# The Effects of Health Shocks on Time Spent in Home Production

Suchika Chopra*

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November 3, 2022

**Abstract**

This paper examines the causal impact of health shocks on time spent in home production among retirees. On the one hand, tightened budget constraints due to the monetary costs of health shocks might induce the substitution of market expenditure with home production. On the other hand, the disutility cost of home production might restrict the time spent on home production. Using Consumption and Activities Mail Survey (CAMS) data, a supplementary study of Health and Retirement Study (HRS), I estimate the effect of being diagnosed with various health conditions as well as changes in subjective health on time spent in home production. Using the difference-in-differences estimator by Callaway and Sant'Anna (2021), I find that diagnosis of a psychiatric condition, the onset of depression, and decline in self-reported health significantly decrease time devoted to home production. The estimates imply up to a 16% decline in time spent in home production relative to the sample mean. I do not find a strong evidence that the decline in home production is being compensated by increasez in help received or in consumption spending.

*Department of Economics, University of Georgia. Email: Suchika.Chopra@uga.edu. I am grateful to Svetlana Pashchenko, Meghan Skira, Martin Gervais, Eli Sellinger-Liebman, and Brantly Callaway for their valuable comments. Special thanks to the attendees of Macro Reading Group, UGA Economics Seminars, CSWEP 2022 workshop, and National Tax Association conference for their helpful feedback. All errors are my own.

# 1 Introduction

People spend around 12% of their non-sleeping time in home production, with even higher number for retirees, 17%.[1] [2] In monetary terms, buying these services is equivalent to 26% of median retirement income.[3] An important feature of home production is that it directly affects effective consumption of people, while at the same time, requiring effort has two implications. On the one hand, people can use home production to protect consumption against income changes, but 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 consequence of health shocks for home production. My focus is on retired people as this group spends more time in home production compared to working-age people, and at the same time, is more likely to experience health shocks.

To be more specific, I focus on the following two effects that health shocks can trigger. First, health shocks increase out-of-pocket medical spending (see, for example, Dobkin, Finkelstein, Kluender, and Notowidigdo, 2018; Poterba, Venti, and Wise, 2017; Cheng, Li, and Vaithianathan, 2018). This tightens budget constraints of people and may lead them to shift their consumption away from market-purchased goods and towards home produced goods, that are cheaper but require time. I will refer to this mechanism as "income effect". Second, health shocks may lead to increased difficulty of performing physical activity, which may reduce time spent in home production. I will refer to this mechanism as "impairing effect".

Understanding the importance of income and impairing effects has important policy implications. A common approach to measuring the negative consequences of health shocks is to look at its monetary effects, i.e., the decline in income and increase in medical spending (Dobkin, Finkelstein, Kluender, and Notowidigdo, 2018). However, taking home production into account can change our conclusions based on the monetary calculations alone. On the one hand, if income effect is imprtant, home production partially insures against health risks, mitigating the losses measured in monetary terms. On the other hand, if impairing effect is important, health shocks are more damaging than suggested by only monetary measures. In the latter case, additional considerations should be given to policies that provide non-pecuniary support to unhealthy people, such home-and-community based care designed to substitute home production.

To understand the extent of these effects on the time use responses of retired individuals aged 65-85, I use data from the longitudinal Health and Retirement Study (HRS), including time use data from the supplemental Consumption and Activities Mail Survey (CAMS) data. I focus on both objective as well as subjective measures of health shocks. Objective measures include doctor-diagnosed conditions such as psychiatric problems, heart attack, cancer, high blood pressure, and lung conditions. Subjective measures include self-reported health and a

[1] American Time Use Survey (ATUS) Data

[2] Home production includes activities such as meal preparation, house cleaning, laundry, shopping, yard work, etc.

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

measure of depression based on the Center for Epidemiologic Studies Depression (CES-D) scale.

