively classified into these categories, the effects of a third group of shocks are also examined, namely "mixed shocks," which exert similar impacts on both ADL and medical spending.[4]

In the second step, I exploit the within-person variation in health and implement the difference-in-differences (DiD) estimator proposed by [Callaway and Sant'Anna, 2021] to identify the causal response of time spent in home production to these health shocks. If there is an income effect in response to health deterioration, it is more likely to be observed in response to costly shocks, whereas the impairing effect is more likely to be observed after impairing shocks.

My analysis reveals several key findings. Firstly, the results robustly support the presence of the impairing effect, as impairing shocks significantly reduce the overall time dedicated to home production. The immediate impact can be as substantial as 16% relative to the average home production time following the shock. These effects primarily manifest in tasks related to housekeeping and meal preparation, with reductions of up to 22% and 12%, respectively. Furthermore, the effects of CES-D depression and self-reported health shocks persist over the long term, while the effects of psychiatric shocks intensify in subsequent periods but diminish over the long term.

I conduct several robustness checks. Firstly, I investigate whether the decline in home production is merely a consequence of deteriorating memory, considering the possibility of cognitive decline following a health shock. Secondly, I exclude individuals residing in nursing homes at the time of the interview or reporting an overnight nursing home stay to ascertain that the impact of a health shock on home production is not primarily driven by individuals who have spent time outside the home and in institutional care following a health shock. Thirdly, I address the concern that the observed impact may reflect the marginal effect of an additional shock, rather than the direct effect of a single shock. Lastly, I present the results using various alternative econometric specifications, including different control groups in conjunction with

[3]As will be discussed later, costly shocks include cancer, heart conditions, chronic lung conditions, and high blood pressure. Impairing shocks include psychiatric condition, depression measured by the CES-D scale, and self-reported health shock.

[4]Mixed shocks include stroke, diabetes, and arthritis.

the standard event study framework. Importantly, the finding that home production decreases following an impairing shock remains robust across all these tests.

Secondly, I do not find robust evidence supporting the presence of an income effect in response to costly shocks, namely cancer, heart conditions, hypertension, and lung conditions, as manifested by an increase in home production. There is a small and statistically insignificant 2% increase in home production time in the immediate period after a cancer diagnosis, equivalent to an additional 0.4 hours. The impact of a heart condition on home production is negligible, while both hypertension and lung conditions exhibit a negative impact. Furthermore, costly shocks do not lead to a sustained increase in home production over the long term. Therefore, my findings do not support the notion that home production serves as a significant mechanism for insuring individuals against the monetary costs of a health shock, nor do they indicate a significant impact of mixed shocks on home production.

As the final part of my analysis, I explore how individuals adapt to the decline in home production. I estimate whether there are changes in the utilization of formal and informal assistance and in consumption spending. The findings indicate variation in the type and extent of support received across different health shocks. Individuals experiencing impairing shocks exhibit a significantly higher likelihood of utilizing both formal and informal assistance, with the impact of impairing shocks on assistance utilization being twice as pronounced as that of costly shocks. The effects are particularly concentrated on assistance received for housekeeping and yard work. However, the increase in assistance does not appear to fully compensate for the decrease in home production time. This result is further supported by the absence of an increase in home production time in response to a spouse's health shock. Specifically, I find that husbands increase their time spent in home production when their wives experience a self-reported health shock but not when they face other types of shocks. Conversely, wives do not increase their home production time when their husbands face a health shock.

I do not find compelling evidence to suggest an increase in consumption spending following impairing shocks. When examining consumption spending categories associated with home production tasks, only self-reported health shocks induce increased spending on housekeeping and yard services. These findings have important policy implications for the structuring of support for home- and community-based services (HCBS). HCBS encompass services such as personal care, chore services, meal delivery, and home health care services provided by skilled professionals. While the expansion of the HCBS program under Medicaid is a priority in federal policy, as evident from President Biden's proposed Build Back Better bill, Medicare currently covers healthcare services provided by skilled professionals for a limited duration.

It is worth noting that there may be alternative channels, beyond the scope of this paper, through which health shocks can affect home production. One possibility is that such shocks could influence individuals' survival probabilities, consequently impacting their engagement in home production. Another mechanism is the potential interplay between health and the utility derived from goods produced within the household. These channels are briefly discussed in more detail in Section 7.

My paper contributes to three strands of literature. Firstly, it aligns with research examining the effects of health shocks on economic outcomes. Numerous studies have documented the impact of health shocks on labor market outcomes ([Blundell et al., 2020b]; [Jeon and Pohl, 2017]), spousal labor supply ([Anand et al., 2022]; [Lee, 2020]), labor earnings ([Prados et al., 2012]), consumption ([Blundell et al., 2020a]; [Dalton and LaFave, 2017]), out-of-pocket medical expenditure, and increased probability of bankruptcy ([Dobkin et al., 2018]). These studies consistently find that negative health shocks have significant and adverse effects on economic outcomes. For instance, [De Nardi et al., 2017] estimate that the lifetime cost of poor health, in terms of out-of-pocket medical spending and income losses, amounts to approximately $1,500 per year. My work contributes by providing evidence that health shocks also influence another important but understudied outcome: the time allocated to home production activities.

The second strand of literature to which my paper is related examines the role of home production in individuals' lives. Several studies have investigated how home production helps mitigate the economic implications of income fluctuations. [Aguiar and Hurst, 2005] show that a decline in food expenditure upon retirement is accompanied by an increase in time dedicated to shopping for and preparing meals, which helps maintain consumption levels. Home production not only alleviates the effects of anticipated income changes but also those arising from unexpected income shocks such as unemployment ([Burda and Hamermesh, 2010]; [Guler and Taskin, 2013]). Moreover, the literature has documented instances where home production may not fully offset the consequences of certain economic shocks. For instance, [Been et al., 2020] find that the shock to housing wealth following the Great Recession significantly reduced consumption expenditure, with home production tasks replacing only 11% of total consumption spending. In light of this literature, my paper contributes by examining the role of home production as a coping mechanism in mitigating the monetary implications of a health shock. The detailed health information in the HRS enables me to categorize various health shocks into groups to identify and test the income effect and the impairing effect.

The third strand of literature to which my paper is related examines the relationship between health and home production. The findings in this literature are inconclusive. Focusing on the association between health and time allocation, [Podor and Halliday, 2012] develop a model in which health influences decisions regarding time spent in market and non-market activities through its impact on productivity. Analyzing data from the American Time Use Survey, they find that individuals with better health allocate more time to both home production and market work, but at the expense of their leisure time. These findings contrast with those of [Gimenez-Nadal and Ortega-Lapiedra, 2013] and [Gimenez-Nadal and Molina, 2015], who observe a negative association. These studies utilize time use survey data from various European countries and report that improved health is associated with increased hours spent in market work, but decreased time devoted to home production tasks. [Gimenez-Nadal and Molina, 2015] argue that the positive association between health and home production time may be specific to the United States. However, this proposition may not hold, as a few other studies using European data yield mixed evidence: while extreme deterioration in self-perceived health leads to a decrease in home production time, mild deterioration leads to an increase ([Leopold and Schulz, 2020]; [Ozturk and Kose, 2019]). It is important to note that all of these papers focus on the working-age population. [Leopold and Schulz, 2020] utilize data from the German Socio-Economic Panel, specifically examining retired couples, and find mixed evidence: home production declines only in cases of serious deterioration in self-reported health.

The results of all the aforementioned studies are based on one variable, which is a self-reported measure of general health, as most of these studies employ cross-sectional time-use surveys.[5] However, these datasets have limited health data, primarily consisting of self-reported health variable, and only in certain waves. My work contributes to this literature in two ways. Firstly, while all the aforementioned studies are descriptive in nature, I utilize panel data and exploit within-individual and across-time variation to understand the causal impact of health shocks on home production. Secondly, I complement these studies by utilizing detailed information derived from the Health and Retirement Study (HRS) health data, which includes subjective and objective health measures, to construct potentially exogenous health shocks. My findings reveal important heterogeneity in the effects based on different health conditions.

The remainder of the paper is organized as follows. Section 2 describes the guiding economic framework. Section 3 describes the data, and presents descriptive statistics. Section 4 presents the empirical framework. Section 5 shows the estimation results, Section 6 shows the implications of the findings. The last section concludes the paper.

2 Conceptual Framework

In this section, I construct a simple static model to illustrate the two mechanisms I study: the impairing effect and the income effect of health shocks on the time spent in home production by retired individuals.

A retired consumer derives utility from two types of consumption goods: market good (c_m) and home-produced good (c_h). Market goods can be entirely purchased (e.g., processed food), whereas home-produced goods require time but are less costly than their market equivalent (e.g., home-cooked food). These two types of consumption goods can be partially substituted.[6] Individuals derive disutility ϕ from hours spent in home production (h).

The home-produced good is, in turn, a function of a market input, d, required for the home-produced good and the home production time, h. Apart from spending on consumption, people also incur out-of-pocket medical expenditure, X, that people spend out of their non-labor income I (e.g., retirement income). The disutility from home production time (ϕ) and out-of-pocket medical expenditure depends on the state of health, s, where $s \in \{healthy, unhealthy\}$. The unhealthy state implies both higher disutility, ϕ, and higher out-of-pocket medical costs, X. The individual maximization problem can be stated as follows:

[5] These provide minute-by-minute information on time use throughout the day.

[6] [Becker, 1965] predicts an elasticity of substitution between market spending and home production of -1, in other words, full substitution. However, papers such as [Been et al., 2020] argue for partial substitutability.

$$\max_{c_m,h,d} \; [u(C) - \phi_s v(h)] \tag{1}$$

where

$$C = f(c_m, c_h) \tag{2}$$

with

$$c_h = g(d, h) \tag{3}$$

such that,

$$c_m + d = I - X_s \tag{4}$$

Taking the derivative with respect to h yields the following first-order condition:

$$\underbrace{u'_C f'_{c_h} \frac{\partial c_h}{\partial h}}_{\text{marginal utility of home-production time}} = \underbrace{\phi_s v'_h}_{\text{marginal disutility of home production time}} \tag{5}$$

An adverse health shock increases the disutility associated with home production tasks, which can decrease the time spent in home production. Home production can be obtained by Equation 5, which shows that a higher disutility, ϕ, can decrease the time spent in home production, h. Another possible effect of health shocks on home production can be through medical expenses. An adverse health shock implies higher out-of-pocket medical costs (X), thereby decreasing the available resources in Equation (4). Tightening the budget constraint can induce a substitution from market goods, c_m, to home-produced goods, c_h, which can therefore increase the time spent in home production, h. Given this theoretical ambiguity, the impact of health shocks on home production is eventually an empirical question.

3 Data

The data used in this study are obtained from the Health and Retirement Study (HRS), which is a nationally representative longitudinal survey of the U.S. population aged 50 years and older, including their spouses. The HRS is conducted by the National Institute on Aging and the University of Michigan, involving interviews with approximately 20,000 individuals every two years. Supplementary studies are also conducted to collect additional information on specific topics. The time use and expenditure data utilized in this paper are collected through a supplementary study called the Consumption and Activities Mail Survey (CAMS). This study involves merging the data from the HRS core interviews with the data from the CAMS, which is administered to a subset of HRS respondents.

A. The Health and Retirement Study: The HRS captures various data, including labor force participation, income, household wealth, social well-being, health conditions, and health spending, including out-of-pocket (OoP) medical expenditure. The HRS provides detailed information on health conditions, including spending data for various medical cost categories such as hospitalization, nursing home care, clinic visits, dental care, outpatient surgery, prescription drugs, home health care, and community care. The recall period for the out-of-pocket medical expenditure is the last two years. Additionally, comprehensive data on functional limitations, such as difficulties in activities of daily living (ADL) and instrumental activities of daily living (IADL), are collected.[7] These functional limitations are used to measure impairment. The HRS also gathers extensive data on cognition and the utilization of formal and informal assistance.

B. The Consumption and Activities Mail Survey: The CAMS collects detailed measures of time use on more than 31 categories and household spending on around 38 items. The time use categories are not mutually exclusive and they do not exhaust all uses of time/hours of the day. The HRS and CAMS are conducted biennially, with the CAMS administered during the off-years of the HRS. Health-related questions in HRS cover the last two years, while time-use questions refer to the past week or month, and consumption-spending questions pertain to the last month or past year. The variables in the CAMS are merged with the preceding HRS wave, for example, CAMS 2001 is merged with HRS 2000. In 2019, approximately 4,666 individuals completed the CAMS. The item response rates for questions related to more than 30 time-use categories in the CAMS are exceptionally high. Figure A3 illustrates the distribution of missing item responses across waves, showing that collectively, 71% of respondents have no missing item responses, 17% have only one missing item, and merely 6% have two missing items. These calculations are detailed in the appendix. To further assess the data quality, I compare the summary statistics and the distribution of various time-use categories in the CAMS with data from the American Time Use Study (ATUS) in Appendix A.2. The ATUS, conducted by the Bureau of Labor Statistics (BLS), is the only survey that comprehensively collects time-use data and represents the U.S. population. Overall, the summary statistics and hour distributions are highly consistent between the CAMS and ATUS datasets.

3.1 Time Use

I specifically utilize time-use activities that are consistently available across all waves. For most categories, respondents were asked to report the number of hours spent on each task during the "last week". However, for less frequent categories, respondents were asked about hours spent in the "last month". To standardize the variables with monthly frequency, I convert them into weekly frequency by dividing the responses by 4.3, which corresponds to the average number of weeks in a month.

The CAMS survey inquires about time spent on various home production tasks. Following the definition of home production employed by [Been et al., 2020] and [Aguiar et al., 2013],[8] I consider time spent in home production as the cumulative duration of the following time-use activities:

[7]The ADL measures refer to whether the respondent experiences difficulty walking across a room, dressing, bathing, eating, and getting in and out of bed. Instrumental ADLs (IADLs) are difficulties using the phone, managing money, taking medications, shopping, and preparing meals.

[8][Been et al., 2020] also use the CAMS to define home production; however, they include the data on time spent on maintaining vehicles in home production, whereas I exclude these data, because they were not collected in the first wave of the CAMS.

- House cleaning
- Washing, ironing, or mending clothes
- Doing yard work or gardening
- Shopping or running errands
- Preparing meals and cleaning up afterward
- Taking care of finances or investments, such as banking, paying bills, balancing the checkbook, doing taxes
- Doing home improvements, including painting, redecorating, or making home repairs

Other tasks may also be considered home production, such as taking care of grandchildren. However, data on this time-use category were not collected in the first six waves of the CAMS. Therefore, I exclude taking care of grandchildren from the definition of home production.

On average, individuals allocate more than 20 hours per week to home production activities, which accounts for approximately 20% of their total non-sleeping hours. In Appendix A I provide additional details regarding the summary statistics and distribution of home production hours, various tasks within the home production domain, and total hours.

3.2 Health Indicators

The HRS gathers information on a set of medically diagnosed chronic health problems, including cancer, heart disease, stroke, diabetes, lung disease, hypertension, arthritis, and major psychiatric problems.[9] "Psychiatric condition" includes emotional or nervous problems. In Appendix D, I test whether the psychiatric condition is related to the death of a spouse, falling, or a wealth shock. In the HRS, respondents are asked whether they have been diagnosed with a given condition by a medical specialist since the last interview. In addition to these objective health measures, comprehensive data on self-reported health and self-reported mental health are also collected. The HRS collates data on several indicators to derive a mental health index using a score on the Center for Epidemiological Studies Depression (CES-D) scale, which ranges between 0 and 8 (CES-D depression hereafter). These indicators measure whether the respondent experienced the following sentiments all or most of the time: "depression", "everything is an effort", "sleep is restless", "felt alone", "felt sad", "could not get going", "felt happy", and "enjoyed life". Per HRS documentation, I consider a CES-D score above the cutoff of 3 as indicative of a positive depression screening. Additionally, a five-point scale is used to measure self-reported health: "excellent", "very good", "good", "fair", and "poor". I group the first three responses as good health and the latter two as bad health.

[9] "Cancer" includes a malignant tumor of any kind except skin cancer. "Chronic lung disease" excludes asthma. "Heart attack" includes coronary heart disease, angina, congestive heart failure, or other heart problems.

3.3 Sample Selection

My merged sample covers the years 2000 to 2019 and includes respondents from both the CAMS and HRS datasets. The focus of my analysis is on retired individuals aged 65 to 85 years. In order to obtain a sample of retirees, where the effects on time use resulting from changes in labor supply and earnings are not significant, I exclude individual-year observations of individuals with annual labor earnings exceeding $3,000, following the approach of [De Nardi et al., 2010].[10] Additionally, I restrict the sample to individuals who have been observed for at least two consecutive waves. These constraints reduce the sample size to 19,797 individual-year observations. All financial variables are adjusted for inflation using the Consumer Price Index (CPI) with 2015 as the base year.

To focus on health shocks, I further narrow down the sample by excluding individuals with preexisting conditions and only including those who receive a new diagnosis. For instance, to examine the impact of cancer, I exclude individuals who enter the sample already diagnosed with cancer. I then identify the survey wave in which each person first reports being diagnosed with a specific condition within the past two years. A person is considered to have experienced a medically diagnosed health shock if they report being diagnosed with a particular condition after not having been diagnosed with the same condition in the previous wave. Subjective health shocks are defined similarly. A person is considered to have experienced a depression shock if their CES-D score is greater than or equal to 3 in the current wave, but less than 3 in the previous wave. Likewise, a person is considered to have experienced a self-reported health shock if they report poor health in the current wave after reporting good health in the previous wave. After applying all the sample restrictions, the number of individual-year observations in the treatment groups ranges between 1,367 and 5,153, depending on the type of shock. The never-treated sample consists of 4,800 to 16,292 individual-year observations.

The average age of individuals in the sample is 74, with women constituting 60% of the sample. The median number of medically diagnosed conditions is 2, with no limitations in activities of daily living (ADL) or instrumental activities of daily living (IADL). Moreover, only 6% of the sample has missing values for at least one task related to home production. Notably, only 9% of the entire sample is covered by Medicaid, while 15% have long-term care insurance.

Tables 4 and 5 present the differences in characteristics between the treated and never-treated groups for the two subjective and eight objective health shocks. There is no discernible difference in age between the treated and never-treated samples. In comparison to the non-treated sample, individuals in the treated sample have a higher incidence of ADL and IADL limitations, and, with the exception of those with cancer or arthritis, they are also more likely to exhibit relatively poor cognition. Unsurprisingly, the treated samples show a greater likelihood of hospitalization, overnight stays in nursing homes, and higher out-of-pocket medical expenditures. The most striking difference between the treated and never-treated samples lies

[10] I include their individual-year observations once their labor earnings become either 0 or decrease to less than $3,000 per annum, and remain below this level for the remaining period of the sample.

in the utilization of assistance. While the treated and never-treated samples for cancer, heart disease, hypertension, and lung disease exhibit minimal disparities in the use of formal and informal assistance, as well as hours of assistance received, the utilization of assistance is significantly higher for the treated samples in the case of psychiatric shock, CES-D depression, and adverse health shocks as defined by self-reported health. Appendix A presents Table A2, which illustrates the correlation among various health conditions.

3.4 Descriptive Analysis

I begin by examining the associations between current health status and time allocated to home production in a cross-sectional analysis. Using ordinary least squares (OLS), I regress the weekly time spent on home production against health indicators such as specific medically diagnosed diseases, an indicator for depression based on the CES-D score, or an indicator of self-reported health. Each regression includes control variables for age, age polynomials, gender, marital status, household size, race, education, and year dummies. Standard errors are clustered at the individual level.

Figure 1 presents the results along with 95% confidence intervals. It illustrates that, on average, individuals with poorer health allocate less time to home production. However, the magnitude of this difference varies depending on the type of health condition and ranges from 0% to 24% of the average weekly home production time. The largest disparity, equivalent to 4 hours, is observed among individuals with and without stroke. Significant differences are observed for all other health conditions, except for cancer and arthritis, where the difference in home production time is not statistically significant. This observation suggests that individuals with good health and those with poor health engage in home production activities differently.

4 Empirical Methodology

I am interested in the causal effect of health shocks on home production time. I exploit variation in the timing of health shocks across individuals. In this case, the usual approach is to estimate two-way fixed effects (TWFE) event study using OLS regression.

$$y_{it} = \beta_i + \gamma_t + X_{it}\alpha + \sum_{r=S}^{-2} \mu_r dr_\tau + \sum_{r=0}^{F} \mu_r dr_\tau + \epsilon_{it} \tag{6}$$

where y_{it} is the time spent in home production for individual i who faces a health shock in year t; β_i and γ_t are the coefficients on individual fixed effects and calendar time fixed effects, respectively; X_{it} represents a vector of potential control variables; dummy variable dr_τ is equal to 1 if $\tau = r$, 0 otherwise; and μ_r are coefficients on these indicators of time periods relative to the onset of the shock. ϵ_{it} is the econometric error.

However, recent econometric research has raised concerns about the causal interpretation of the difference-in-differences estimator with time-varying treatment, particularly due to heterogeneity in treatment effects within units over time or between groups treated at different times

([Borusyak et al., 2021]; [de Chaisemartin and D'Haultfœuille, 2020]; [Goodman-Bacon, 2021]; [Sun and Abraham, 2021]). This heterogeneity leads to "forbidden comparisons" when earlier treated units become the control groups for later treated units, resulting in biased estimates.

The effect of a health shock on home production may vary among individuals who experience the shock in different waves. For example, individuals who encounter a health shock at a later period may be chronologically older. Consequently, if the effect of a health shock differs over time, the estimation of μ_r may be biased due to the aforementioned forbidden comparisons. For instance, individuals who have recently experienced a health shock may not significantly decrease home production (possibly due to a weak impairing channel), while the control group (previously treated) may experience a significant decrease. Thus, compared to individuals treated early, those who have recently faced a health shock may experience an increase in home production.

To address these concerns, I employ the difference-in-difference (DiD) estimator proposed by [Callaway and Sant'Anna, 2021], hereafter referred to as CS. This estimator gives zero weight to forbidden comparisons. I exploit the variation in the timing of health shocks to estimate group-time average treatment effects. Groups are based on the first time an individual faces a shock. My data covers 10 waves of the HRS and CAMS. Every wave except the first (whereby construction no individual is treated) includes individuals who receive their first shock in that wave. As mentioned in the previous section, I exclude individuals who enter the sample with pre-diagnosed health conditions. Therefore, the variation in treatment timing yields nine timing groups, denoted by g. I estimate the group-time average treatment effect for each group g in each time period t by comparing the individuals in g to those that were not yet treated in time period t (including never treated individuals). I then aggregate these group-time average treatment effects to estimate the impact of health shocks on home production. In Appendix B.4, I estimate CS using only those not yet (but eventually) treated as the control group and then using only those never treated as the control group.

For these average treatment effects to be causally identified, the parallel trends assumption must hold. Therefore, I must assume that in the absence of a health shock, the average potential outcomes for the treatment group g after year g would have evolved in parallel with those individuals who never experienced a particular health shock or encountered it later. Thus, ATT(g, t) can be identified by comparing the expected change in outcome for group g between periods $g-1$ and t to that for a control group at period t. Formally,

$$ATT(g,t) = E[Y_t - Y_{g-1}|G_g = 1] - E[Y_t - Y_{g-1}|C_t = 0] \tag{7}$$

where G_g is a dummy variable that equals 1 for units in treatment group g; C_t is a dummy that equals 0 for individuals either not yet treated or never treated at time t; Y_t is the average outcome variable at time t; and Y_{g-1} is the average outcome the year before the treatment.[11]

[11] In the first step, I denote by Y_t out-of-pocket medical costs and difficulties in daily living. I use the aggregated ATT to arrive at a relative ranking that categorizes the shocks into costly and impairing shocks. In the second step, to arrive at my main results, I consider Y_t as the weekly time spent in home production and its various tasks.

To examine how the effects of health shocks on home production evolve over time, I aggregate these $ATT(g,t)$ using an event study specification. For each relative event period e (year elapsed after the treatment), the effect of shock after e periods is given by

$$\theta_D(e) = \sum_{g=2}^{t} \mathbb{1}\{g + e \leq t\} ATT(g, g+e) P(G = g | g + e \leq t) \tag{8}$$

I present and plot the estimates of $\theta_D(e)$ for each outcome.[12] In Appendix B.4, I also explore two alternative approaches to estimate the impact of health shocks on home production time and compare them with the CS approach described above. The first approach is the standard TWFE specification. The second approach involves forming treatment groups based on the age at which individuals are treated, as opposed to the first wave.[13] These estimators yield qualitatively similar results.

In order to interpret $\theta_D(e)$ in the post-treatment period as the causal impact of health shocks on home production, we require exogeneity of health shocks. In other words, there are no time-varying unobservables that affect treatment (the health shock) and home production. As a first step, I use the onset of new health events. These health conditions are diagnosed by a doctor or a medical professional. Although individuals may anticipate these health events (e.g., due to family past history), the timing of the shock is unanticipated. I restrict my sample to people with a new diagnosis of a given health shock. As mentioned previously, I exclude people with preexisting conditions. Furthermore, in the robustness checks below, I test if the impact on home production of a given health shock is a marginal impact of an additional shock. Additionally, I demonstrate that the evolution of difficulties in daily living (which can be thought of as a measure of general health) exhibits no discernible patterns of deterioration preceding a given health shock. Finally, I use the procedure described by [Rambachan and Roth, 2023] to test the sensitivity of my estimates to potential violations of the parallel trends assumption (for a detailed discussion, see the results section).

Reverse causality presents an additional challenge. It is conceivable that not engaging in home production activities, such as cooking meals or failing to maintain a clean household, could contribute to health deterioration. Conversely, excessive engagement in home production activities might result in a health shock, given the possibility of overexertion. If reverse causality exists, it may be reasonable to assume that it was initiated in the short-term (immediate two years) preceding the disease diagnosis, because the disease was not detected in the previous survey conducted two years ago. However, despite utilizing the health diagnosis information in this study, it is not feasible to completely eliminate the potential for reverse causality.

[12]Based on the total relative time periods, the event study graphs have nine post-treatment periods; however, I show event study estimates for only four post-treatment periods because there are noisy estimates in the later periods. One period is equivalent to two years, given the structure of the HRS and CAMS. The highest mass is observed at the relative time period 0, which is the first period observed after the shock.

[13]In Appendix B.4, I also explain why this is not my preferred specification.

4.1 Categorization of Health Shocks

I employ the method proposed by [Callaway and Sant'Anna, 2021] to estimate changes in out-of-pocket medical spending and difficulties in daily living following a health shock. Table 2 shows the increase in medical cost and daily living limitations in the first period following a given health shock and their relative rankings in terms of severity. Based on these rankings, I classify the shocks into three groups: costly, impairing, and mixed shocks.

Among the health shocks examined, cancer, heart conditions, hypertension, and lung conditions are categorized as costly shocks. Columns 1 and 2 illustrate that cancer leads to a substantial and statistically significant increase in medical expenses, followed by heart problems, stroke, hypertension, and lung conditions, respectively. The observed increase in medical costs during the first period after these shocks ranges from \$629 (lung condition) to \$1038 (cancer). There is a visible break in the magnitude of the increase for other shocks.[14]

Columns 3-6 reveal that among the costly shocks, hypertension has the least impact on activities of daily living (ADL) and instrumental activities of daily living (IADL). Cancer, heart conditions, and lung conditions also rank among the three least impairing shocks in terms of daily living difficulties. Stroke induces the highest increase in daily living limitations despite being highly costly, therefore, I exclude it from the group of costly shocks and include it in the category of mixed shocks.

The second group, impairing shocks, encompasses shocks characterized by a relatively lower increase in out-of-pocket medical expenses but a higher increase in daily living difficulties. Table 2 demonstrates that psychiatric conditions, CES-D depression, and self-reported health shocks result in significant increases in ADL limitations. These shocks are found to be the least costly among those considered in this study. Psychiatric shocks are associated with a substantial increase of 0.27 ADL and 0.3 IADL during the initial period following the shock. Similarly, CES-D depression and self-reported health shocks exhibit comparable effects on daily limitations.

The data-driven classification of health shocks into two distinct groups based on their impact is quite pronounced. Among the impairing shocks, the smallest increase in activities of daily living (ADL) and instrumental activities of daily living (IADL) is twice as high as the largest increase observed in the costly shocks. Similarly, the lowest increase in out-of-pocket (OoP) medical costs among the costly shocks is more than double the magnitude of the highest increase among impairing shocks. It is worth noting that the ranking of shocks with higher monetary costs remains consistent when alternative measures of medical cost increase are considered, as presented in Table A4 in Appendix B.1. Moreover, I compare the raw distribution of the change in OoP medical costs for treated and never treated individuals. Costly shocks exhibit a noticeable shift towards higher costs for the treated group, whereas impairing shocks show a similar distribution for both treated and never treated groups, as depicted in Figure A5. As stroke, diabetes, and arthritis do not meet the established criteria, they are excluded from

[14]Papers studying the out-of-pocket medical costs of health shocks, such as [Fong, 2019], [Cheng et al., 2019], also find cancer, hypertension, and heart diseases to be costly shocks.

these groups. Stroke leads to higher medical expenses and greater difficulties in daily living, while diabetes and arthritis are neither costly nor highly impairing. These three conditions are categorized as mixed shocks, and their effects on home production are discussed in the subsequent section.

It is important to acknowledge that despite a significant increase in ADLs following impairing shocks, these shocks do not result in substantial out-of-pocket medical expenses compared to costly shocks. Higher levels of ADLs and IADLs may be associated with an increased likelihood of entering nursing homes, which can be financially burdensome. The proportion of individuals reporting overnight nursing home stays upon diagnosis of a health shock ranges from 6.5% to 7.5% for impairing shocks. Although these figures are comparable to costly shocks, they are significantly lower than the prevalence of nursing home entry following a stroke (15%). Therefore, the probability of entering a nursing home is similar for both impairing and costly shocks. Importantly, the rise in out-of-pocket medical expenses is not significantly driven by nursing home expenditure for costly shocks and impairing shocks. It is mainly driven by hospital visits, medication costs, and doctor consultations. This finding is also supported by the fact that Medicare covers the initial 100 days of skilled nursing facility (SNF) stays, and conditional on having a nursing home stay, approximately 81% of the sample spent fewer than 100 nights in SNFs during the same period as the health shock.

Furthermore, the association between nursing home utilization and increase in ADLs is approximately twice as strong as the association between impairing shocks and ADLs. This indicates that the increase in ADLs after impairing shocks may not be as severe as for individuals who require nursing home care, thereby explaining the relatively low incidence of nursing home entry following impairing shocks. Finally, I also investigate if respondents who experience impairing shocks subsequently attrite from the sample. However, only around 6% of respondents cease participation due to death or other reasons following a psychiatric shock, 8% for self-reported health shocks, and 7% for CES-D depression shocks. In the case of costly shocks, these figures surpass 8%, with the exception of hypertension, where the corresponding proportion is around 5

5 Results

I analyze the effects of three types of health shocks on home production: costly shocks, impairing shocks, and mixed shocks.[15] The estimation results are presented in Table 3, where each shock's coefficients represent the impact in the first period following the shock. It is important to note that the time-use variables in CAMS are merged with the health variables from the preceding HRS wave. Therefore, these coefficients reflect the influence of a health shock on home production at least one year after the shock occurrence.

[15] Additional channels through which health shocks can influence home production are discussed in Section 7.

5.1 Effects of Costly Shocks

Panel A in Table 3 examines the impact of costly shocks on total home production and its various tasks. Column 1 reveals that there is no significant increase in total home production, except for cancer shock. Cancer leads to a small increase of 0.4 hours (p-value = 0.604) in home production time during the first period following diagnosis, representing a 2% increase relative to the average home production time. However, this increase is statistically insignificant. The influence of a heart condition on home production is negligible. While costly shocks are more likely to affect home production through the income effect by encouraging a shift towards the consumption of more home-produced goods, I find the opposite effect for high blood pressure and lung condition shocks. This may point out a potential limitation of my study that arises from the use of ADLs and IADLs as measures of disutility. It is plausible that ADLs and IADLs do not comprehensively capture the full extent of disability. For instance, although lung conditions may not be strongly associated with high ADLs and IADLs, individuals with such conditions may encounter difficulties in performing specific household tasks, such as cleaning, due to the potential use of aerosols that could exacerbate breathing difficulties, thereby decreasing overall home production.

Columns 2-7 provide more detailed information on the various tasks of home production. Apart from a significant increase of 0.41 hours in yard work and gardening following a cancer shock (a 20% increase relative to the average time spent on gardening and yard work), there are no significant increases in hours allocated to these tasks.

To gain a deeper understanding of the long-term impact of health shocks on home production, Figure 2 presents the event study plots. The decrease in home production after a lung condition or high blood pressure diagnosis, discussed previously, is only temporary. Overall, there is no evidence of an increase in home production in either the short run or the long run for the costly shocks.

Furthermore, the decline in the ability to carry out home production can offset the income effect, even for costly shocks. To control for the non-monetary cost of these health shocks, I exclude individuals who report any ADL or IADL limitations in the entire sample. The results, presented in Table A5 in Appendix B.1, indicate that the impact of cancer and heart condition on home production is positive. However, despite the increase in magnitude compared to the baseline results, these effects are not statistically significant. The impacts of high blood pressure and lung condition are similar to the baseline findings.

5.2 Effects of Impairing Shocks

I next examine the effects of impairing shocks on home production. Column 1, Panel B, in Table 3 demonstrates that all shocks classified as impairing shocks lead to a significant decrease in home production time immediately following the shock. The most pronounced impact is observed for psychiatric shocks. The diagnosis of a psychiatric condition reduces weekly home production time by 3.2 hours (p-value = 0.007), representing a 16% decline relative to the average time spent on home production.

The other two impairing shocks also result in substantial decreases in home production. The onset of depression, as measured by the CES-D score, reduces average home production time by 1.12 hours in the initial period (p-value = 0.048). Similarly, self-reported health shocks decrease the average time spent on home production by 1 hour (p-value = 0.062).

The decline in total home production is primarily driven by the major components of home production, namely, meal preparation and housekeeping tasks. A psychiatric shock decreases the time spent on these tasks by 0.7 hours (p-value = 0.074) and 1.4 hours (p-value = 0.002), respectively. In relation to the baseline means, these estimates indicate a decline of 12% and 22% in the time spent on meal preparation and housekeeping, respectively. Likewise, CES-D depression and self-reported health shocks significantly reduce meal preparation time by approximately 0.5 hours each, followed by a decrease in time spent on housekeeping and gardening tasks.

The event study graphs in Figure 3 illustrate that the impact of a health shock on home production continues over an extended period. The impact of a psychiatric shock persists for two subsequent periods before diminishing to a smaller, statistically insignificant estimate. The effects of CES-D depression and self-reported health shocks persist for a more extended duration. Similarly, the event study graphs for meal preparation and housekeeping tasks in Figure 4 indicate that the impact of a health shock on home production is not limited to the immediate period following the shock. In Appendix E, I examine the heterogeneity of these effects by gender and marital status at the time of the shock (results are presented in Tables A11–A13).

5.3 Effects of Mixed Shocks

Lastly, I present the findings regarding the impact of mixed shocks. Panel C in Table 3 presents the short-term results for stroke, diabetes, and arthritis. Column 1 indicates that total home production decreases for all these shocks, but none of the effects are statistically significant. Columns 2-7 provide detailed results for individual tasks of home production and reveal two key points. Firstly, the direction of the impact varies for all these shocks. For instance, while meal preparation time increases following a diagnosis of diabetes and arthritis, it decreases after a stroke, and the response of housekeeping time is the opposite. Secondly, the effects are not statistically significant, except for stroke, which decreases meal preparation time by 0.7 hours, representing an 11% decline relative to the average meal preparation time.

In Appendix B.3, Figure A9 displays the event study plots for the mixed shocks. Total home production exhibits a downward trend in the long run after a stroke and arthritis diagnosis; however, these impacts are not statistically significant. Furthermore, although home production demonstrates a declining trend prior to the onset of diabetes, it does not have a significant impact on home production after the shock. Among other unexplored factors, the absence of any significant impact on home production for mixed shocks could be attributed to the income effect and impairing effect canceling each other out.

5.4 Identifying Assumptions and Robustness Check for Impairing Effect

To interpret the coefficients from the event study as the causal effect of an impairing shock, it is necessary to assume that, in the absence of a health shock, the average home production would have followed a parallel trajectory for both the treated and never treated groups. This assumption supports that there should be no declining trends in home production time leading up to the shock. While Figure 3 visually suggests this is the case for all impairing shocks, I conduct additional tests to assess the sensitivity of my estimates to potential violations of the parallel trends assumption. Following the approach outlined by [Rambachan and Roth, 2023], I compare the 95% confidence intervals obtained from my primary model against those obtained after allowing for deviations from a linear trend of up to an arbitrary amount, M. The results for the first-period estimates after the shock are presented in Figure A8 in Appendix B.2. It demonstrates that, even when accounting for non-linear trends within a flexible range, the null hypothesis that there is no effect of a specific health shock on home production can be rejected. Notably, this holds particularly true for psychiatric shocks and CES-D depression. In the remainder of this section, I present robustness checks of the main results for impairing shocks using alternative specifications. Overall, the main findings demonstrate robustness.

Nursing Home Use

To investigate whether the impact of a health shock on home production is primarily driven by individuals with severe impairments, I implement two specifications that exclude individuals who (1) reside in a nursing home at the time of the interview and (2) report an overnight nursing home stay since the previous wave if they did not report any overnight nursing home stay in the previous wave. In Appendix B.2, Table A6, column 1, I present the results indicating that average home production still decreases in the first period after the shock, even after excluding individuals residing in a nursing home at the time of the interview. The magnitude of the decline is comparable to the baseline results for all impairing shocks examined. It is worth noting that individuals residing in nursing homes inherently engage in less home production compared to those living at home, often requiring information from proxy respondents. Therefore, the observed decrease in home production, even after excluding nursing home residents, provides additional evidence that the decline in the baseline specification is not a mechanical result due to not residing in one's home. Moreover, when excluding individuals whose nursing home stay coincides with the timing of the health shock, the baseline results not only remain robust but also increase in magnitude (column 2 in Table A6). This finding suggests that the baseline results are not solely driven by individuals with severe impairments.

Decline in Cognition

In this section, I test whether the drop in home production is a mechanical function of deteriorating memory coinciding with a health shock. It is documented that two out of the three impairing shocks considered in this study, namely, diagnosis of a psychiatric condition and CES-D depression, are commonly associated with cognitive impairment ([Lee et al., 2012]; [for Disease Control et al., 2021]). Such impairment may lead to short-term forgetfulness and affect the recall of time-use responses. Based on the summary statistics, people diagnosed with a psychiatric condition and CES-D depression are more likely to have poor self-reported memory (by 15 and 22 percentage points, respectively). Given the possibility of a decline in cognition, I estimate the DiD model after a series of exclusions. I do so by excluding the people whose memory state worsens between the period before and after the shock. I employ two measures to capture the decline in cognition – Langa-Weir classification and self-reported memory.

The Langa-Weir classification of cognition function ([Langa et al., 2020]) is a researcher-contributed data set that provides a summary score for cognition using measures[16] from the core HRS interview.[17] This score is used to classify respondents into three Langa-Weir categories: Normal, Cognitively Impaired but not Demented (CIND), and Demented.

The second measure I use to capture the decline in cognition is self-reported memory. Respondents are asked to rate their memory at the time of the interview. I categorize "excellent", "very good", and "good" responses as good memory, and "fair" and "poor" as bad or impaired memory. In Table A7, I exclude the people whose memory state worsens after the shock. For example, people who move from Langa-Weir category Normal to CIND or from CIND to Demented are excluded from column 1.

Results in Table A7, Appendix B.2, suggest that the baseline impact of impairing health shocks is not predominantly driven by poor recall or forgetfulness of the respondents who suffered a health shock. Column 1, which displays the results with Langa-Weir restrictions, indicates that the effects of psychiatric conditions and CES-D depression on home production exhibit a moderate reduction in magnitude and decreased statistical significance compared to the baseline findings. However, the impact of self-reported health shocks remains largely unchanged. Column 2 shows the impact of a health shock on home production of the people with self-reported memory restriction is roughly similar to the baseline results, with a significant decline in home production of more than 3 hours and 1 hour (significant at the 10% level) after a psychiatric shock and CES-D depression, respectively. The impact of self-reported health shocks decreases relative to the baseline results.

Marginal Effect of an Additional Shock

The impact of a health shock on home production in the baseline results could reflect not only the direct effect of one shock but also the marginal effect of an additional shock. I address and inspect this concern in three ways. First, I condition the baseline specification on the pres-

[16] These measures include information on memory assessments, an assessment of limitations in five IADLs, and the respondent's assessment of difficulty completing the interview because of cognitive impairment.

[17] It can be downloaded from the HRS website: https://hrsdata.isr.umich.edu/data-products/langa-weir-classification-cognitive-function

ence of a given number of total medically diagnosed conditions. For example, from the summary statistics, it is known that people with and without a psychiatric condition have, on average, two other medically diagnosed conditions. Therefore, in one specification, I exclude people who report being diagnosed with more than two medically diagnosed conditions (other than the shock itself) in the observed sample period. Second, since the [Callaway and Sant'Anna, 2021] specification allows for the parallel trends assumption to hold after controlling for covariates, I control for the total number of medically diagnosed conditions (other than the shock itself). Third, I examine the evolution of the number of ADL and the number of medically diagnosed conditions other than the shock itself both before and after the shock. Significant pre-trends in any of these variables would indicate gradual health degradation even prior to the shock in question. However, an absence of significant pre-trends would be reassuring that the shock in question is indeed a shock and the baseline results are not picking up the marginal effect of an additional shock.

As seen in Table A8, Appendix B.2, controlling for the number of other medically diagnosed conditions in column 1 does not change the baseline results remarkably in the short and long run. Columns 2 and 3 exclude people with more than two and one other medically diagnosed conditions, respectively. The first-period impacts of psychiatric condition and self-reported health shock on home production are in line with the baseline results.

Figure A7 charts the evolution of ADL and the number of other medically diagnosed conditions before and after the shock. A discernible jump in ADL can be observed before and after an impairing shock. Moreover, no noticeable pre-trends seem to exist in the number of medically diagnosed diseases.

I further test the sensitivity of the baseline results using several other econometric specifications. In the main specification, I include the not-yet and never treated individuals as control groups. In Appendix B.4, I consider two additional specifications with control groups as strictly not-yet treated and strictly never treated, respectively. I also control for several important covariates in the main specifications: age, age polynomial, gender, race, marital status, years of education, and the number of members in the household. I also show results from a standard event study specification.

Attrition poses another threat to the identifying assumption if it is correlated with the post-treatment outcome. In another specification, I restrict the sample to those who do not attrite the sample. Attrition or no response could be due to leaving the sample or death. Finally, in the main specification, the treatment cohorts are based on the first calendar "year" of treatment. However, treatment cohorts can also be created based on the age at which treatment is faced for the first time. Therefore, I further test the robustness of the baseline results using age-based treatment cohort groups as well.[18] The impact of a psychiatric shock on time spent in home production is very robust to all these specifications. For all of them, the impact is around 3 hours weekly and is statistically significant at the 5% level. Similarly, the impact of CES-D depression and that of self-reported health shock on time spent in home production are robust

[18]More details on how the age-based treatment cohorts are created can be found in Appendix B.4.

for most of the aforementioned specifications, and the magnitudes are similar to those in the main specification.

6 Possible Adjustments to Decrease in Home Production

My findings in the previous section highlight that while costly shocks and mixed shocks do not have significant effects, home production decreases when individuals face impairing shocks. In this section, I examine whether there is evidence that people with impairing health shocks make alternative adjustments to offset the decrease in home production. Specifically, I consider two alternatives – whether individuals seek inter- and intrahousehold help or buy home production equivalent services from the market.

6.1 Use of Help

In this section, I begin by investigating whether individuals experiencing health shocks are more likely to seek assistance, both formal and informal, for their home production-related tasks. HRS provides data on the utilization of assistance received by respondents and the helpers who aid them with ADL and IADL. This information includes details about the relationship between the respondents and the helpers, the total hours of assistance received, and the specific difficulties for which help was required. Using this information, I categorize the nature of assistance into formal and informal. Formal assistance encompasses aid provided by organizations, institutional employees, paid helpers, or professionals within the past month. On the other hand, informal assistance refers to help provided by spouses, children, grandchildren, or other relatives within the past month. The measures of formal and informal help are not mutually exclusive, as individuals may receive assistance from various types of helpers simultaneously.

Table A9, Column 1 presents the findings regarding the likelihood of receiving formal help in the short run, specifically in the first period following a health shock. The results indicate that individuals with a psychiatric condition, CES-D depression, and self-reported health shock exhibit an increase of 6, 4, and 2.3 percentage points, respectively, in the likelihood of receiving formal help. Similarly, Column 2 demonstrates that the likelihood of receiving informal help follows a similar trend. The likelihood of receiving informal assistance increases by 10, 6, and 7 percentage points for individuals with a psychiatric condition, CES-D depression, and self-reported health shock, respectively. When examining specific home production-related tasks, the most significant increase in reliance on help is observed in tasks related to housework and yard work for all impairing shocks (Columns 3-7). Furthermore, the increase in the likelihood of seeking assistance persists over a longer duration. In particular, the increase is more sustained for individuals with CES-D depression and self-reported health shock compared to those with a psychiatric shock.

To provide a comparative analysis, I also examine the impact of costly shocks, namely cancer, heart condition, high blood pressure, and lung condition, on the likelihood of seeking assistance. However, the effects of these costly shocks on both formal and informal help received are considerably smaller compared to impairing shocks. In Table A9, the impact of most costly shocks is not statistically significant, indicating a minimal influence on the likelihood of utilizing help. Similarly, in the long run, the effects of costly shocks on formal and informal assistance are negligible in magnitude and lack statistical significance.

Next, I explore whether the assistance received compensates for the loss of home production time. Column 8 in Table A9 reveals a significant increase in the number of weekly hours of help received. This increase is comparable to the decline in total hours of home production following CES-D depression and self-reported health shocks. Specifically, following a psychiatric shock, the hours of help received increased by 1.7 hours, which corresponds to half of the decrease in home production. This finding suggests that the reduction in home production may be partially offset by the increased amount of assistance. However, it is important to note that the survey only captures information on the hours of help received from respondents who report functional limitations. Therefore, the hours of help may not exclusively pertain to home production tasks.[19]

The preceding findings primarily focus on the extensive margin of help received. To delve into the intensive margin of assistance, I conduct further analysis on the nature of informal help received. Specifically, I examine the impact of a spouse's health shock on the individual's own time devoted to home production. Table A14 demonstrates that husbands significantly increase their total home production time by 2.3 hours when their wives experience a self-reported health shock. This increase is primarily attributed to the additional time allocated to meal preparation and housekeeping tasks, each contributing approximately 1 hour. The event study graph depicting husbands' total home production following their wives' self-reported health shock reveals a significant positive shift in coefficients after the occurrence of the shock. However, no significant changes are observed in husbands' home production time when their wives encounter a psychiatric or CES-D depression shock. Likewise, there is no significant alteration in wives' home production time when their husbands face any impairing shocks (refer to Table A15). This discrepancy may be attributed to the relatively greater margin available to husbands to adjust the time spent in home production, as compared to wives, who, on average, work 40% more in home production tasks. Consistent with this gendered response in home production due to a spouse's illness, [Dalton and LaFave, 2017] find in a relatively younger sample (with a mean age of 47 years) that husbands increase their home production by approximately 1.9 hours per week in response to severe limitations in their wives' daily activities. Overall, these findings indicate an increase in the utilization of help on the extensive margin. However, due to the limitations in the data regarding the utilization of help, it remains uncertain whether this increase adequately compensates for the decrease in home production.

[19] It is worth mentioning that in the HRS, the hours of help received cannot be directly linked to total home production or its specific tasks. Additionally, the available data do not allow for a distinction between formal and informal types of assistance.

6.2 Consumption Spending

I examine whether individuals react to a decline in home production by increasing their consumption spending. Respondents were surveyed regarding their expenditure across 39 spending categories in the CAMS waves, with consumption spending data collected at the household level. I investigate the impact on both total non-medical consumption spending and spending within categories corresponding to various home production tasks. The CAMS dataset facilitates the mapping of home production categories to these spending categories. The following presents the mapping between market spending (on the left) and home production time categories (on the right):

- Housekeeping services $\Longleftrightarrow$ House cleaning; washing, ironing, or mending clothes
- Gardening services $\Longleftrightarrow$ Yard work or gardening
- Home repair services $\Longleftrightarrow$ Doing home improvements, including painting, redecorating, or making home repairs
- Dining out $\Longleftrightarrow$ Preparing meals and cleaning up afterward

I combine expenditure on housekeeping services and gardening services since, in the first wave (2001), respondents were collectively asked about spending on these two categories. All spending figures have been transformed into a log of monthly figures.[20]

Table A10 displays the impact of impairing shocks on consumption spending during the first two periods following the shock.[21]Notably, spending on purchasing house and yard services appears to be the most responsive spending category to health shocks, with no substantial increases observed in expenditure on other services or total non-medical spending. Furthermore, although expenditure on housekeeping and yard services decreases by approximately 30 percent following a psychiatric shock, it significantly increases by around 20 percent following CES-D depression and self-reported health shocks. However, the event study graphs indicate a rising trend prior to CES-D depression and self-reported health shocks, which could potentially violate the identifying assumption of no pre-trends. Hence, caution must be exercised when interpreting these results as a causal effect of health shocks and evidence supporting a reverse substitution away from home production and towards market spending. The lack of robust evidence for reverse substitution may be attributed to a decline in the utility derived from consumption

[20]It is worth noting that although the CAMS aims to align time-use and spending categories, the mapping may have overlooked certain relevant categories of home production or spending. For instance, while time spent managing money is a time-use category, its corresponding spending category is not captured in the CAMS. Similarly, money spent on purchasing meal preparation services may be more appropriately mapped to time spent cooking meals and cleaning afterward rather than dining out. Dining out may increase not only as a substitution away from home production but also decrease as a consequence of poor health, given that food consumed outside the home tends to be higher in fat, cholesterol, and calories soni2022effects. Consequently, it is plausible that the estimated effect on consumption spending substitution represents a lower bound.

[21]While time-use data is collected for the previous week, spending data have a different look-back period, with most categories allowing respondents to report consumption expenditure over the last year. As a result, there may only be partial overlap when the health shock occurs within the same 12-month window as the reference period for consumption spending.

itself after a health shock, as discussed in [Blundell et al., 2020a] and related literature. A decrease in utility stemming from consumption might diminish the need to compensate for the decrease in home production through increased market spending.

7 Conclusion and Discussion

Individuals have the ability to substitute their consumption spending with home production as a means to safeguard their overall consumption levels when faced with a decline in monetary resources. Previous research has established an increase in home production in response to income changes such as retirement or unemployment. However, engaging in home production requires physical effort. Therefore, if individuals experience a negative shock to their ability to exert effort, home production can become an additional burden. Given that health shocks can simultaneously impact both monetary resources and the ability to exert effort, this study examines the effects of health shocks on the time allocated to home production. Two channels are studied: the income effect, which is likely to increase in home production, and the impairing effect, which can diminish home production.

The analysis reveals a significant decline in home production following impairing health shocks. This decline is primarily driven by essential tasks related to well-being, such as meal preparation and housekeeping. Furthermore, the decrease in home production is not temporary. While the effect diminishes after a few periods for psychiatric shocks, it persists in the long run for shocks related to depression measured through the CES-D score and self-reported health shocks. To ensure the robustness of the results and gain insights into the nature of the shocks, several sensitivity tests are conducted. These tests involve considering various alternative econometric specifications and exploring the role of cognitive decline in driving the results. Moreover, I do not find strong evidence in favor of the income effect. Specifically, home production does not increase in response to health shocks associated with a substantial rise in out-of-pocket medical costs (costly shocks). Additionally, no evidence is found for any impact of mixed shocks on home production. Collectively, these findings highlight that home production does not serve as a mitigating mechanism in the face of health shocks.

I further investigate potential strategies individuals employ to compensate for the decline in home production, namely the utilization of inter- and intra-household help and an increase in consumption spending. Examining the extensive margin, I find a substantial increase in the likelihood of individuals receiving both formal and informal help in response to impairing health shocks. Specifically, there is a notable increase in assistance with housekeeping and yard work tasks. However, it remains challenging to determine whether the additional hours of help received effectively offset the loss of home production. Furthermore, my findings indicate weak evidence of spouses increasing their own time spent on home production when their partners experience health shocks. While husbands tend to devote more time to home production when their wives face self-reported health shocks, this pattern does not hold for other types of shocks, nor does it apply to wives when their husbands face any health shocks. Additionally, there is limited evidence supporting a substitution toward increased consumption spending. Apart from a rise in the purchase of housekeeping and yard services following CES-D depression and self-reported health shocks, spending on other consumption categories related to time-use does not increase despite the decrease in home production.

It is worth noting that there may be alternative channels, beyond the scope of this paper, through which health shocks can affect home production. One possibility is that such shocks could influence individuals' survival probabilities, consequently impacting their engagement in home production. For instance, a decline in survival probability due to a health shock might reduce home production for two reasons. Firstly, individuals may choose to allocate more time to leisure activities, hobbies, and spending time with family members, thereby reducing the time devoted to home production. Secondly, the expected decrease in life expectancy could result in a positive wealth effect, effectively increasing per-period wealth for the remaining lifespan. This effect may weaken the income channel discussed in this paper by mitigating the extent of budgetary constraints and thereby reducing the need to allocate additional time to home production as a substitute for consumption spending. To explore this further, I analyze data on self-reported probabilities of living beyond age 80. The findings reveal a significant decline in the expected survival probability following a heart attack (by 6%), CES-D depression (9%), and self-reported health issues (6.7%). Hence, the impairing effect estimated in this paper might partially capture the consequences of reduced survival probabilities. However, the change in expected survival probability following psychiatric shocks, which is the primary driver of the impairing effect, is positive but not statistically significant at the 5% level.

Another potential mechanism through which health can impact home production is the potential interplay between health and the utility derived from goods produced within the household. Health shocks have the capacity to alter individuals' preferences in this context. On one hand, home production can play a role in maintaining health by facilitating healthy eating habits, which may necessitate increased time spent on meal preparation. On the other hand, a health shock could diminish the marginal utility derived from home-produced goods and overall consumption. While previous research by [Blundell et al., 2020a] has examined changes in utility for luxury and leisure goods following a health shock, the evidence regarding the impact of adverse health on the utility of necessities, particularly food consumption, remains inconclusive.

There are certain limitations within the data that may impede the detection of the impact of health shocks on home production. One such limitation is the time lag between health and time-use data. As previously mentioned, the time-use data in the CAMS are merged with health data from the preceding wave of the HRS, resulting in a potential time lag of up to three years between the shock and the measurement of home production time. This time lag restricts the ability to capture short-term changes in home production in response to a health shock, particularly for costly shocks that do not lead to significant limitations in activities of daily living (ADL). The impact of such shocks on home production may be transient and thus not fully captured by the estimates presented. Overall, this time lag means that the results may underestimate the actual impact of health shocks on home production.

Another limitation is that even though the number of time-use activities reported in the CAMS may be sufficient enough to provide a picture of overall time use in a typical week, data on certain categories where individuals with bad health may allocate time differently are not collected. For example, information on time spent resting, which may differ from time spent sleeping, is not included. Finally, the measure of ADL and IADL used to capture the disutility induced by health shocks may not fully capture the associated costs. For instance, even though a lung condition may not result in a significant increase in ADL and IADL, the use of aerosols during house cleaning may hinder individuals with such conditions from engaging in certain home production tasks.

The US population is aging, and as people age, they are more likely to experience adverse health shocks. The aging population strongly prefers to age at home. According to the American Association of Retired Persons, 77% of individuals aged 50 and above want to remain in their homes in the long run ([Davis, 2021]). However, aging in one's home requires understanding how health shocks affect the time spent producing goods at home. My results show how different types of health shocks impact people's time spent in home production differentially and whether reliance on help with home production-related tasks changes in response to these shocks.

My findings suggest that when home production is taken into account, health shocks are more damaging than suggested by only monetary costs. Therefore, additional considerations should be given to policies such as Home- and Community-Based Services (HCBS) that provide non-pecuniary support to unhealthy people. HCBS include services such as personal care, chore services, and meal delivery along with home health care services (health care by a skilled professional). Although Medicaid expansion of the HCBS program is a priority for federal policy, as is evident from President Biden's proposed Build Back Better bill. However, Medicare only covers health care services provided by a skilled professional and for a limited period of time. My results, therefore, have important policy implications for structuring support for the expansion of HCBS.

Furthermore, future studies should explore additional channels through which health shocks can impact home production. One such mechanism to consider is the potential change in the marginal utility of consumption following a health shock. Additionally, adjustments in life expectancy could be another avenue worth investigating. For instance, if individuals expect a shorter lifespan after a health shock, such as a cancer diagnosis, it could lead to increased monetary resources available in each period, which may have implications for home production that oppose the income effect considered in this paper. Another area for future research is examining how health shocks influence individuals and their spouses, particularly retirees, in terms of re-entering the labor force.

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Main Figures and Tables

Table 1: Descriptive Statistics

	Full Sample	
	Mean	Median
Age	74.22	74.00
Women	0.60	-
No. of HH members	1.99	2.00
Married	0.62	-
Widowed	0.25	-
ADL Limitations	0.31	0.00
IADL Limitations	0.25	0.00
Other Diagnosed Conditions	2.49	2.00
Time-Use (Weekly)		
Home Production	20.70	17.47
Missing Values	0.06	-
Total Hours	157.80	157.60
Out-of-Pocket Medical Spending		
Total	2895.42	1549.65
Retirement Income	24270.93	15491.40
Ratio of Medical Cost to Income	0.41	0.09
Covered by		
Medicaid	0.09	-
Long Term Care Insurance	0.15	-
N	19797	

Notes: Activities of daily living (ADL) and instrumental ADL (IADL) limitations range from 0 to 5. Medically diagnosed conditions are cancer, heart condition, hypertension, lung condition, diabetes, arthritis, psychiatric condition, and stroke. Retirement income is the sum of social security income, pension, and annuity income. The ratio of medical cost to income is the ratio of out-of-pocket medical spending to total retirement income.

Table 2: Impact of Health Shocks on Medical Cost, ADL, and IADL

	OoP Medical Cost (Dollar)		ADL		IADL	
	(Change)	(Rank)	(Change)	(Rank)	(Change)	(Rank)
	(1)	(2)	(3)	(4)	(5)	(6)
Cancer	1037.7***	1	0.112***	5	0.0521	8
	(238.5)		(0.0360)		(0.0321)	
Heart	1009.9***	2	0.0421	8	0.0963***	5
	(178.2)		(0.0314)		(0.0279)	
Stroke	703.6***	3	0.298***	1	0.381***	1
	(239.7)		(0.0638)		(0.0649)	
High Blood Pressure	652.4***	4	0.0252	9	0.0172	10
	(163.3)		(0.0257)		(0.0228)	
Lung	628.7**	5	0.0694	7	0.0810*	6
	(255.4)		(0.0491)		(0.0435)	
Diabetes	414.6*	6	0.0219	10	0.0729*	7
	(218.7)		(0.0358)		(0.0383)	
Self-Reported Health	297.2**	7	0.223***	3	0.166***	4
	(142.5)		(0.0274)		(0.0262)	
Psychiatric	251.1	8	0.268***	2	0.323***	2
	(277.5)		(0.0693)		(0.0650)	
CES-D Dep	177.5	9	0.190***	4	0.235***	3
	(163.5)		(0.0302)		(0.0313)	
Arthritis	-167.3	10	0.0904***	6	0.0468	9
	(183.1)		(0.0291)		(0.0308)	

Notes: This table presents the increase in medical cost and daily living limitations in the first period following a given health shock and their relative rankings in terms of severity. Coefficients represent the impact of health shocks estimated using difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. The control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. The top 1 percentile of real out-of-pocket medical costs is excluded. Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Impact on Home Production and Its Components

	(1) **Total Home Production**	(2) Meal Preparation	(3) House keeping, Laundry	(4) Yard work, Gardening	(5) Shopping, Errands	(6) Managing Finances	(7) Home Repair
Costly Shocks				**Panel A**			
Cancer	0.41	0.14	0.03	0.41***	0.19	-0.06	0.06
	(0.78)	(0.29)	(0.33)	(0.15)	(0.18)	(0.06)	(0.07)
Pre-treatment mean	20.93	6.42	6.72	2.14	3.70	0.78	0.54
N	15465	16293	16127	16319	16319	16363	16304
Heart Condition	-0.00	0.04	0.05	-0.09	-0.11	-0.04	-0.06
	(0.61)	(0.22)	(0.27)	(0.14)	(0.16)	(0.05)	(0.06)
Pre-treatment mean	21.46	6.63	6.94	2.18	3.78	0.79	0.55
N	13634	14332	14215	14368	14408	14420	14423
High Blood Pressure	-1.07	-0.08	-0.23	-0.08	-0.23	-0.04	-0.07
	(0.69)	(0.26)	(0.28)	(0.16)	(0.17)	(0.05)	(0.06)
Pre-treatment mean	21.89	6.54	6.74	2.44	3.87	0.82	0.65
N	7412	7820	7742	7809	7886	7879	7850
Lung Condition	-2.33**	-0.25	-0.53	-0.25	-0.14	-0.01	0.07
	(1.05)	(0.41)	(0.43)	(0.18)	(0.22)	(0.06)	(0.08)
Pre-treatment mean	20.81	6.37	6.57	2.17	3.73	0.79	0.55
N	16453	17312	17135	17323	17340	17327	17307
Impairing Shocks				**Panel B**			
Psychiatric Condition	-3.16***	-0.74*	-1.41***	-0.36	-0.32	-0.07	0.06
	(1.16)	(0.42)	(0.45)	(0.23)	(0.23)	(0.08)	(0.05)
Pre-treatment mean	20.76	6.37	6.47	2.19	3.72	0.80	0.55
N	15596	16381	16243	16404	16441	16430	16403
CES-D Depression	-1.12**	-0.50**	-0.12	-0.02	-0.08	-0.02	0.02
	(0.57)	(0.21)	(0.24)	(0.11)	(0.13)	(0.04)	(0.05)
Pre-treatment mean	21.27	6.48	6.54	2.32	3.86	0.82	0.60
N	14460	15200	15040	15198	15248	15269	15209
Self-Reported Health	-0.99*	-0.55***	-0.34	-0.25**	0.02	0.01	0.02
	(0.53)	(0.20)	(0.22)	(0.11)	(0.12)	(0.04)	(0.05)
Pre-treatment mean	21.94	6.68	6.81	2.38	3.97	0.82	0.61
N	13794	14572	14390	14522	14596	14587	14564
Mixed Shocks				**Panel C**			
Stroke	-0.65	-0.71**	0.15	-0.06	-0.07	0.02	0.12
	(0.93)	(0.34)	(0.42)	(0.22)	(0.21)	(0.07)	(0.08)
Pre-treatment mean	21	7	7	2	4	1	1
N	17062	17969	17772	17992	18019	18017	18000
Diabetes	-0.37	0.05	-0.14	-0.27	-0.15	0.04	-0.02
	(0.78)	(0.31)	(0.37)	(0.18)	(0.19)	(0.06)	(0.08)
Pre-treatment mean	21	7	7	2	4	1	1
N	14753	15487	15358	15513	15549	15536	15534
Arthritis	-1.04	0.24	-0.19	-0.23	0.30	-0.00	-0.05
	(0.78)	(0.32)	(0.31)	(0.18)	(0.19)	(0.06)	(0.07)
Pre-treatment mean	21	6	6	3	4	1	1
N	5888	6237	6131	6170	6223	6187	6188

Notes: This table presents the results of the impact of health shocks on time spent in home production, estimated using the difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. The coefficients presented reflect the impact measured in hours per week in the first period following the occurrence of the shock. Top 1 percentile of all time use is excluded from the analysis. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Panel A shows the impact of costly shocks on total home production and its various tasks. Panel B shows the impact of impairing shocks on total home production and its various tasks. Panel C shows the impact of mixed shocks. Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Descriptive Statistics

	Cancer		Heart		High BP		Lung		Psychiatric Condition		CESD Depression		Self-Reported Health	
	Ever Treated	Never Treated	Ever Treated	Never Treated	Ever Treated	Never Treated	Ever Treated	Never Treated	Ever Treated	Never Treated	Ever Treated	Never Treated	Ever Treated	Never Treated
Age	74.49	74.09	74.69	73.95	74.70	74.12	74.17	74.33	74.75	74.48	74.49	74.24	74.61	74.20
Women (%)	0.51	0.62	0.56	0.65	0.64	0.57	0.65	0.59	0.76	0.56	0.67	0.54	0.59	0.60
No. of HH members	1.95	2.01	1.97	1.98	1.92	1.98	1.99	2.00	1.99	2.00	2.03	1.99	1.99	1.94
Married (%)	0.67	0.61	0.65	0.61	0.58	0.66	0.56	0.64	0.54	0.65	0.61	0.67	0.62	0.66
Widowed (%)	0.20	0.26	0.25	0.25	0.27	0.23	0.29	0.24	0.32	0.24	0.26	0.21	0.24	0.24
Attrition from Sample (%)	0.47	0.47	0.47	0.46	0.43	0.49	0.50	0.47	0.47	0.48	0.47	0.45	0.50	0.42
ADL Limitations	0.26	0.31	0.30	0.24	0.24	0.20	0.44	0.26	0.56	0.23	0.39	0.13	0.32	0.08
IADL Limitations	0.20	0.25	0.24	0.19	0.19	0.17	0.29	0.22	0.47	0.18	0.31	0.09	0.27	0.07
Other Diagnosed Conditions	2.18	2.28	2.27	1.97	1.61	1.48	2.63	2.28	2.42	2.23	2.64	2.20	2.64	2.04
Time-Use (Weekly)														
Home Production	18.92	20.98	20.46	21.50	22.08	21.42	20.31	20.74	20.52	20.69	20.88	21.05	20.12	22.08
Missing Values (%)	0.06	0.06	0.05	0.06	0.06	0.06	0.06	0.06	0.05	0.06	0.06	0.05	0.06	0.05
Total Hours	156.39	157.53	158.14	157.93	160.67	158.80	156.79	158.02	158.14	158.29	158.18	160.74	156.21	162.88
Cognition														
Normal (%)	0.79	0.77	0.78	0.80	0.80	0.81	0.77	0.78	0.71	0.79	0.75	0.84	0.76	0.86
Cognitively Impaired not Demented (%)	0.17	0.18	0.17	0.17	0.17	0.15	0.20	0.17	0.20	0.17	0.19	0.14	0.20	0.12
Demented (%)	0.04	0.05	0.05	0.04	0.03	0.03	0.04	0.04	0.08	0.04	0.06	0.02	0.04	0.02
Utilization of														
Formal Help (%)	0.03	0.03	0.03	0.03	0.03	0.02	0.04	0.03	0.07	0.02	0.05	0.01	0.04	0.01
Informal Help (%)	0.11	0.12	0.13	0.09	0.10	0.08	0.15	0.11	0.20	0.10	0.15	0.06	0.13	0.04
Help Hours (last month)	12.83	14.43	14.21	10.21	10.16	9.32	14.09	13.14	31.40	10.46	17.80	5.39	16.10	3.39
Nursing Home Overnight Stay	0.04	0.03	0.05	0.03	0.04	0.03	0.05	0.03	0.05	0.03	0.05	0.02	0.05	0.02
Nights in Nursing Home	6.33	4.70	3.82	3.46	3.18	3.66	4.45	4.32	8.15	3.12	6.31	1.75	6.30	1.10
Hospitalized	0.35	0.27	0.37	0.22	0.27	0.24	0.38	0.27	0.35	0.28	0.32	0.26	0.33	0.21
Out-of-Pocket Medical Spending														
Total	3061.78	2795.26	3246.57	2464.12	2668.27	2445.93	2940.31	2823.51	3045.12	2809.53	3146.34	2662.10	2983.78	2615.85
Nursing Home, Hosp	146.46	113.64	125.45	77.31	102.14	102.73	151.13	109.67	136.25	112.45	133.77	91.83	123.13	73.18
Doctor Visit	357.69	258.67	294.50	244.78	260.57	261.59	243.51	279.92	330.51	262.68	333.27	250.14	297.84	256.02
Drugs	1397.73	1448.01	1698.98	1204.75	1260.33	1056.24	1653.83	1399.48	1682.01	1415.63	1615.06	1308.66	1549.13	1220.15
Home Care	6.68	8.12	9.54	7.01	7.51	7.43	8.81	8.28	10.49	6.95	9.58	6.86	8.32	6.85
Covered by														
Medicaid (%)	0.07	0.10	0.07	0.08	0.07	0.06	0.13	0.08	0.13	0.07	0.09	0.05	0.09	0.04
Long Term Care Ins (%)	0.18	0.15	0.16	0.15	0.16	0.18	0.13	0.16	0.17	0.16	0.14	0.17	0.14	0.19
Wealth														
Total Net Wealth	524075	461838	495408	489861	506789	629836	374382	507504	441427	515839	460428	561288	446218	602281
Net Non Housing Wealth	339740	307637	330021	324896	339303	432667	235036	340455	313512	343428	305584	380016	296396	409050
Housing Wealth	196118	169306	175759	182091	179559	211495	149324	182840	152275	186586	163195	200429	164455	210438
N	2110	14722	3461	11414	3358	4800	1544	16292	1367	15533	4908	10793	5153	9872

Notes: The term “Ever Treated” refers to individuals who have received treatment for a specific health shock at any point during the observed sample period. On the other hand, “Never Treated” refers to individuals who have never received treatment for the given health shock throughout the observed sample period. The attrition from the sample represents the percentage of individuals who cease to participate in the surveys due to various reasons, including mortality or other factors. ”Other diagnosed conditions” denotes the cumulative count of medically diagnosed conditions, excluding the specific condition indicated in the column header. The three cognition categories utilized in this study are derived from the Langa-Weir cognition classification ([Langa et al., 2020]).

Table 5: Descriptive Statistics (Continued)

	Stroke		Diabetes		Arthritis	
	Treated	Not Treated	Treated	Not Treated	Treated	Not Treated
Age	75.00	74.15	74.16	74.41	74.55	73.98
Women (%)	0.59	0.61	0.58	0.62	0.56	0.46
No. of HH members	1.93	1.99	2.05	1.95	1.98	2.01
Married (%)	0.63	0.62	0.58	0.62	0.64	0.66
Widowed (%)	0.24	0.25	0.25	0.25	0.25	0.20
Attrition from Sample (%)	0.51	0.47	0.42	0.49	0.42	0.51
ADL Limitations	0.46	0.26	0.34	0.25	0.16	0.15
IADL Limitations	0.39	0.20	0.26	0.20	0.16	0.19
Other Diagnosed Conditions	2.66	2.33	2.43	2.11	1.53	1.45
Time-Use (Weekly)						
Home Production	19.45	21.16	20.80	21.41	20.96	20.04
Missing Values (%)	0.06	0.06	0.06	0.06	0.05	0.05
Total Hours	157.01	158.61	158.60	159.51	158.83	153.59
Cognition						
Normal (%)	0.74	0.79	0.77	0.80	0.80	0.79
Cognitively Impaired not Demented (%)	0.19	0.17	0.19	0.16	0.17	0.17
Demented (%)	0.07	0.04	0.04	0.04	0.03	0.04
Utilization of						
Formal Help (%)	0.06	0.03	0.04	0.03	0.02	0.02
Informal Help (%)	0.18	0.10	0.13	0.10	0.08	0.08
Help Hours (last month)	24.84	10.67	15.03	10.77	6.97	11.96
Nursing Home Overnight Stay	0.07	0.03	0.04	0.03	0.03	0.02
Nights in Nursing Home	8.33	2.76	3.84	3.61	4.09	3.47
Hospitalized	0.41	0.27	0.31	0.27	0.25	0.23
Out-of-Pocket Medical Spending						
Total	3084.01	2770.68	2847.62	2784.82	2504.39	2376.96
Nursing Home, Hosp	162.88	101.44	134.30	108.62	81.40	67.61
Doctor Visit	287.76	277.61	283.40	270.74	261.71	223.19
Drugs	1674.50	1403.81	1406.86	1369.09	1225.66	1132.91
Home Care	9.28	7.49	8.37	8.73	5.11	3.07
Covered by						
Medicaid (%)	0.09	0.09	0.09	0.07	0.06	0.07
Long Term Care Ins (%)	0.16	0.16	0.13	0.17	0.19	0.17
Wealth						
Total Net Wealth	426922	494845	419420	539628	509687	538616
Net Non Housing Wealth	285336	329429	268594	365378	327972	359765
Housing Wealth	162010	178636	165716	187786	193435	197159
N	1620	16912	2200	13808	2636	3820

Notes: The term “Treated” refers to individuals who have received treatment for a specific health shock at any point during the observed sample period. On the other hand, “Not Treated” refers to individuals who have never received treatment for the given health shock throughout the observed sample period. The attrition from the sample represents the percentage of individuals who cease to participate in the surveys due to various reasons, including mortality or other factors. ”Other diagnosed conditions” denotes the cumulative count of medically diagnosed conditions, excluding the specific condition indicated in the column header. The three cognition categories utilized in this study are derived from the Langa-Weir cognition classification ([Langa et al., 2020]).

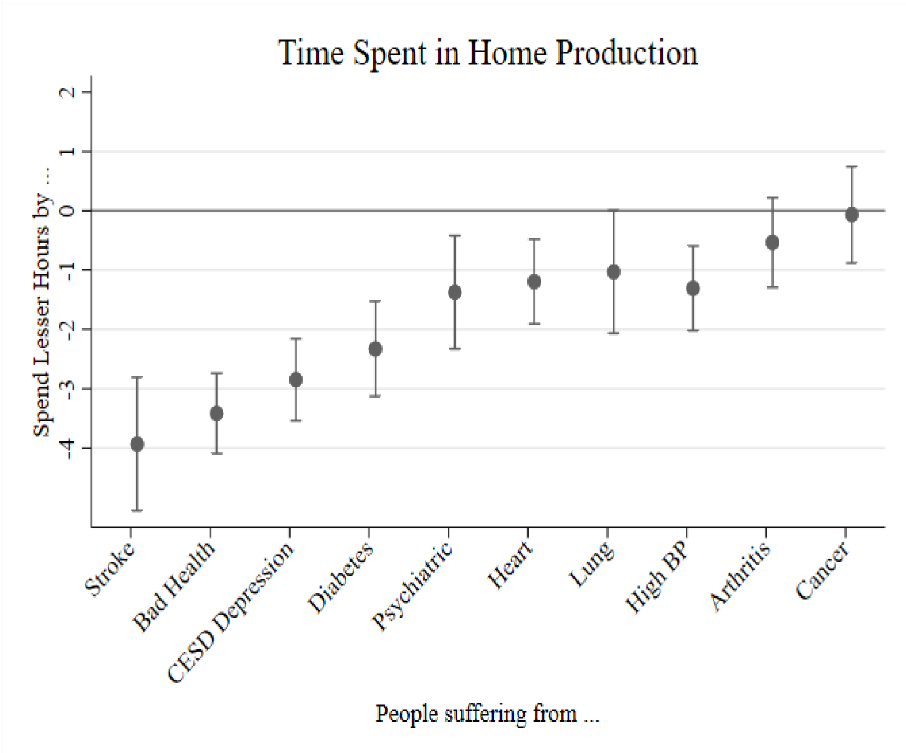
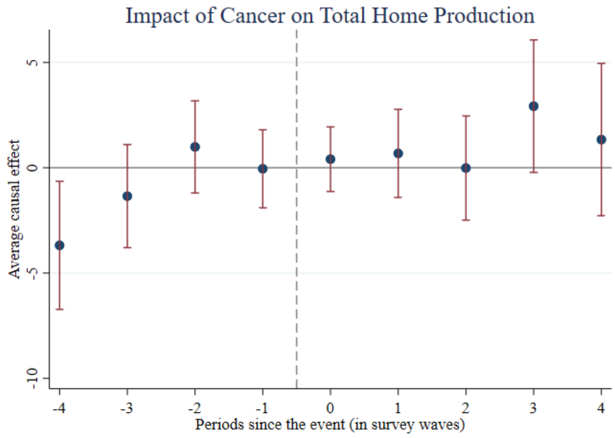
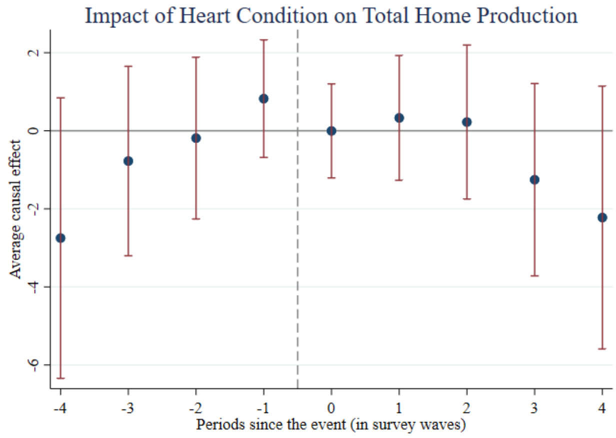


Figure 1: Home Production by Current Health Status

Notes: This figure shows the links between current health status and time spent in home production in cross-section using ordinary least squares (OLS). Weekly time spent in home production is regressed on a given health indicator. Estimates with 95% confidence intervals displayed after controlling for age, age polynomial, gender, marital status, number of household members, race, education, and time fixed-effects.



(a)



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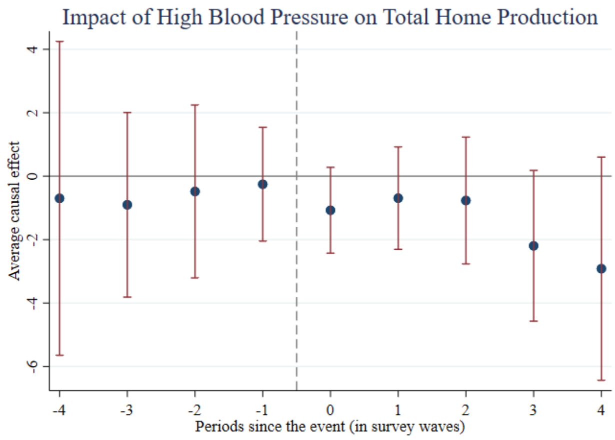

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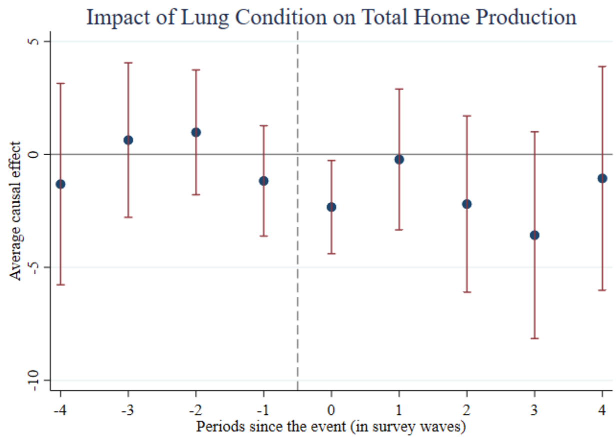
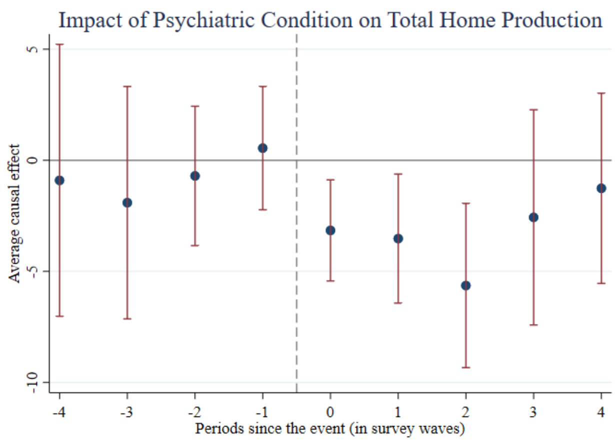


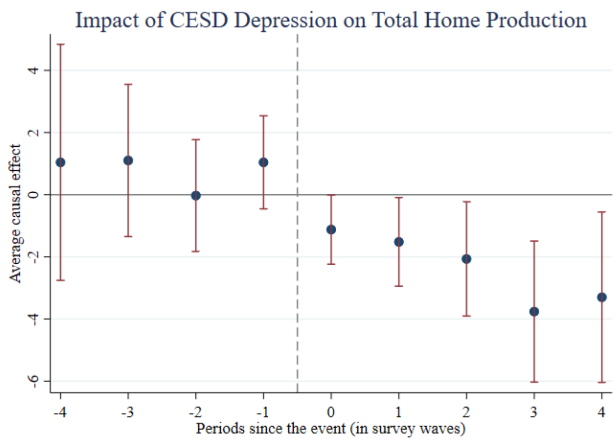
(d)

Figure 2: Impact of Costly Health Shocks on Time Spent in Home Production

Notes: These event study graphs present the results for many post-treatment periods, expanding the results corresponding to column 1 in Table 3. Each point within the figures represents the estimated effects during a specific time period relative to the treatment period, wherein period 0 signifies the initial wave observed subsequent to the initiation of the treatment. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Considering the biannual nature of the survey waves, a two-year interval exists between consecutive periods displayed on the x-axis. The vertical lines depicted denote the 95% confidence intervals.



(a)



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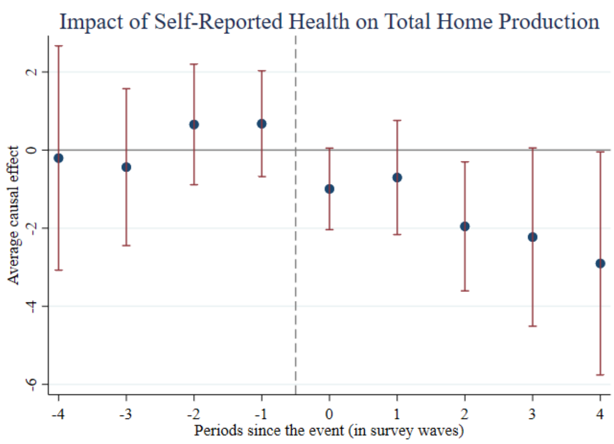
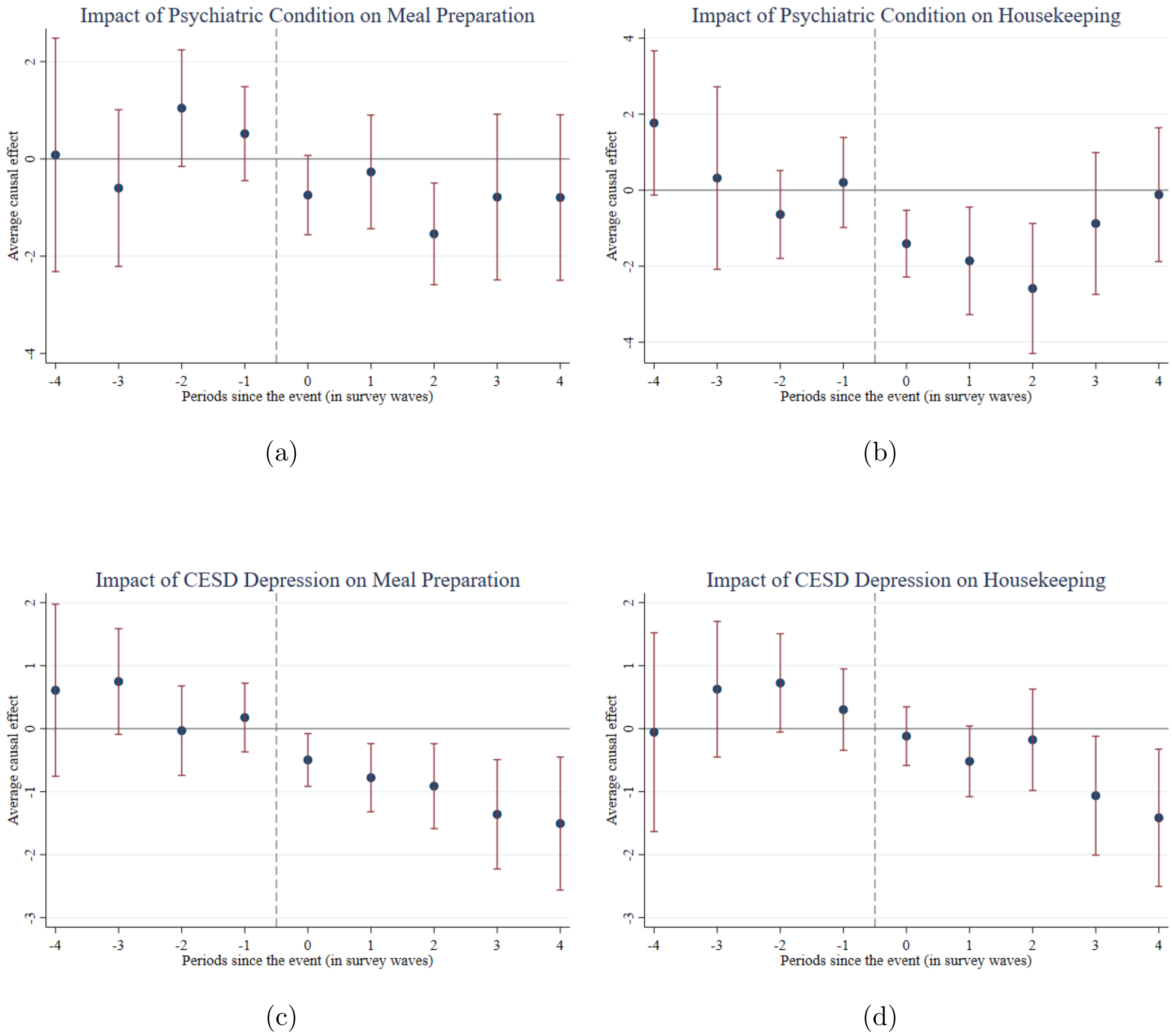


(c)

Figure 3: Impact of Impairing Health Shocks on Time Spent in Home Production

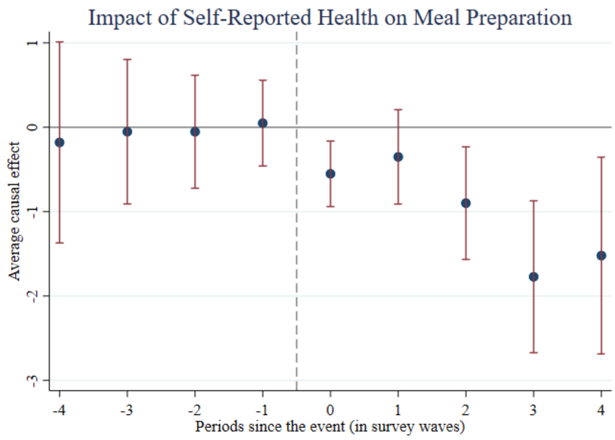
Notes: These event study graphs present the results for many post-treatment periods, expanding the results corresponding to column 1 in Table 3. Each point within the figures represents the estimated effects during a specific time period relative to the treatment period, wherein period 0 signifies the initial wave observed subsequent to the initiation of the treatment. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Considering the biannual nature of the survey waves, a two-year interval exists between consecutive periods displayed on the x-axis. The vertical lines depicted denote the 95% confidence intervals.



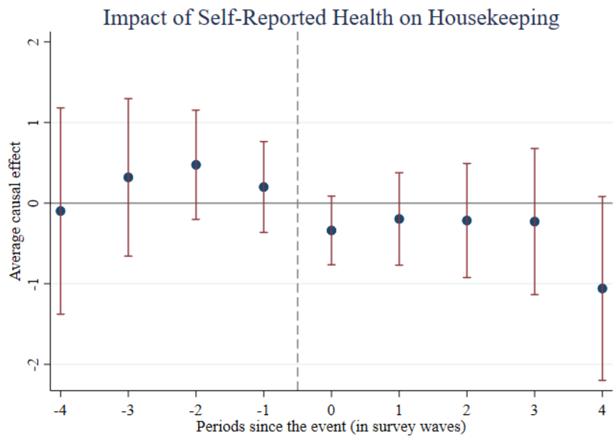
(a) (b) (c) (d)

Figure 4: Impact of Impairing Shocks on Meal Preparation and Housekeeping

Notes: These event study graphs present the results for many post-treatment periods, expanding the results corresponding to column 2 and 3 (meal preparation and housekeeping plus laundry) in Table 3. Each point within the figures represents the estimated effects during a specific time period relative to the treatment period, wherein period 0 signifies the initial wave observed subsequent to the initiation of the treatment. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Considering the biannual nature of the survey waves, a two-year interval exists between consecutive periods displayed on the x-axis. The vertical lines depicted denote the 95% confidence intervals.



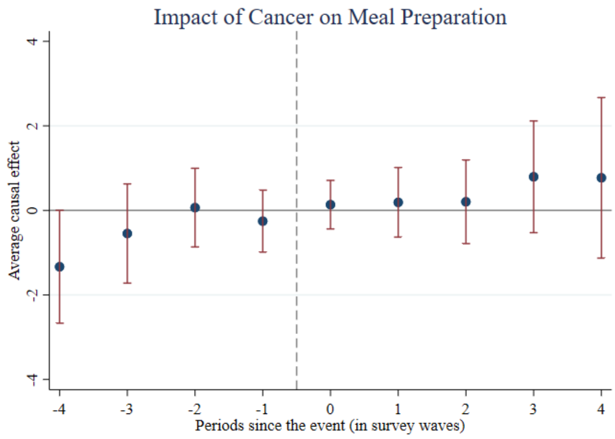
(a)



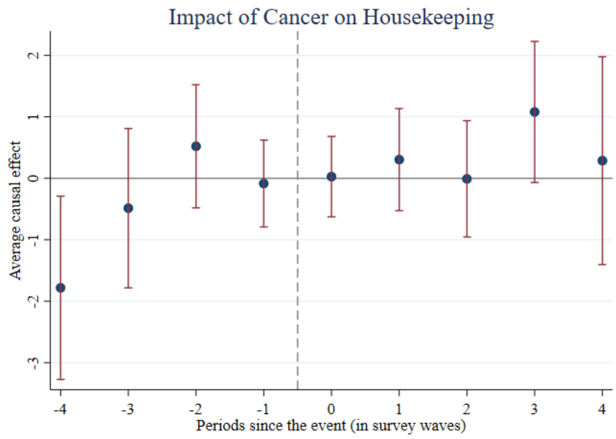
(b)

Figure 5: Impact of Impairing Shocks on Meal Preparation and Housekeeping (Contd.)

Notes: These event study graphs present the results for many post-treatment periods, expanding the results corresponding to column 2 and 3 (meal preparation and housekeeping plus laundry) in Table 3. Each point within the figures represents the estimated effects during a specific time period relative to the treatment period, wherein period 0 signifies the initial wave observed subsequent to the initiation of the treatment. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Considering the biannual nature of the survey waves, a two-year interval exists between consecutive periods displayed on the x-axis. The vertical lines depicted denote the 95% confidence intervals.



(a)



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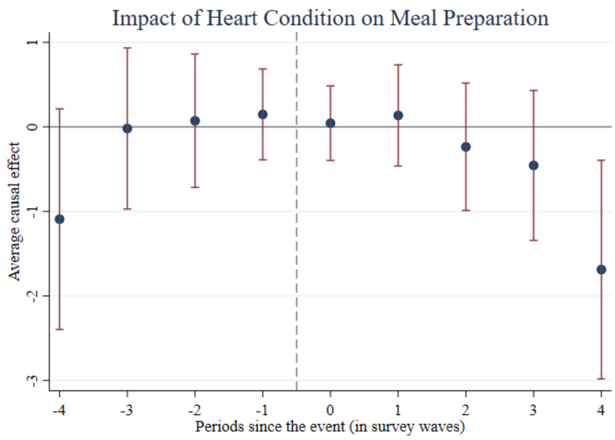

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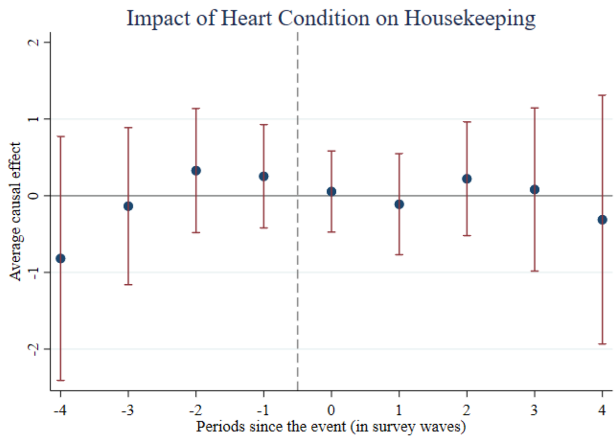
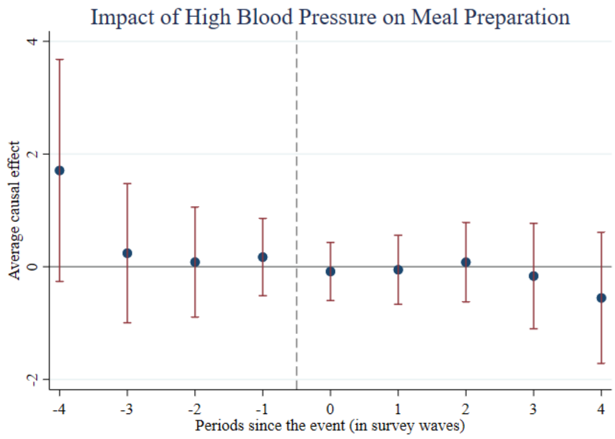


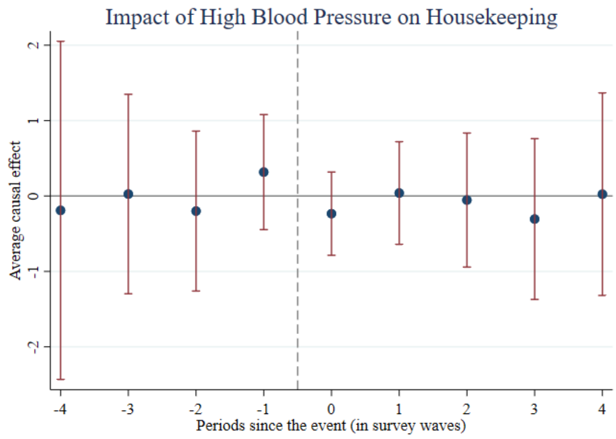
(d)

Figure 6: Impact of Costly Shocks on Meal Preparation and Housekeeping

Notes: These event study graphs present the results for many post-treatment periods, expanding the results corresponding to column 2 and 3 (meal preparation and housekeeping plus laundry) in Table 3. Each point within the figures represents the estimated effects during a specific time period relative to the treatment period, wherein period 0 signifies the initial wave observed subsequent to the initiation of the treatment. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Considering the biannual nature of the survey waves, a two-year interval exists between consecutive periods displayed on the x-axis. The vertical lines depicted denote the 95% confidence intervals.



(a)



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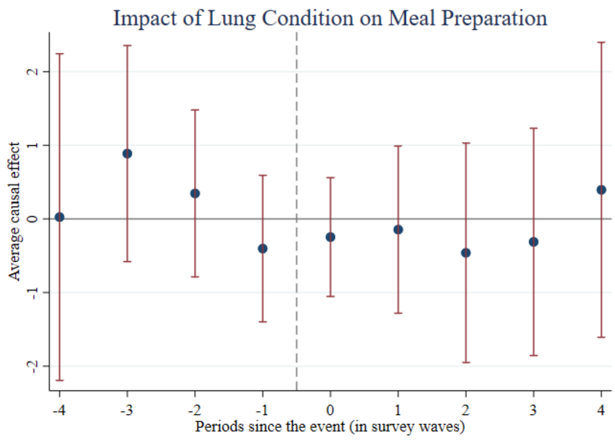

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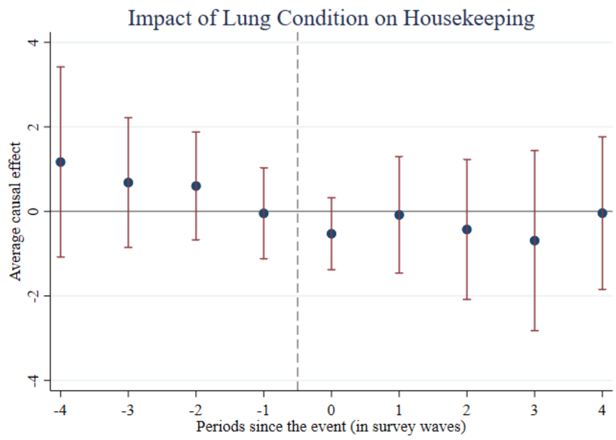

(d)

Figure 7: Impact of Costly Shocks on Meal Preparation and Housekeeping (Contd.)

Notes: These event study graphs present the results for many post-treatment periods, expanding the results corresponding to column 2 and 3 (meal preparation and housekeeping plus laundry) in Table 3. Each point within the figures represents the estimated effects during a specific time period relative to the treatment period, wherein period 0 signifies the initial wave observed subsequent to the initiation of the treatment. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Considering the biannual nature of the survey waves, a two-year interval exists between consecutive periods displayed on the x-axis. The vertical lines depicted denote the 95% confidence intervals.

Appendix: The Effects of Health Shocks on Time Spent in Home Production

Suchika Chopra

May 29, 2025

A Data

Figure A1 presents the proportion of total non-sleeping hours dedicated to home production and other activities. Home production accounts for a significant portion (20%) of time, second only to leisure activities (39%). Table A1 provides summary statistics for total hours spent on home production and its individual components. On average, individuals spend more than 20 hours per week on home production. Among the various tasks involved in home production, meal preparation and cleaning afterward consume the most time.

Graph (a) in Figure A2 illustrates the distribution of total home production hours. Approximately 7% of the sample reports no hours spent on home production, which is not uncommon based on comparisons with the American Time Use Survey (ATUS) discussed later in this section. Graph (b) in Figure A2 displays the distribution of total hours. Time-use information on additional categories has been included in CAMS questionnaires in different waves. I use the supplementary time-use data provided in each wave to construct the variable representing the cumulative hours reported for each respective period. Although the distribution peaks around 168 hours, indicating a typical week, there is considerable variation around the mean. This wide distribution may be attributed to the survey instrument allowing for double counting of hours. It is possible that individuals engage in multiple tasks simultaneously or that certain tasks align with more than one time-use activity surveyed in CAMS. This could explain the tendency to over-report hours. Conversely, the recall method used in CAMS may lead to under-reporting of total hours, as respondents are likely to forget some tasks over the past month or week.[1]

Another potential explanation for under or over-reporting is the respondent's misinterpretation of the recall period. For instance, some activities have a weekly recall period, while others have a monthly recall period. Respondents may mistakenly report hours based on a different recall period. To investigate this issue, I examine the distribution of hours of sleep per week among those who report total hours of less than 100 per week. It is well-documented that adults

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[1] For more information, see [Hurd et al., 2007].

generally require 7-8 hours of sleep per day ([Hirshkowitz et al., 2015]) Sleep serves as a useful reference as it there is less variation in this activity and no other time-use activity commands some definitive number of hours. Graph (c) in Figure A2 provides evidence supporting the confusion related to recall periods. Among those who under-report weekly total hours, approximately 30% report sleeping between 7-8 hours, which corresponds to a reasonable amount of sleep in a day rather than a week.

Table A1: Descriptive Stats of Home Production

	mean	p50	p75	p95
House Cleaning	4.30	3.00	6.00	14.00
Wash/Iron/Mend	2.26	2.00	3.00	8.00
Meals Prep	6.30	5.00	9.00	20.00
Yard Work/Garden	2.09	0.00	3.00	10.00
Shop/Run Errands	3.66	3.00	5.00	10.00
Money Management	0.79	0.47	0.93	2.79
Home Improvements	0.53	0.00	0.47	2.79
Total Home Production	20.60	17.40	28.40	50.86

Notes: This table shows the summary statistics for total home production hours as well as the components of home production. All variables have been trimmed by top 1 percentile. Source: Consumption and Activities Mail Survey data.

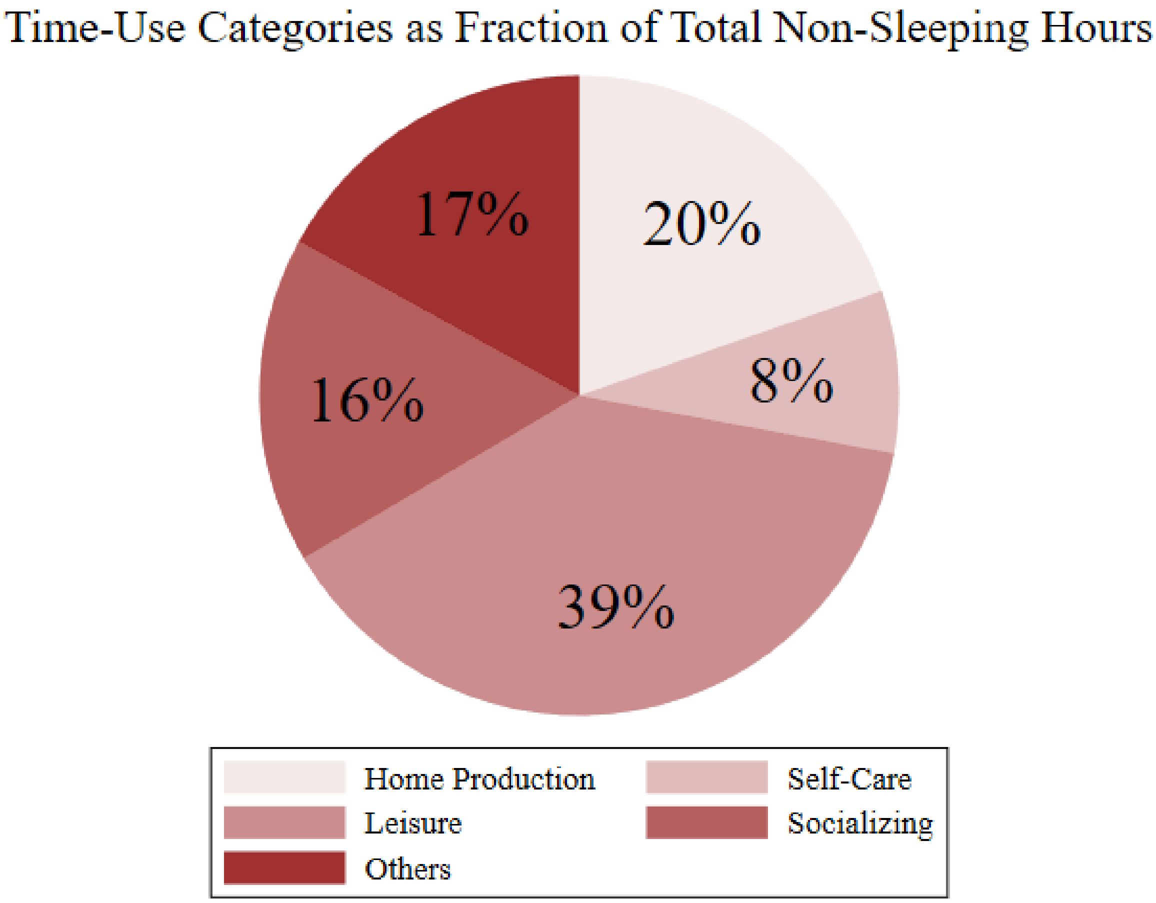
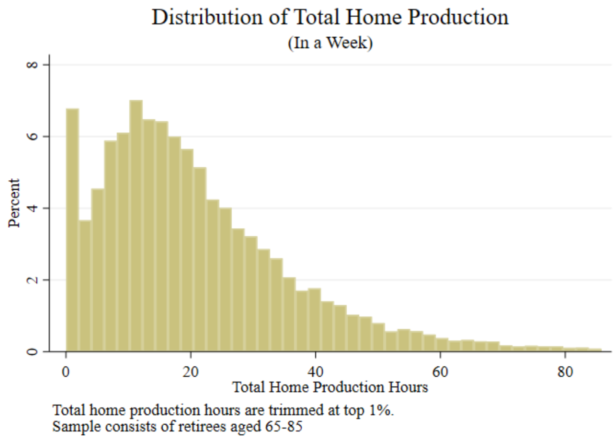
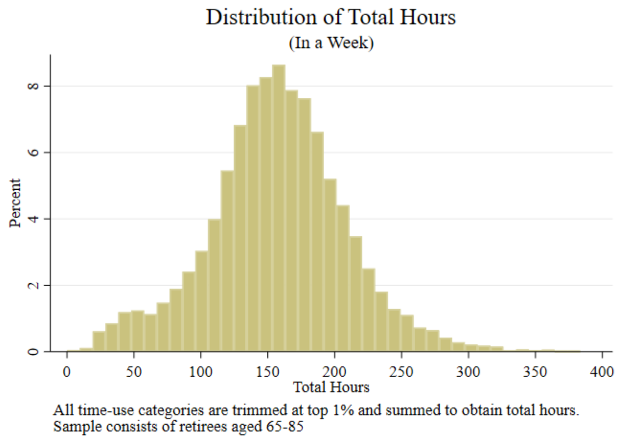


Figure A1: Composition of Non-Sleeping Hours

Notes: This figure shows the total home production as a fraction of total non-sleeping hours. "Other" category includes walking, sports/exercising, working for pay, using computer praying/meditating, volunteer work. "Socializing" includes helping other, showing affection, religious service, attend meetings, visiting in person, phone/letters/emails. "Leisure" includes watching TV, reading papers, magazines, books, listening to music, play cards/games, attending concerts, movies, and lectures, sing/play instruments, doing arts and crafts. "Self-care" includes personal grooming, and managing own medical condition.



(a)



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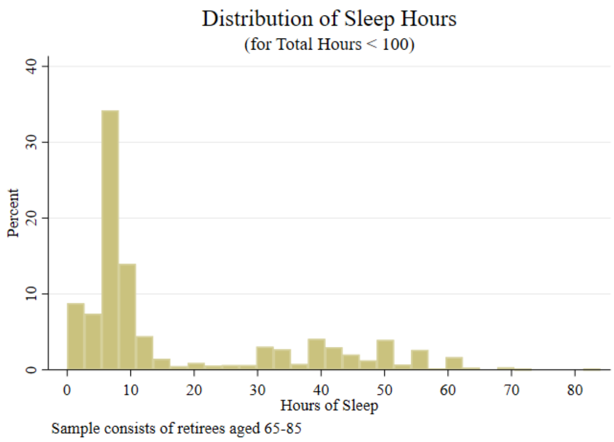


(c)

Figure A2: Distribution of Total Hours, Home production, and Sleep Hours

Notes: These graphs show the distribution of hours in various categories in a week. All time-use categories are truncated at top 1%. Graph (a) shows the distribution of total home production hours, where home production includes meal preparation, house cleaning, laundry, yard work, running errands, managing money, and doing home improvements. Graph (b) shows the distribution of total hours reported. Time-use information on additional categories has been included in CAMS questionnaires in different waves. I use the supplementary time-use data provided in each wave to construct the variable representing the cumulative hours reported for each respective period. Graph (c) shows the distribution of the reported sleep hours.

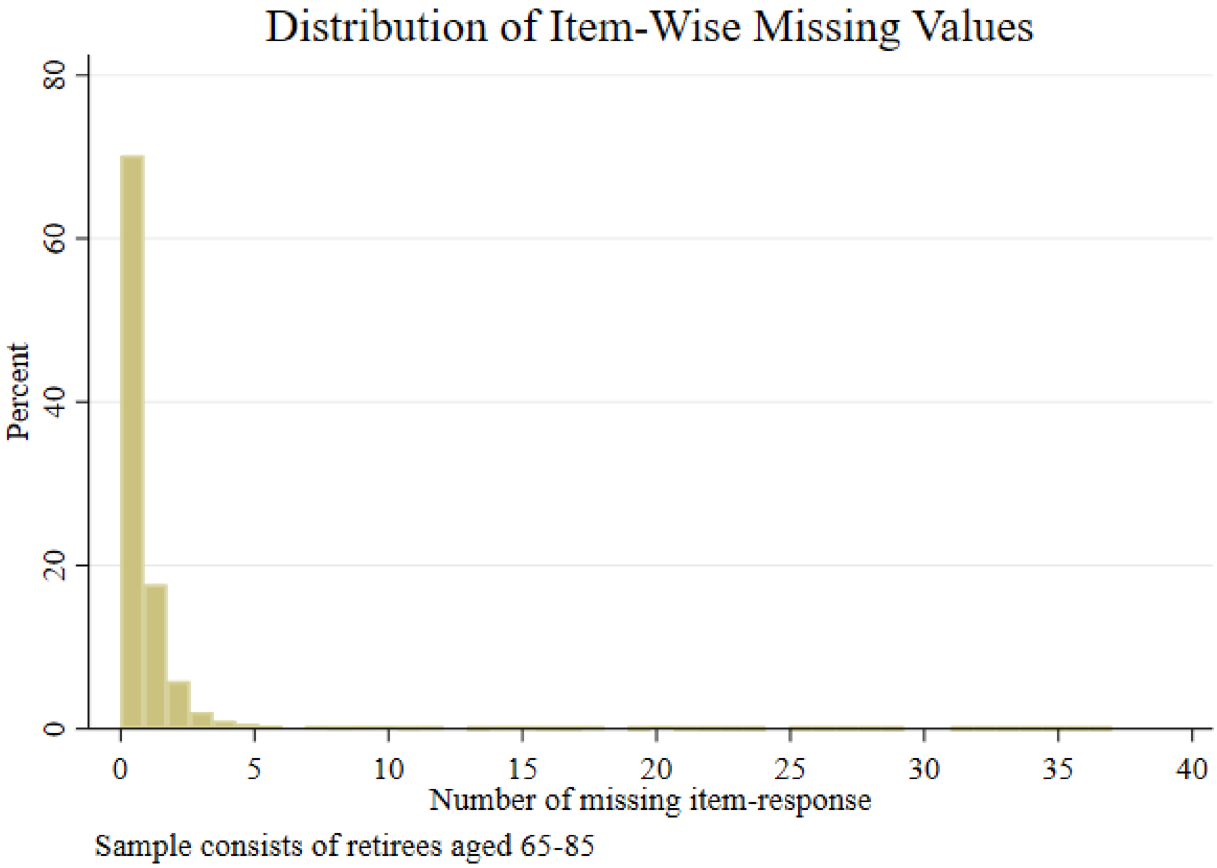


Figure A3: Distribution of Item-Response Rate

Notes: This graph depicts the percentage of individuals whose responses are missing, categorized according to the number of assets for which they lack information. For instance, the bar over "0" signifies that approximately 70% of the sample do not have missing response for any time-use categories. CAMS collects data on more than 30 time-use categories.

A.1 Correlation among health shocks

Even though I study the impact of individual health shocks, it is important to recognize that some of the health conditions may be correlated. In the Table A2, I calculate the likeliness of people suffering from two conditions throughout their observed sample period, irrespective of the order in which individuals face them. I find that CES-D depression and psychiatric condition are highly correlated. Not surprisingly, bad self-reported health is highly correlated with all the other health conditions, especially, CES-D depression, followed by lung and heart condition. Finally, cancer is least associated with any other health conditions.

	Psychiatric Condition	Lung	High Blood Pressure	CES-D Depression	Diabetes	Arthritis	Self-Reported Health	Stroke	Heart	Cancer
Psychiatric Condition	1									
Lung	0.158**	1								
High Blood Pressure	0.0684**	0.0336*	1							
CES-D Depression	0.302**	0.142**	0.0952**	1						
Diabetes	0.0768**	0.0445**	0.174**	0.0886**	1					
Arthritis	0.117**	0.0900**	0.110**	0.150**	0.0516**	1				
Self-Reported Health	0.199**	0.240**	0.151**	0.383**	0.203**	0.138**	1			
Stroke	0.0818**	0.0586**	0.118**	0.110**	0.0816**	0.0279	0.143**	1		
Heart	0.0915**	0.135**	0.159**	0.108**	0.109**	0.103**	0.229**	0.163**	1	
Cancer	0.00479	0.0708**	0.0218	0.0282	0.0147	0.0287	0.103**	0.000665	0.0454**	1
N	4471									

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

Table A2: Correlation among health shocks

Notes: This table illustrates the correlation between different health conditions. These correlations are computed by examining whether an individual experienced a concurrent occurrence of heart conditions over the observed period, regardless of the sequential order in which these health conditions occur. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

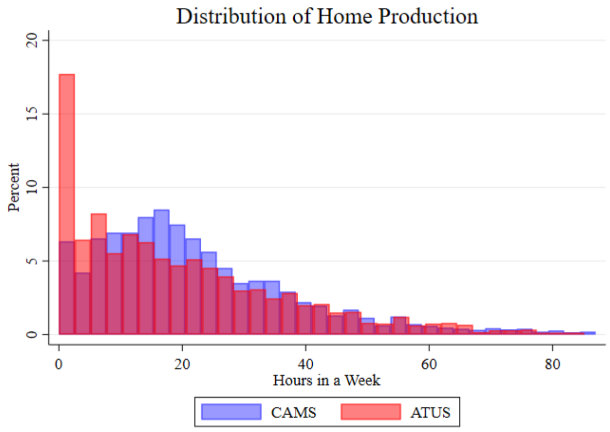
A.2 Data Quality

In this section, I compare Consumption and Activities Mail Survey data (CAMS) and American Time Use Survey data (ATUS). It is important to note that this comparison has limitations due to differences in sampling, interview mode, and recall period. CAMS employs a paper and pencil questionnaire that asks respondents to recall their time use over the past month or week, while ATUS conducts interviews using computer-assisted telephone technology and employs the diary method to cover the 24 hours of the previous day. These methodological disparities are expected to result in some variations in the summary statistics. However, despite these dissimilarities, CAMS and ATUS yield reasonably similar results.

To compare the time use of healthy and unhealthy respondents between CAMS and ATUS, data from the 2015 survey wave of CAMS is utilized. While health information is available for CAMS respondents in every wave through the corresponding Health and Retirement Study (HRS), ATUS does not regularly collect health information. The most recent health module in ATUS was conducted between 2014 and 2016. The Eating and Health Module in ATUS only gathers self-reported health information, which is then used to categorize respondents as healthy or unhealthy[2] respondents in the following table.

Table A3 presents weighted averages by health status for selected categories. CAMS records slightly higher home production by an additional 2 hours per week compared to ATUS. This is because a greater proportion of ATUS respondents report zero hours of home production, as evident from the distribution comparison in Figure A4. CAMS also reports higher time spent on personal care and caring for others by approximately 2 hours. ATUS, on the other hand, records more time spent on watching TV. The time spent in voluntary and organizational meetings, as well as eating and drinking, is similar across the two surveys. However, CAMS reports higher time spent on phone and email use, listening to music, and leisure activities. These differences may arise from the inclusion of secondary activities in CAMS. These descriptive findings align with previous research by [Hurd et al., 2007]. Similar patterns are observed when examining statistics by health categorization, with healthy individuals dedicating significantly more time to home production and leisure. Figure A4 provides a visual comparison of the distribution of these categories. ATUS reports a higher proportion of zero hours in various categories. Overall, the distributions of all categories appear quite similar, particularly for home production, leisure, eating, and drinking.

[2]In both the datasets, healthy refers to excellent, very good, good health. Unhealthy refers to fair and poor health.



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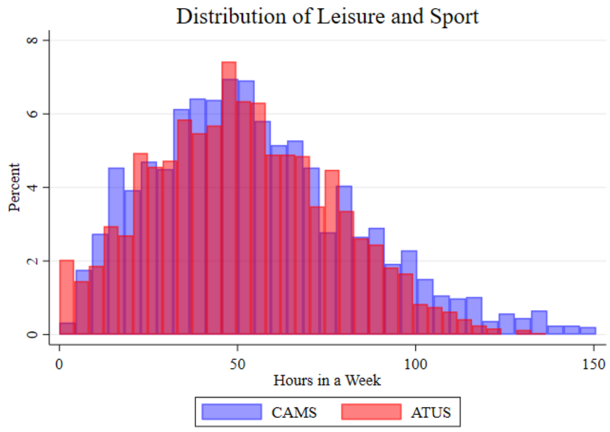

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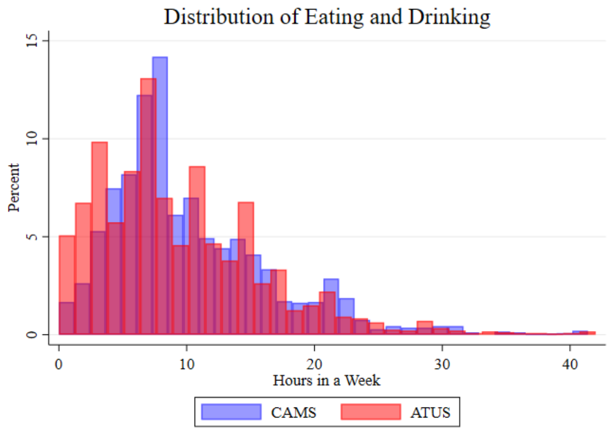

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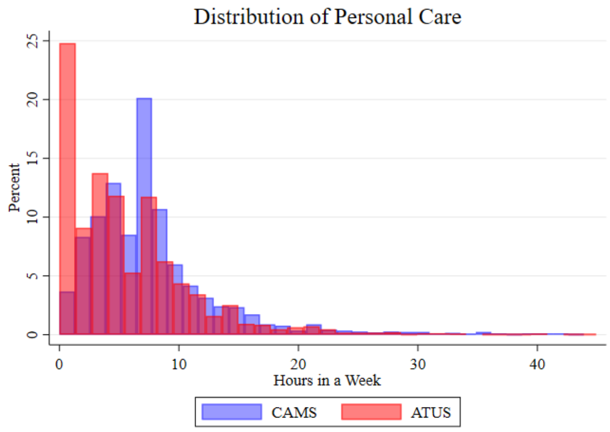

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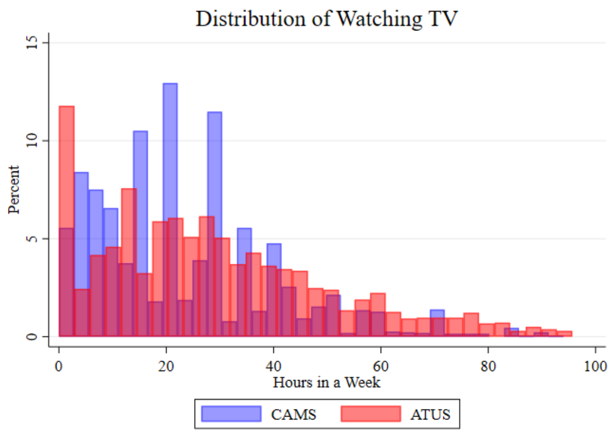

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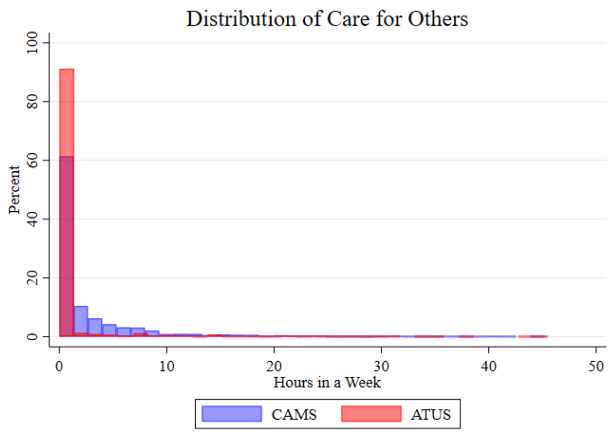


(f)

Figure A4: CAMS vs. ATUS (Distribution of Hours)

Notes: This figure compares the distribution of hours for specific time-use categories using data from the Consumption and Activities Mail Survey (CAMS) and the American Time Use Survey (ATUS). Due to limited availability of health information in the ATUS, only the 2015 wave is used. All time-use measures are converted to weekly hours for comparability.

Table A3: Comparison of CAMS with ATUS (2015)

	CAMS (N=1727)			ATUS (N=2412)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Men	Women	All	Men	Women	All
Home Production						
Healthy	19.47	25.93	23.27	18.18	23.66	21.23
Unhealthy	15.65	22.37	19.57	14.52	18.58	16.78
Total	18.52	25.06	22.36	17.36	22.52	20.24
Using Phone and Email						
Healthy	4.01	7.09	5.84	1.18	2.71	2.03
Unhealthy	3.34	6.06	4.91	0.75	1.93	1.41
Total	3.84	6.85	5.62	1.08	2.54	1.89
Watching TV						
Healthy	24.03	23.78	23.88	29.25	24.15	26.39
Unhealthy	24.49	24.01	24.21	38.11	33.06	35.32
Total	24.14	23.83	23.96	31.24	26.09	28.36
Listening/Playing Music						
Healthy	4.47	5.38	5.01	0.47	0.26	0.35
Unhealthy	4.31	3.60	3.89	1.51	0.66	1.04
Total	4.43	4.95	4.74	0.70	0.35	0.51
Voluntary and Religious Meetings						
Healthy	1.82	2.47	2.20	1.86	2.42	2.17
Unhealthy	1.78	1.56	1.65	1.25	2.15	1.76
Total	1.81	2.25	2.07	1.72	2.36	2.08
Personal Care						
Healthy	6.45	8.11	7.43	4.26	6.14	5.31
Unhealthy	8.27	8.43	8.36	3.62	7.28	5.63
Total	6.90	8.18	7.65	4.12	6.39	5.38
Leisure and Sport						
Healthy	55.14	59.72	57.84	51.52	45.77	48.31
Unhealthy	47.36	51.24	49.61	62.60	53.49	57.52
Total	53.28	57.75	55.91	54.00	47.49	50.37
Care for Others						
Healthy	2.57	3.38	3.05	0.95	1.31	1.15
Unhealthy	1.50	3.18	2.49	0.42	0.81	0.64
Total	2.31	3.33	2.92	0.83	1.20	1.04
Eating and Drinking						
Healthy	10.95	10.89	10.91	10.88	9.41	10.06
Unhealthy	9.74	10.01	9.90	9.21	8.11	8.60
Total	10.65	10.68	10.67	10.51	9.12	9.73

Notes: This table provides a comparative analysis of specific time-use categories based on the health status of individuals, utilizing data from the Consumption and Activities Mail Survey (CAMS) and the American Time Use Survey (ATUS). Due to the limited availability of health information in the ATUS data, only the 2015 wave was utilized for this comparison. To ensure consistency, all time-use measurements have been converted into weekly hours.

B Robustness Checks

B.1 Income Effect

Table A4: Impact on Medical Spending

	(1) Ln OOPMX	(2) Fract med x/income
High Blood Pressure	0.661***	0.0339*
	(0.114)	(0.0161)
Cancer	0.514***	0.0658**
	(0.125)	(0.0249)
Heart	0.339***	0.0467**
	(0.0987)	(0.0170)
Stroke	0.306*	0.0894**
	(0.138)	(0.0273)
Diabetes	0.305*	0.0363
	(0.120)	(0.0224)
Lung	0.259	0.0643*
	(0.159)	(0.0270)
Psychiatric	0.284	0.00879
	(0.165)	(0.0311)
Self-Rported Health	0.151	0.0247
	(0.0807)	(0.0144)
CESD Depression	0.114	0.0154
	(0.0912)	(0.0167)
Arthritis	0.0905	0.00346
	(0.113)	(0.0163)

Top 1 pctile of Fraction is excluded

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents the increase in medical cost and daily living limitations in the first period following a given health shock and their relative rankings in terms of severity. Two measures of medical spending are used: 1. Log of Out-of-Pocket medical spending; 2. Ratio of out-of-pocket medical spending over the sum of social security income and pension of an individual. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Coefficients represent the impact of health shocks estimated using difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. Top 1 percentile of real out-of-pocket medical costs is excluded. Standard errors in parentheses.

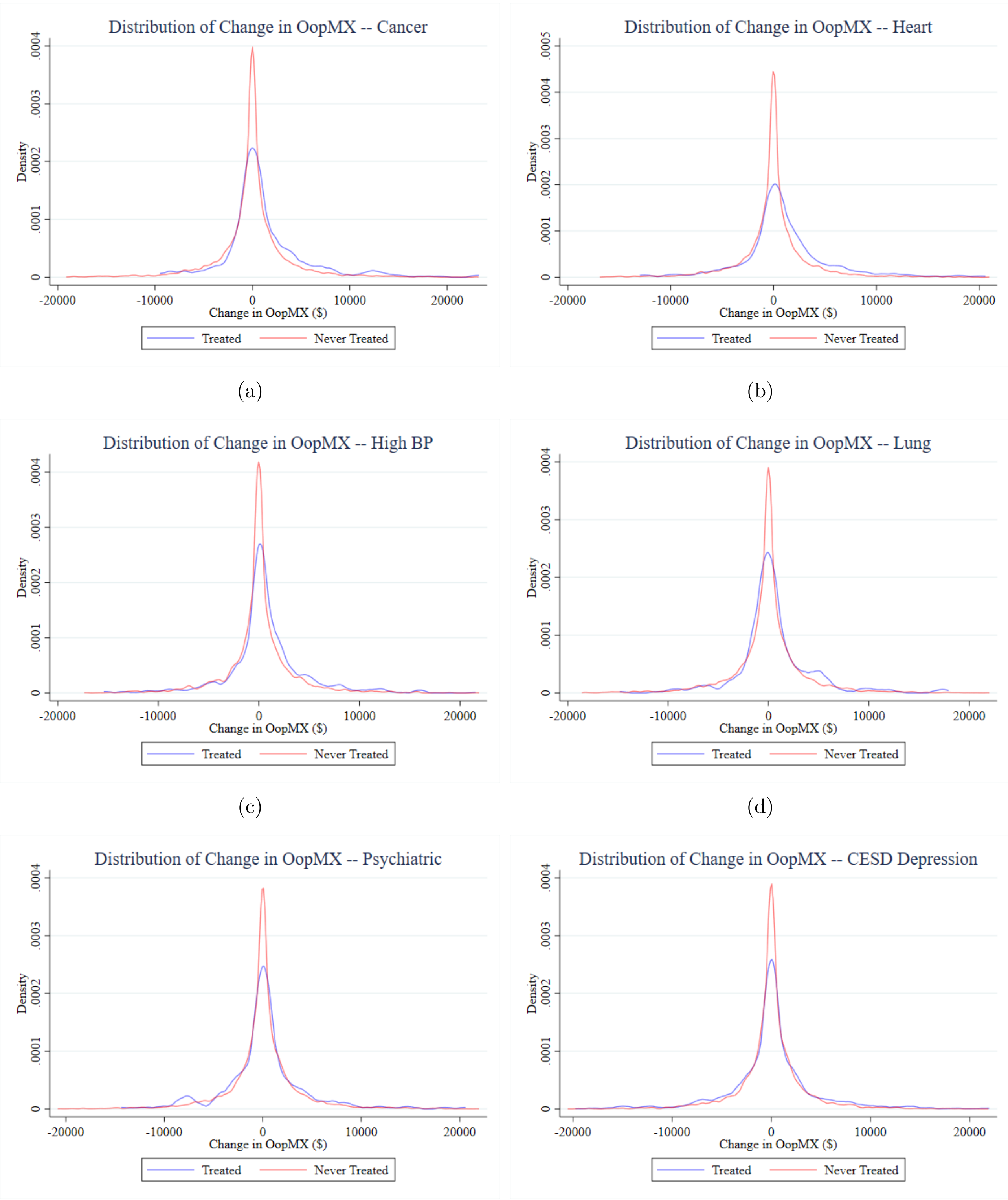
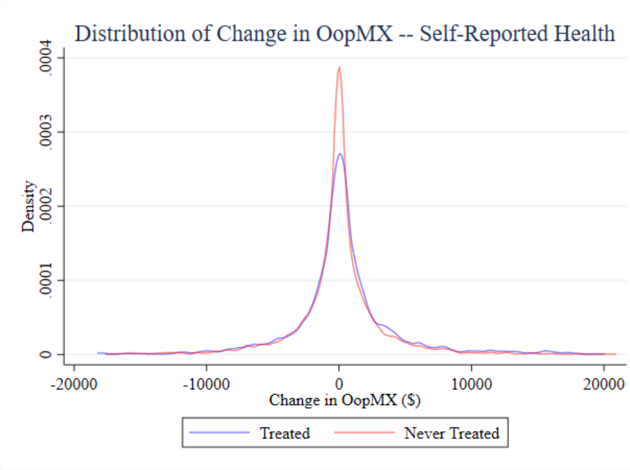
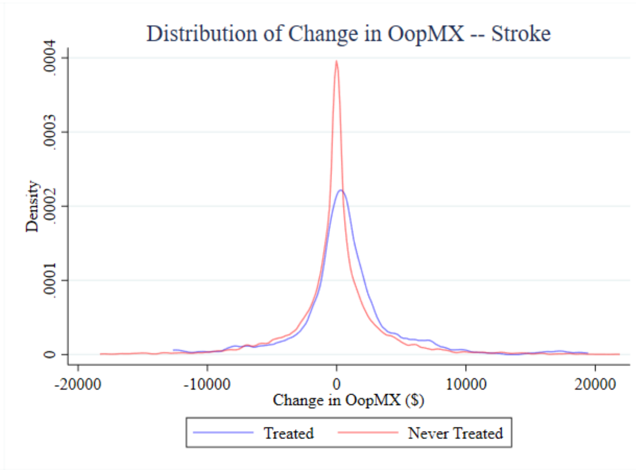


Figure A5: Distribution of Change in Out-of-Pocket Medical Spending

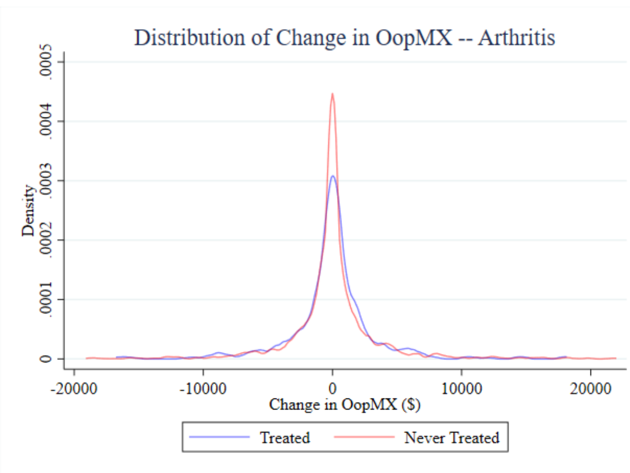
Notes: This figure presents a comparison of the distributions of changes in Out-of-Pocket (OoP) medical costs between individuals who received treatment and those who have never received treatment in response to a specific shock. For treated individuals, the distribution is based on changes in OoP spending between the period before and immediately after the shock. For untreated individuals, the distribution is based on the average change across all periods.



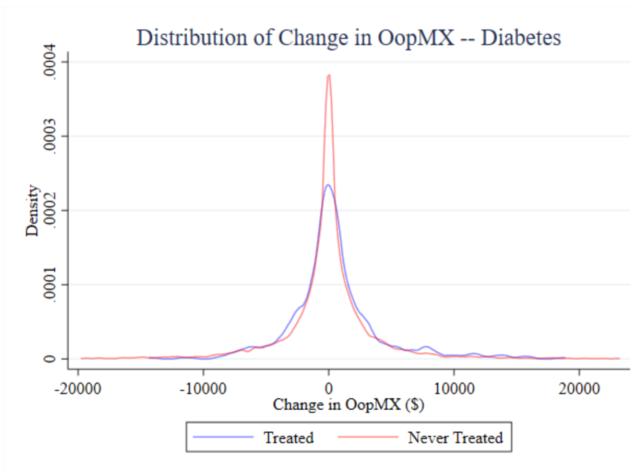
(a)



(b)



(c)



(d)

Figure A6: Distribution of Change in Out-of-Pocket Medical Spending (Contd.)

Notes: This figure presents a comparison of the distributions of changes in Out-of-Pocket (OoP) medical costs between individuals who received treatment and those who have never received treatment in response to a specific shock. The distribution for treated individuals is derived by assessing the change in OoP medical spending between the period prior to the shock and the immediate period after. Conversely, for the group of individuals who have never received treatment (referred to as "not treated" in this context), the change in OoP medical expenses is calculated as the average change observed across all periods in the sample.

Table A5: Impact on Home Production (without Daily Living Limitations)

	(1) Home Production (No ADLs)	(2) Home Production (No IADLs)
Cancer	0.27	1.08
	(0.94)	(0.87)
Heart Condition	0.63	0.23
	(0.73)	(0.77)
High Blood Pressure	-1.98**	-2.08**
	(0.81)	(0.82)
Lung Condition	-2.08	-2.13
	(1.48)	(1.38)

Standard errors in parentheses

Control Group: not yet+never treated.

Column 1 excludes individuals who ever reported ADLs greater than 0.

Column 2 excludes individuals who ever reported IADLs greater than 0

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

Notes: This table presents the results of the impact of health shocks on time spent in home production after excluding individuals who ever report any Activities of Daily Living and Instrumental ADL limitations in the observed sample. Column 1 excludes individuals who reported ADLs greater than 0. Column 2 excludes individuals with IADLs greater than 0. The coefficients are estimated using the difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. The coefficients presented reflect the impact measured in number of daily living limitations in the first period following the occurrence of the shock. Top 1 percentile of all time use is excluded from the analysis. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.2 Impairing Effect

Table A6: Impact on Home Production (Excluding Nursing Home Utilization)

	(1) Overnight Nursing Home Stay	(2) Currently in Nursing Home	(3) Enter Nursing Home (same wave as shock)
Psychiatric Condition	-4.156***	-3.253***	-3.223***
	(1.278)	(1.187)	(1.207)
CESD Depression	-0.729	-1.101*	-1.037*
	(0.605)	(0.580)	(0.586)
Self-Reported Health	-1.259**	-0.915*	-1.174**
	(0.583)	(0.544)	(0.551)

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

Notes: This table presents the results of the impact of health shocks on time spent in home production after excluding individuals who report utilizing nursing homes in the observed sample. Column 1 excludes individuals who reside in a nursing home at the time of interview (their information is reported by proxy respondents). Column 2 excludes individuals who reported an overnight stay in a nursing home in the period coinciding with the onset of a given health shock. The coefficients are estimated using the difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. The coefficients presented reflect the impact measured in hours per week in the first period following the occurrence of the shock. Top 1 percentile of all time use is excluded from the analysis. Standard errors in parentheses.

Table A7: Impact on Home Production (Adjusting for Cognition)

	(1) Home Production (Exclusion on Langa-Weir)	(2) Home Production (Exclusion on Self-Reported Memory)
Psychiatric Condition	-2.415*	-3.704***
	(1.238)	(1.255)
CESD Depression	-0.925	-1.053*
	(0.631)	(0.615)
Self-Reported Health	-1.004*	-0.872
	(0.584)	(0.551)

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

Notes: This table presents the results of the impact of health shocks on time spent in home production after excluding individuals whose cognition declines between the period before and after a given health shock. Column 1 excludes individuals whose memory state worsens based on Langa Weir cognition score. Column 2 excludes individuals whose memory state worsens based on self-reported memory score. The coefficients are estimated using the difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. The coefficients presented reflect the impact measured in hours per week in the first period following the occurrence of the shock. Top 1 percentile of all time use is excluded from the analysis. Standard errors in parentheses.

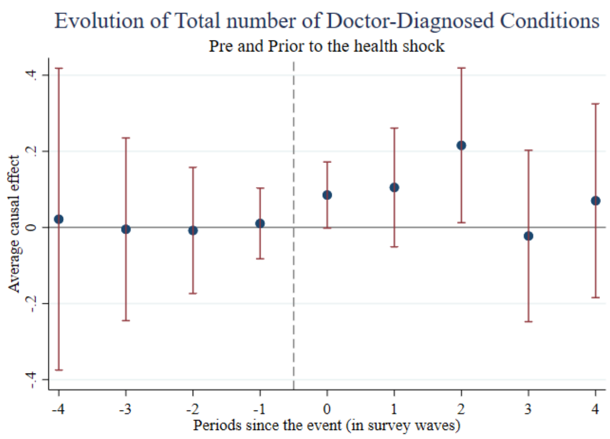
Table A8: Impact on Home Production (Adjusting for Other Health Conditions)

	(1) Home Production	(2) Home Production	(3) Home Production
Psychiatric Condition	-3.097***	-4.747***	-6.011***
	(1.161)	(1.395)	(1.686)
CESD Depression	-1.150**	0.0650	-0.0676
	(0.573)	(0.708)	(0.991)
Self-Reported Health	-1.025*	-1.125*	-0.738
	(0.540)	(0.641)	(0.857)
Other doctor-diagnosed conditions	Y	N	N
Conditions > 3 excluded	N	Y	N
Conditions > 2 excluded	N	N	Y

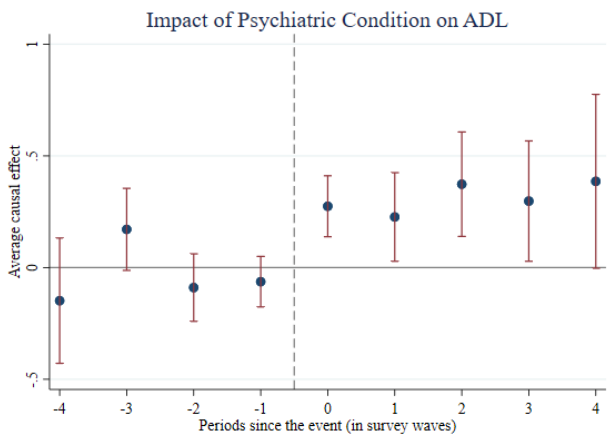
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Control Group: not yet and never treated individuals. Column 1 controls for doctor diagnosed conditions. Column 2 excludes people with more than 3 other conditions. Column 3 excludes people with more than 2 other condition.

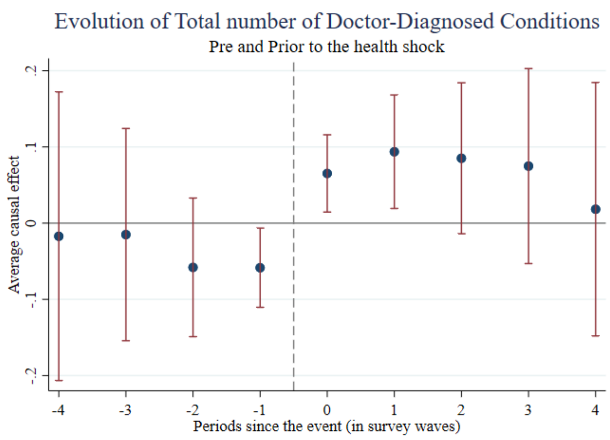
Notes: This table presents the results of the impact of health shocks on time spent in home production after controlling for the number of medically diagnosed conditions apart from the specific condition under analysis. The coefficients are estimated using the difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. The coefficients presented reflect the impact measured in hours per week in the first period following the occurrence of the shock. Top 1 percentile of all time use is excluded from the analysis. Standard errors in parentheses.



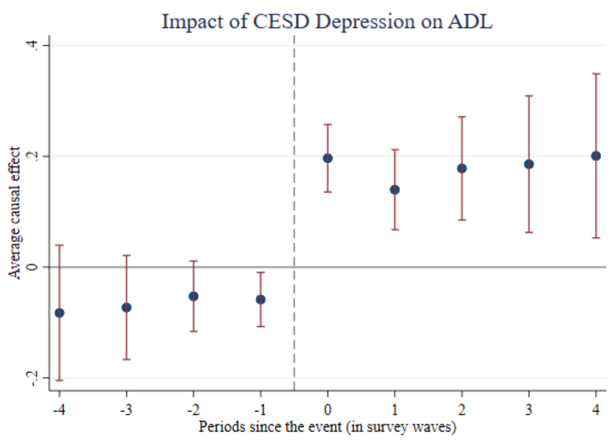
(a) Psychiatric Shock



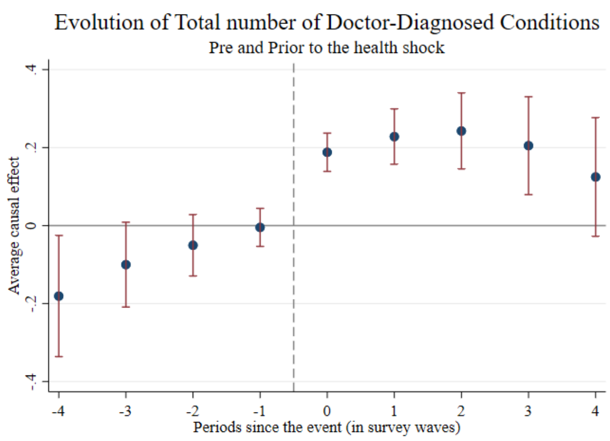
(b) Psychiatric Shock



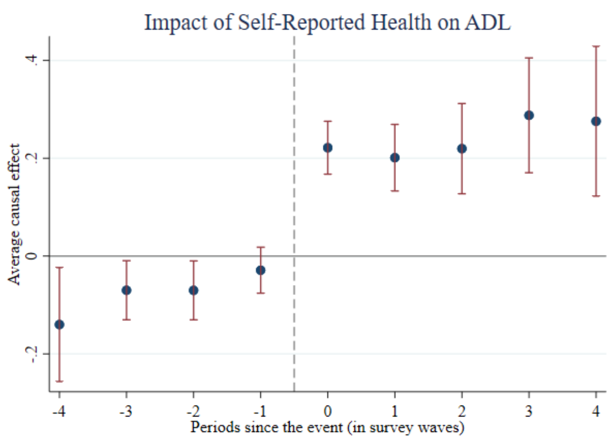
(c) CES-D Depression Shock



(d) CES-D Depression Shock



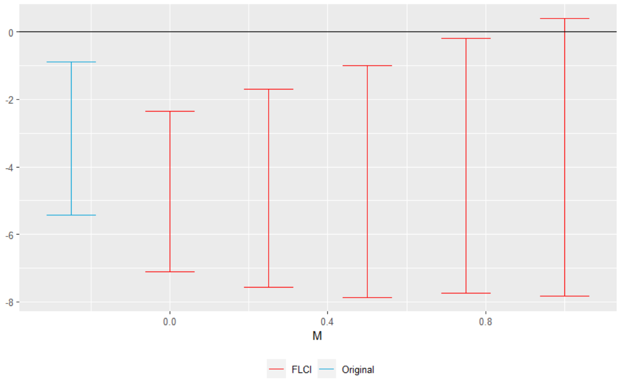
(e) Self-Reported Health Shock



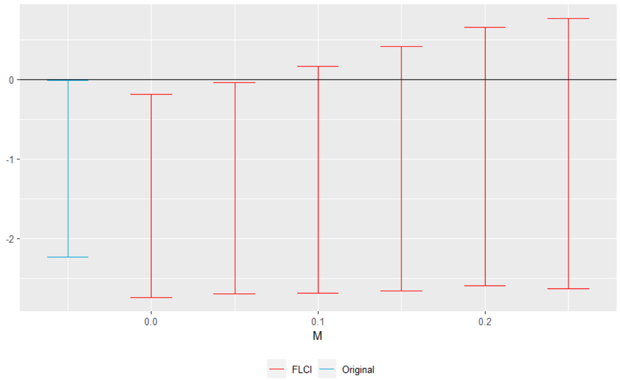
(f) Self-Reported Health Shock

Figure A7: Evolution of Doctor-Diagnosed Conditions and ADLs

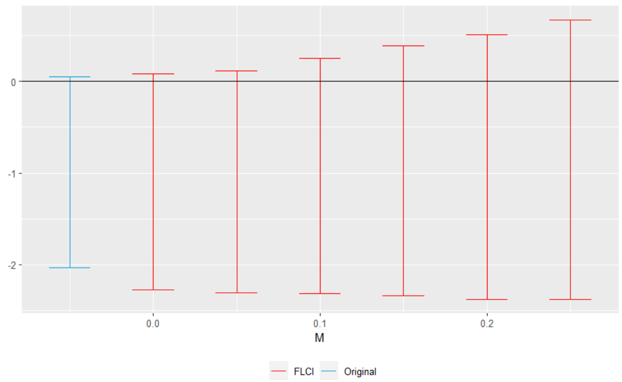
Notes: These event study graphs show the evolution of doctor-diagnosed conditions and activities of daily living limitations prior and post the shock. Each point within the figures represents the estimated effects during a specific time period relative to the treatment period, wherein period 0 signifies the initial wave observed subsequent to the initiation of the treatment. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Considering the biannual nature of the survey waves, a two-year interval exists between consecutive periods displayed on the x-axis. The vertical lines depicted denote the 95% confidence intervals.



(a) Psychiatric Shock



(b) CES-D Depression Shock

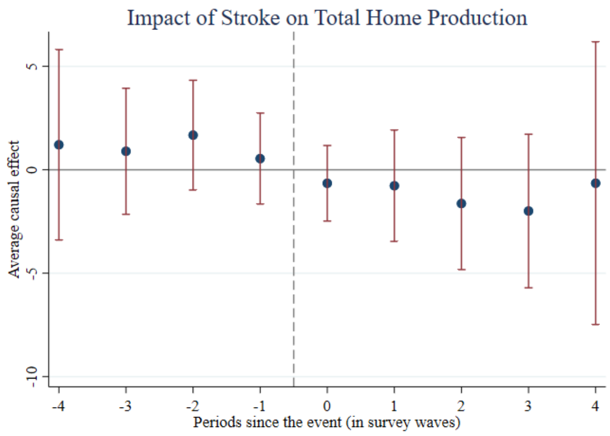


(c) Self-Reported Health

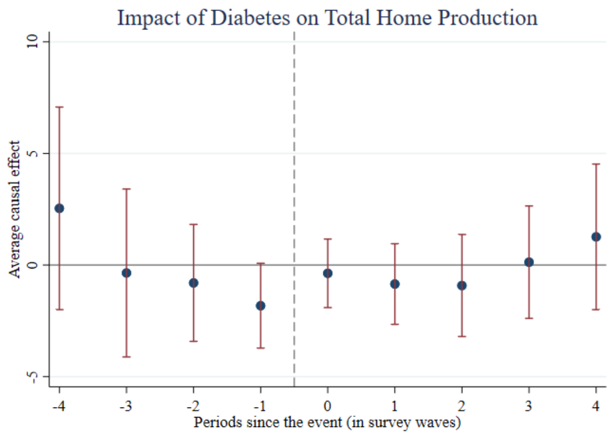
Figure A8: Effects on Home Production: Parallel Trends Test

Notes: The presented graphs examine the parallel trends assumption of the estimated effects on home production, with the aim of identifying potential violations, as outlined by [Rambachan and Roth, 2023]. In each figure, the blue bar (first bar) represents the 95% confidence interval of the primary baseline event study estimate for the initial period following the shock. Conversely, the red bars (subsequent bars) indicate the corresponding 95% confidence intervals when allowing for deviations in parallel trends of up to a specified arbitrary threshold, denoted as M. Essentially, M signifies the maximum allowable deviation in the slope of an underlying linear trend between two periods.

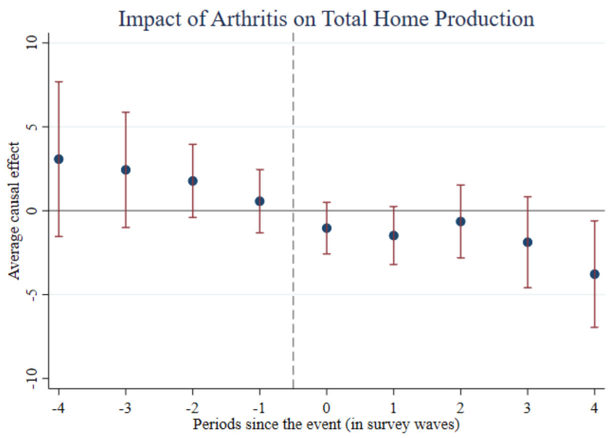
B.3 Mixed Shocks



(a) Stroke



(b) Diabetes



(c) Arthritis

Figure A9: Event Study Plots: Mixed Shocks and Total Home Production

Notes: These event study graphs present the results for many post-treatment periods, expanding the results corresponding to column 1 in Table 3. Each point within the figures represents the estimated effects during a specific time period relative to the treatment period, wherein period 0 signifies the initial wave observed subsequent to the initiation of the treatment. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Considering the biannual nature of the survey waves, a two-year interval exists between consecutive periods displayed on the x-axis. The vertical lines depicted denote the 95% confidence intervals.

B.4 Various Econometric Specifications

In this section, I show results from various alternate specification. The main results are represented by blue dot. The estimator developed by [Callaway and Sant'Anna, 2021] allows for controlling for covariates. This becomes particularly important if there may be covariate specific trends. For example, there can be age-specific trends in home production. Therefore, I extend the main specification by adding covariates such as age, polynomial of age, number of members in the household, gender, and race. The results are depicted by hollow triangle and follow the main results closely in magnitude and direction.

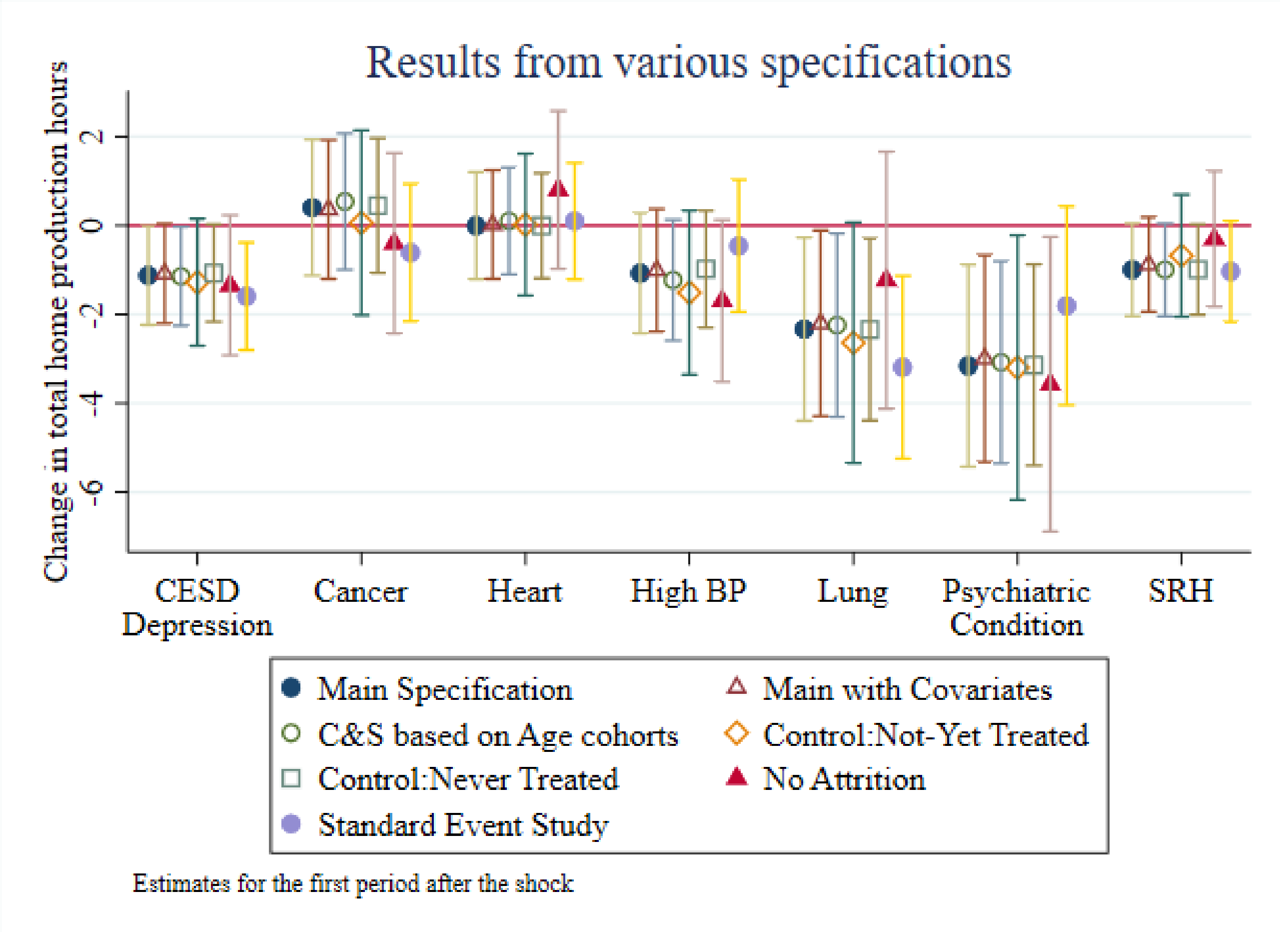


Figure A10: Alternate Specifications

Notes: This graph presents the results for various alternate specifications. Each point represents the estimated effects in the first period after the initiation of the treatment. *Main Specification* refers to the baseline specification outlined in Section 5. *Main with Covariates* pertains to the main specification, but with additional controls for age, age polynomials, household size, gender, and race. In the *C&S based on Age cohorts* approach, treatment groups are determined based on the age at which individuals first encounter the health shock, as opposed to survey waves. The *Control:Not-Yet Treated* and *Control:Never Treated* specifications solely employ the mentioned groups as controls. The *No Attrition* specification restricts the sample to individuals who remain within the sample throughout the observation period, without experiencing attrition due to mortality or non-reporting. The *Standard Event Study* is a conventional specification employing individual fixed effects, rather than the estimator devised by [Callaway and Sant'Anna, 2021]. The vertical lines depicted denote the 95% confidence intervals.

In another specification, I create treatment groups on the basis of age at which individual first faces the health shock. This is different from the main specification where treatment groups are based on the wave an individual first faces a health shock. The results for this specification are depicted by hollow circles and resemble closely with the main results. This is not the preferred specification because even though HRS is conducted biennially, some individuals may have an age gap of odd years between two waves, depending on the time of of interview. Therefore, I have to re-code ages for many individuals to avoid making treatment groups with very little observations.

In the specification denoted by hollow diamond and hollow square, I consider stricter control groups as compared to the main specifications. In the former specification, control group consists of individuals who have not been treated yet but will be treated eventually at some later stage in the sample period observed. In the latter specification, the control group consists of individuals who are not treated at all in the sample period observed. The results for both these specifications closely resemble the main results, however, the specification with not-yet treated as control groups estimates relatively bigger confidence intervals.

To limit the survival bias, in the specification denoted by solid red triangle, I limit the sample to individuals who do not leave the sample either due to death or due to non-reporting. The estimates have bigger confidence intervals compared to the main results. However, the results for self-reported health are not robust to this specification.

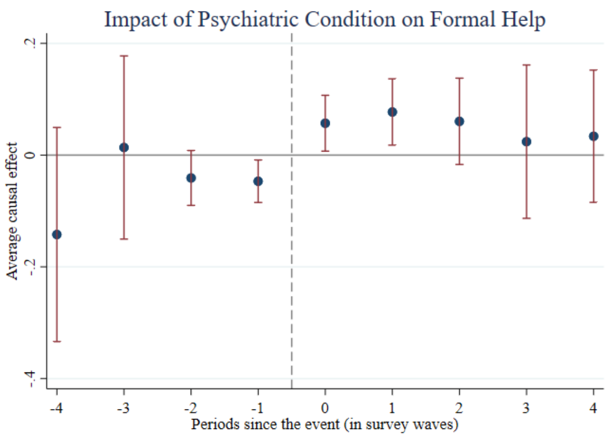
Finally, I consider a standard event study specification with individual fixed effects. Estimates are denoted by a purple dot. While results for CES-D depression and self-reported health are robust, estimates for psychiatric shock are smaller in magnitude and not significant for this specification. Overall, the results for impairing shocks are robust to the various alternative specifications used in this section.

C Alternatives to Decline in Home Production

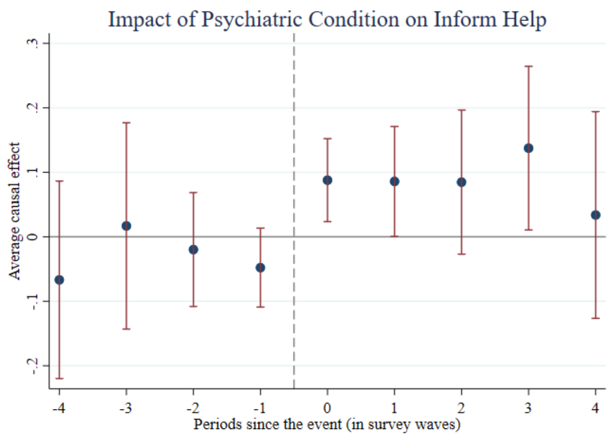
Table A9: Impact on Utilization of Help

	(1) Formal Help	(2) Inform Help	(3) Meal Prep	(4) Shopping	(5) Taking Medication	(6) Housekeeping and Yard Work	(7) Managing Money	(8) Hours of Help
Cancer	0.026*	0.052***	0.027**	0.037**	0.009	0.002	0.001	1.108***
	(0.013)	(0.018)	(0.012)	(0.016)	(0.007)	(0.025)	(0.010)	(0.406)
Pre-treatment mean	0.014	0.062	0.011	0.024	0.005	0.186	0.015	0.596
N	15465	15465	14707	14998	15133	15285	14778	15162
Heart Condition	0.003	0.029**	0.008	0.026**	-0.000	0.045**	0.013	0.168
	(0.009)	(0.015)	(0.008)	(0.011)	(0.005)	(0.022)	(0.008)	(0.339)
Pre-treatment mean	0.017	0.084	0.016	0.038	0.008	0.208	0.018	1.021
N	13634	13634	13061	13291	13316	13502	13058	13414
High Blood Pressure	0.013*	0.001	0.006	0.006	0.000	0.033*	-0.004	0.366
	(0.007)	(0.013)	(0.007)	(0.010)	(0.003)	(0.019)	(0.006)	(0.346)
Pre-treatment mean	0.006	0.052	0.008	0.024	0.002	0.148	0.013	0.479
N	7412	7412	7074	7191	7037	7343	7124	7317
Lung Condition	0.009	-0.019	0.027**	0.017	0.007	0.009	-0.018	0.492
	(0.012)	(0.023)	(0.014)	(0.021)	(0.009)	(0.033)	(0.012)	(0.711)
Pre-treatment mean	0.015	0.107	0.013	0.042	0.003	0.351	0.020	1.229
N	16453	16453	15675	15973	16094	16274	15739	16153
Psychiatric Condition	0.055**	0.098***	0.066***	0.046**	0.049***	0.058*	0.086***	1.729*
	(0.022)	(0.029)	(0.023)	(0.022)	(0.018)	(0.033)	(0.024)	(1.041)
Pre-treatment mean	0.029	0.126	0.041	0.070	0.015	0.244	0.041	2.194
N	15596	15596	14868	15149	15278	15444	14921	15333
CESD Depression	0.035***	0.063***	0.042***	0.046***	0.009	0.090***	0.049***	1.587***
	(0.008)	(0.015)	(0.010)	(0.011)	(0.006)	(0.019)	(0.010)	(0.336)
Pre-treatment mean	0.015	0.081	0.019	0.035	0.010	0.245	0.019	0.907
N	14460	14460	13814	14073	14111	14331	13795	14248
Self-Reported Health	0.023***	0.074***	0.025***	0.047***	0.008*	0.120***	0.025***	1.418***
	(0.008)	(0.013)	(0.008)	(0.010)	(0.005)	(0.018)	(0.008)	(0.325)
Pre-treatment mean	0.014	0.064	0.022	0.030	0.008	0.211	0.021	0.727
N	13794	13794	13171	13497	13485	13686	13204	13627

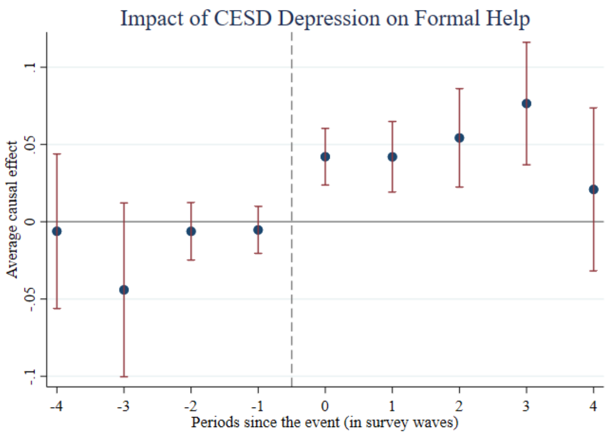
Notes: This table presents the results of the impact of health shocks on various measures of receiving help. Columns 1 to 7 represent binary variables indicating whether help of a specific nature was received. Column 8 displays the number of hours of assistance received per week. The coefficients are estimated using the difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. The coefficients presented reflect the impact measured in hours per week in the first period following the occurrence of the shock. Top 1 percentile of all time use is excluded from the analysis. Sample only includes individuals with non-missing home production information. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



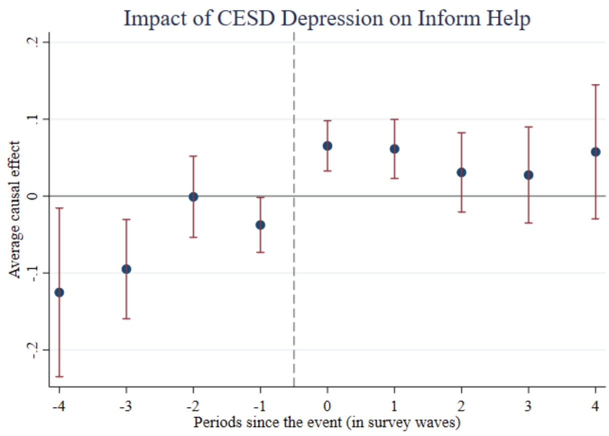
(a) Psychiatric Shock



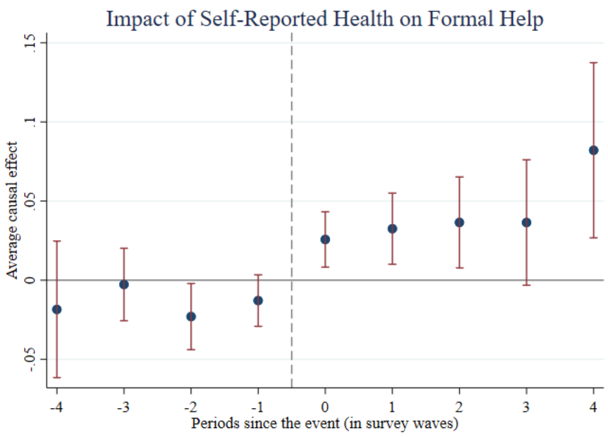
(b) Psychiatric Shock



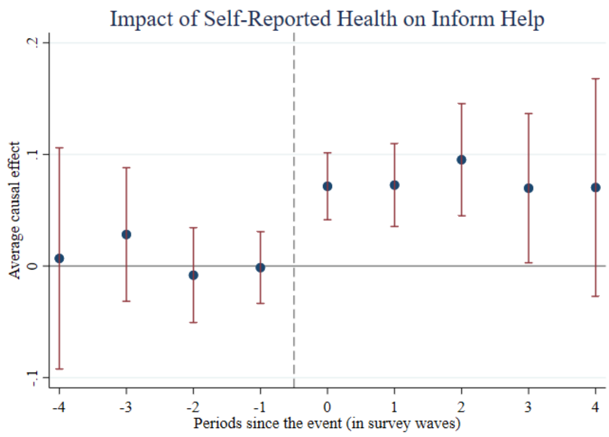
(c) CES-D Depression Shock



(d) CES-D Depression Shock



(e) Self-Reported Health Shock



(f) Self-Reported Health Shock

Figure A11: Effects on Utilization of Help: Impairing Shocks

Note: These event study graphs present the results for many post-treatment periods, expanding the results corresponding to column (1) and (2) from Table A9. Informal help refers to the help provided by family or relatives. Formal help refers to the help provided by professionals. Each point within the figures represents the estimated effects during a specific time period relative to the treatment period, wherein period 0 signifies the initial wave observed subsequent to the initiation of the treatment. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Considering the biannual nature of the survey waves, a two-year interval exists between consecutive periods displayed on the x-axis. The vertical lines depicted denote the 95% confidence intervals.

Table A10: Impact on Consumtpion Spending

	(1) House and Yard Services	(2) Dining Out	(3) Home Maintenance Services	(4) Total Spending (Excluding medical Spending)
Psychiatric				
Event Period 1	-0.33*	0.17	0.07	0.07
	(0.18)	(0.23)	(0.16)	(0.06)
Event Period 2	-0.42*	-0.18	0.22	0.12
	(0.24)	(0.28)	(0.18)	(0.11)
N	9201	9298	10528	10905
CESD Depression				
Event Period 1	0.17*	-0.22*	-0.11	-0.00
	(0.10)	(0.11)	(0.08)	(0.03)
Event Period 2	0.04	0.04	-0.19**	-0.02
	(0.12)	(0.13)	(0.10)	(0.04)
N	8301	8338	9765	10080
Self-Reported Health				
Event Period 1	0.04	0.02	0.03	-0.03
	(0.09)	(0.13)	(0.08)	(0.03)
Event Period 2	0.22**	-0.19	-0.14	-0.05
	(0.11)	(0.15)	(0.10)	(0.04)
N	8001	8076	9299	9611

Notes: This table presents the results of the impact of health shocks on various categories of household spending. The outcome variables are log of spending per month in a given category. The coefficients are estimated using the difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Sample consists of individuals with non-missing home production values. Top 1 percentile of all time use is excluded from the analysis. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

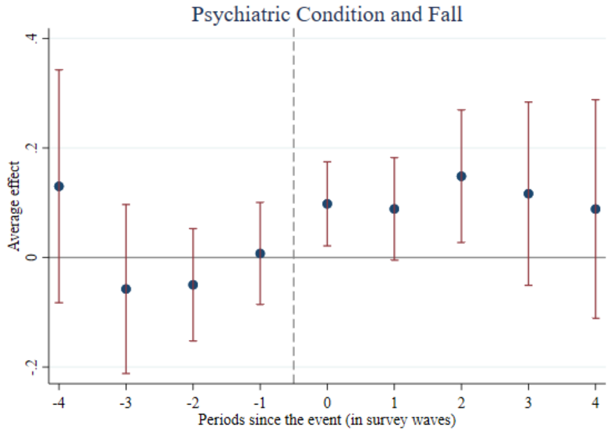
D What is a Psychiatric Shock?

While other health shocks used in this paper have a clear definition of the nature of these shocks, we don't fully understand what these "psychiatric, emotional or nervous" conditions are. I look at three events that may be coinciding with the diagnosis of a psychiatric condition and affecting the time spent in home production at the same time. These events include falling down, the death of a partner, and moving to a smaller house. I use housing wealth as a proxy for the size of housing. Figure A12 shows the results.

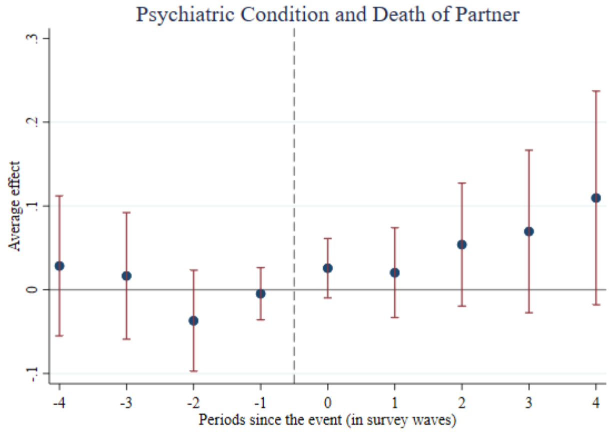
The likelihood of falling down in the same period as the diagnosis psychiatric shock increases significantly, indicating that falling down does coincide with the onset of a psychiatric condition. This is in line with the findings in the medical literature that risk of falling down is often exacerbated by mental health problems ([Bunn et al., 2014]).

Another plausible reason for a psychiatric shock can be the death of a spouse, which mechanically leads to lower home production. However, I do not find a statistically significant increase in the death of spouse in the same period when psychiatric shock is observed for the first time. Similarly, diagnosis of psychiatric shock is not significantly associated with a housing wealth decline.

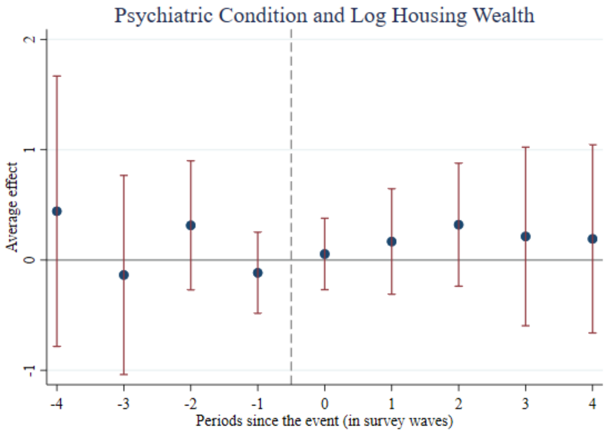
Further, to understand how closely psychiatric shock and depression are related, I also examine the evolution of CES-D-8 score, which ranges from 0-8, prior and post the diagnosis of psychiatric shock. Figure A13 shows a visible jump in the CES-D score in the same period as the diagnosis of psychiatric condition. This highlights two insights. First, there is no visible worsening in self-reported mental health prior to the diagnosis of psychiatric shocks. Second, jump in CES-D score post shock indicates that self-reported depression may be one of the factors behind diagnosis of psychiatric shock.



(a) Fall



(b) Death of Spouse



(c) Housing Wealth Decline

Figure A12: Events Coinciding with Psychiatric Shock

Note: These event study graphs present the association of the onset of psychiatric shocks with the event of falling, death of spouse, and log of housing wealth. Each point within the figures represents the estimated effects during a specific time period relative to the treatment period, wherein period 0 signifies the initial wave observed subsequent to the initiation of the treatment. The coefficients are estimated using the difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Considering the biannual nature of the survey waves, a two-year interval exists between consecutive periods displayed on the x-axis. The vertical lines depicted denote the 95% confidence intervals.

Raw CES-D-8 Score

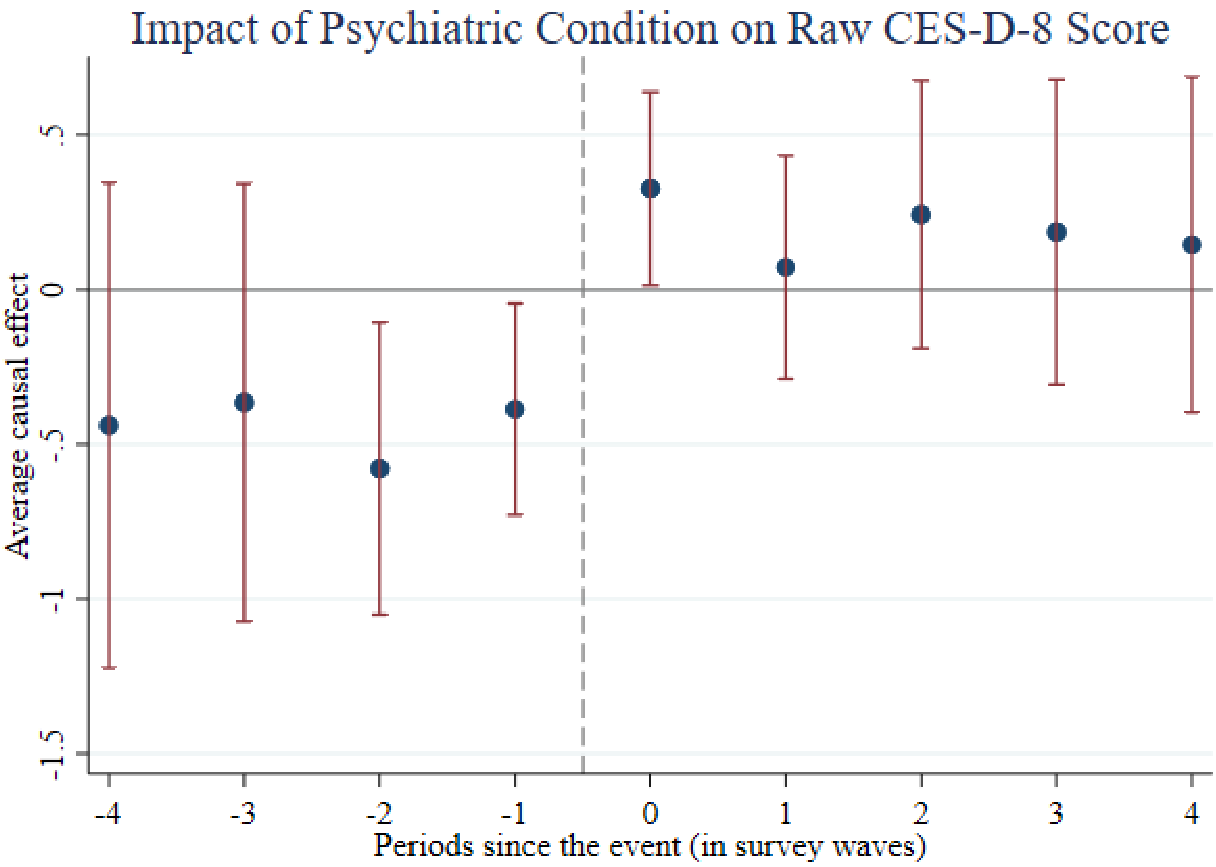


Figure A13: Psychiatric Shock and Depression

Note: These event study graphs present the association of the onset of psychiatric shocks with the onset of CES-D depression. Each point within the figures represents the estimated effects during a specific time period relative to the treatment period, wherein period 0 signifies the initial wave observed subsequent to the initiation of the treatment. The coefficients are estimated using the difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Considering the biannual nature of the survey waves, a two-year interval exists between consecutive periods displayed on the x-axis. The vertical lines depicted denote the 95% confidence intervals.

E Heterogeneity

In this section, I condition the main results on gender and marital status. Exploring this heterogeneity is important as a lot of home production tasks may be gendered, i.e commonly performed by a specific gender. Similarly, since home production is a public good in a household, the impact of health on time spent may be different for people with different marital status.

Main results conditioned on gender and marital status

Tables A11 to A13 show that decrease in men's total home production is higher as compared to women for all the shocks in group 2. However, specifically, for meal prep and housekeeping (including laundry), decline in women's hours is greater than men. This could be because of the gendered nature of the housekeeping and meal preparation activities. I also find that decline in total home production, meal prep, and housekeeping is greater and significant for married individuals as they face a health shock. This result particularly holds for psychiatric condition and CES-D depression. The converse holds for self-reported health.

Table A11: Impact on Total Home Production (by Marital Status and Gender)

	(1) All	(2) Women	(3) Men	(4) Married	(5) Single
Psychiatric	-3.129**	-2.695*	-4.319+	-3.800*	-2.381
	(1.165)	(1.356)	(2.257)	(1.553)	(1.985)
CES-D Depression	-1.164*	-1.035	-1.278	-1.411+	-0.853
	(0.558)	(0.688)	(0.959)	(0.741)	(0.883)
Self-Reported Health	-0.924+	-0.610	-1.306+	-0.527	-1.446
	(0.528)	(0.718)	(0.775)	(0.666)	(0.903)

Notes: This table presents the results of the impact of health shocks on time spent in home production for married, single, men and women sub-samples. The outcome variable is hours of home production per week. The coefficients are estimated using the difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Top 1 percentile of all time use is excluded from the analysis. Standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A12: Impact on Housekeeping and Laundry Time

	(1) All	(2) Women	(3) Men	(4) Married	(5) Single
Psychiatric	-1.419**	-1.480*	-1.029+	-1.535*	-1.006
	(0.449)	(0.575)	(0.536)	(0.602)	(0.763)
CES-D Depression	-0.163	-0.310	0.169	-0.202	-0.198
	(0.235)	(0.329)	(0.294)	(0.328)	(0.381)
Self-Reported Health	-0.319	-0.531	-0.0174	-0.0787	-0.574
	(0.218)	(0.323)	(0.270)	(0.273)	(0.388)

Notes: This table presents the results of the impact of health shocks on time spent in house cleaning and laundry for married, single, men and women sub-samples. The coefficients are estimated as hours per week using the difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Top 1 percentile of all time use is excluded from the analysis. Standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A13: Impact on Meal Preparation Time

	(1) All	(2) Women	(3) Men	(4) Married	(5) Single
Psychiatric	-0.720+	-0.689	-0.594	-0.909+	-0.351
	(0.417)	(0.526)	(0.557)	(0.527)	(0.734)
CES-D Depression	-0.510*	-0.632*	-0.219	-0.550*	-0.337
	(0.209)	(0.282)	(0.292)	(0.273)	(0.359)
Self-Reported Health	-0.542**	-0.723*	-0.302	-0.501+	-0.616*
	(0.197)	(0.287)	(0.255)	(0.259)	(0.313)

Notes: This table presents the results of the impact of health shocks on time spent in meal preparation for married, single, men and women sub-samples. The coefficients are estimated as hours per week using the difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Top 1 percentile of all time use is excluded from the analysis. Standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Impact on own home production following spouse's health shock

Table A14 and A15 show that husbands significantly increase the time spent in total home production by 2.3 hours (along with meal prep, housekeeping) when wife faces a self-reported health shock. Event study graphs for husband's total home production (in response to wife's Self-reported health shock) in figure A14 show a significant positive shift in coefficients post shock. No significant change in husband's time for wife's psychiatric and CESD depression shock. On the other hand, wives decrease their total home production (including meal prep and housekeeping) when husband faces psychiatric shock. For other shocks, her home production declines but is not statistically significant. Event study graphs in figure A14 also show that the coefficients after the shock are all negative (although not significant or weakly statistically significant), whereas coefficients before the shock are positive.

Overall it seems that men's total home production is more responsive to health shocks. His total home production decreases more when he faces the shock, and increases when his wife faces the shock (especially, self-reported health shock).

Table A14: Wife's Shock, Husband's Home Production

	(1) HP	(2) Meal Prep	(3) Housekeeping	(4) Shopping	(5) Home Maint.	(6) Yard work
Psychiatric	-0.00887	-0.189	-0.385	0.236	0.0125	-0.280
	(1.032)	(0.451)	(0.666)	(0.272)	(0.134)	(0.296)
CES-D Depression	0.156	-0.394	0.0237	0.0935	-0.0662	0.0108
	(0.780)	(0.301)	(0.431)	(0.228)	(0.0989)	(0.240)
Self-Reported Health	2.362^{*}	0.751^{*}	0.931^{**}	0.0672	0.0655	-0.263
	(0.990)	(0.364)	(0.349)	(0.257)	(0.117)	(0.241)

Notes: This table presents the results of the impact of wife's health shocks on husband's time spent in home production. The coefficients are estimated as hours per week using the difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Top 1 percentile of all time use is excluded from the analysis. Standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

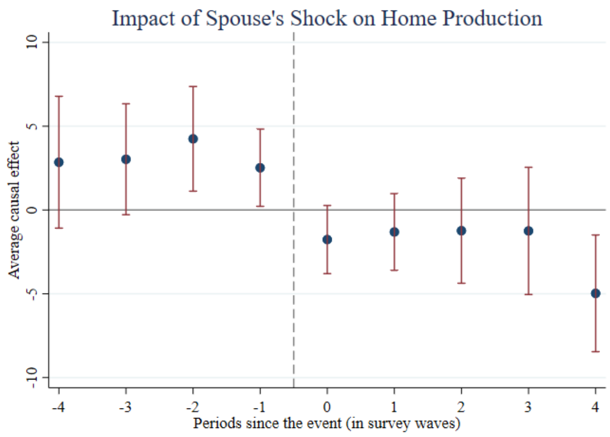
Table A15: Husband's Shock, Wife's Home Production

	(1) HP	(2) Meal Prep	(3) Housekeeping	(4) Shopping	(5) Home Maint.	(6) Yard work
Psychiatric	-1.766^{+}	-0.806^{+}	-1.042^{*}	-0.312	0.00428	0.00340
	(1.038)	(0.429)	(0.473)	(0.205)	(0.0681)	(0.164)
CES-D Depression	-1.506	-0.614	-0.835	-0.156	0.0636	0.206
	(0.970)	(0.398)	(0.514)	(0.196)	(0.0634)	(0.156)
Self-Reported Health	-1.160	0.0212	-0.674	-0.512^{*}	-0.0591	-0.171
	(0.996)	(0.390)	(0.682)	(0.231)	(0.0697)	(0.177)

Notes: This table presents the results of the impact of husband's health shocks on wife's time spent in home production. The coefficients are estimated as hours per week using the difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Top 1 percentile of all time use is excluded from the analysis. Standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Psychiatric Condition

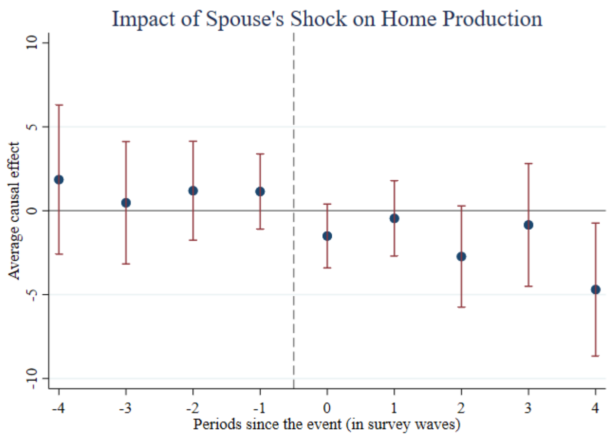
Wife's HP



Husband's HP

CES-D Depression

Wife's HP



Husband's HP

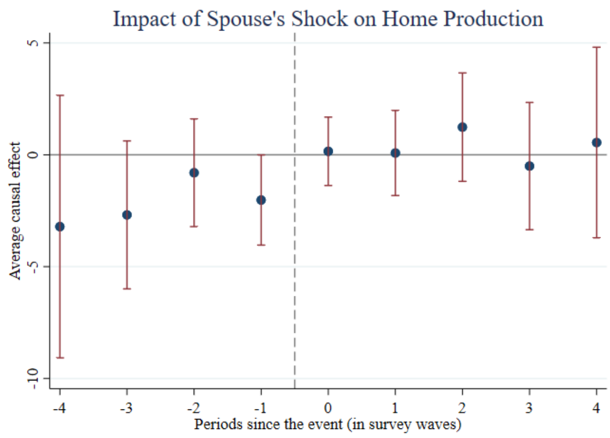
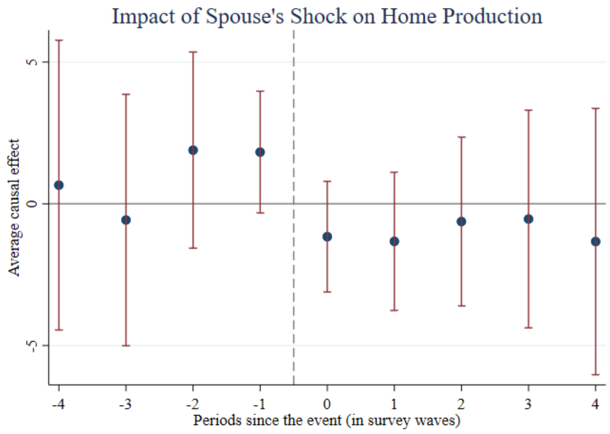


Figure A14: Impact of Spouse's Health Shocks on Own Home Production

Note: These event study graphs show the impact of spouse's health shocks on own time spent in home production. Each point within the figures represents the estimated effects during a specific time period relative to the treatment period, wherein period 0 signifies the initial wave observed subsequent to the initiation of the treatment. The coefficients are estimated using the difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Considering the biannual nature of the survey waves, a two-year interval exists between consecutive periods displayed on the x-axis. The vertical lines depicted denote the 95% confidence intervals.

Self-Reported Health

Wife's HP



Husband's HP

Figure A15: Impact of Spouse's Health Shocks on Own Home Production (Contd.)

Note: These event study graphs show the impact of spouse's health shocks on own time spent in home production. Each point within the figures represents the estimated effects during a specific time period relative to the treatment period, wherein period 0 signifies the initial wave observed subsequent to the initiation of the treatment. The coefficients are estimated using the difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Considering the biannual nature of the survey waves, a two-year interval exists between consecutive periods displayed on the x-axis. The vertical lines depicted denote the 95% confidence intervals.

F Other Categories of Time use

Table A16: Impact of Health Shocks on Other Time Use Categories

	(1) Doctor Visit	(2) Excercise	(3) Socializing	(4) Passive Leisure	(5) Sleeping	(6) Watching TV
Cancer	-0.38*	0.83*	1.73*	0.12	-0.04	-0.60
	(0.23)	(0.46)	(0.89)	(0.91)	(1.01)	(0.83)
N	11,231	15,873	14,992	15,145	16,201	16,260
Heart Condition	-0.12	-0.74**	0.05	-0.40	0.02	-0.30
	(0.20)	(0.38)	(0.71)	(0.85)	(0.83)	(0.69)
N	9,743	13,998	13,192	13,334	14,275	14,339
High Blood Pressure	-0.09	0.07	1.17	0.89	0.85	-0.55
	(0.17)	(0.44)	(0.85)	(0.88)	(0.88)	(0.68)
N	4,705	7,634	7,142	7,268	7,822	7,862
Lung Condition	-0.03	-0.30	-0.62	1.54	-1.72	0.75
	(0.25)	(0.61)	(1.09)	(1.18)	(1.31)	(1.08)
N	12,061	16,880	15,929	16,130	17,242	17,281
Psychiatric Condition	-0.28	-0.72	-1.42	-2.30*	-0.03	-3.39***
	(0.29)	(0.66)	(1.15)	(1.34)	(1.55)	(1.10)
N	11,273	16,015	15,143	15,303	16,315	16,385
CESD Depression	-0.10	-0.24	-0.53	-0.35	0.53	0.79
	(0.14)	(0.34)	(0.60)	(0.70)	(0.75)	(0.59)
N	10,053	14,804	13,960	14,100	15,141	15,163
Self-Reported Health	-0.11	0.02	0.20	0.42	-0.20	-0.65
	(0.15)	(0.31)	(0.58)	(0.67)	(0.69)	(0.55)
N	9,553	14,197	13,366	13,535	14,515	14,551
Stroke	0.20	1.26**	-0.95	-0.10	0.35	0.21
	(0.28)	(0.56)	(1.06)	(1.32)	(1.47)	(1.14)
N	12,506	17,519	16,580	16,732	17,902	17,932
Diabetes	0.17	0.68	2.33**	0.38	-0.46	-1.07
	(0.22)	(0.50)	(0.97)	(1.06)	(1.12)	(0.86)
N	10,487	15,119	14,317	14,488	15,438	15,491
Arthritis	0.25	-0.10	-1.05	-0.06	-0.12	0.94
	(0.16)	(0.47)	(0.89)	(0.97)	(0.96)	(0.72)
N	3,991	6,031	5,664	5,767	6,202	6,198

Standard errors in parentheses

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

Notes: This table presents the results of the impact of health shocks on time use categories other than home production, estimated using the difference-in-differences estimator by [Callaway and Sant'Anna, 2021]. The coefficients presented reflect the impact measured in hours per week in the first period following the occurrence of the shock. Top 1 percentile of all time use is excluded from the analysis. Control group used in this estimation comprises individuals who have not received any treatment and have never been treated within the observed sample. Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$