To understand the importance of income and impairing effects, I use a two steps strategy. First, I divide different health shocks into three groups. Group 1 includes health shocks that are costly but are less physically impairing. I refer to these shocks as "costly shocks". Group 2 includes shocks that are not costly but result in high physical impairment. I refer to these shocks as "impairing shocks". I measure the costliness of the shocks by the increase in out-of-pocket medical spending, and the extent of physical impairment – by the increase in limitations in activities in daily living (ADL)[4] As not all health shocks can be classified into this mutually exclusive categories, I also examine the effects of a third group of shocks – mixed shocks, i,e., the one that have similar effects on both ADL and medical spending.[5] In the second step, I exploit within-person variation in health and implement the modified difference-in-differences (DiD) estimator of Callaway and Sant'Anna (2021) to identify the causal response of home production time to these health shocks. If there is income effect in response to health deterioration, we are more likely to observe it in response to costly shocks, while the impairing effects are more likely to be observed after impairing shocks.

My analysis yields several findings. First, I find strong evidence for impairing effect as impairing shocks significantly decrease total home production time. The impact can be as high as 16% of the average home production time in the immediate period after the shock. I find that these effects are concentrated in housekeeping tasks and time spent on meal preparation. A decrease in time spent on housekeeping and meal preparation can be as high as 22% and 12% of the average time spent on the respective tasks. Additionally, the impact persists for CES-D depression and self-reported health shocks in the long run. The effects of psychiatric shock increase in the subsequent periods before dissipating in the long run.

I perform several robustness checks to test the sensitivity of these results. First, given the possibility of a decline in cognition upon a health shock, I examine whether the drop in home production is a mechanical function of a deteriorating memory. Second, to ensure that the impact on home production is not driven predominantly by severely debilitated individuals, I exclude individuals who reside in a nursing home at the time of the interview or report an overnight nursing home stay. Third, I address and inspect the concern that the impact of a health shock in the baseline results could reflect not the plain effect of one shock but a marginal effect of an additional shock. Fourth, I present results with various alternate econometric specifications, such as considering different control groups along with the standard event study framework. The result that home production decreases followed by an impairing shock is robust to all the tests.

In my second set of results, I do not find strong evidence to support that costly shocks, consisting of cancer, heart condition, hypertension, and lung condition, display income effect (increase in home production). Cancer increases home production time by 0.4 hours in the first period after the diagnosis. This represents a small and statistically insignificant 2% increase

[4] As discussed later, costly shocks include cancer, heart condition, chronic lung condition, high blood pressure. Impairing shocks include psychiatric condition, depression measured by CES-D scale, self-reported health.

[5] Mixed shocks include stroke, diabetes, and arthritis

relative to the average home production time. The impact of a heart condition on home production time is insignificant. I find negative impact of hypertension and lung condition on home production time. Costly shocks do not increase home production in the long run either. All in all, I do not find evidence that home production plays an essential role in insuring individuals against the monetary costs of a health shock. Similarly, I do not find evidence that mixed shocks significantly impact home production.

As a final part of my analysis, I examine how individuals facing impairing shocks adjust to the decline in home production. I estimate whether there are changes in the receipt of formal help, informal help, and spending on consumption. I find that the type and generosity of support differ across health shocks. The likelihood of utilizing formal and informal help is significantly higher for individuals who face impairing shocks. My estimates suggest that the impact of impairing shocks on the utilization of help is twice that of costly shocks. Much of the impact is concentrated on help received for housekeeping and yard work tasks. However, the increase in help does not seem to offset the decrease in home production time. This is also reflected by the lack of increase in home production time in response to the spouse's health shock. I find that while husbands increase their time spent in home production when their wives face a shock to self-reported health, this does not hold when she faces other shocks. Similarly, wives' home production does not increase when their husbands face any health shocks.

I do not find compelling evidence for increase in consumption spending. Upon examining consumption spending categories corresponding to the home production tasks, only self-reported health shocks induce increased spending on purchasing housekeeping and yard services.

My paper relates to three strands of literature. First is the literature studying the effects of health shocks on economic outcomes. Several studies have documented the impact of health shocks on own labor market outcomes (Blundell, Britton, Dias, and French, 2020; Jeon and Pohl, 2017; Smith, 1999), spousal labor supply (Anand, Dague, and Wagner, 2021; Lee, 2019), labor earnings (Prados, 2012), consumption (Blundell, Borella, Commault, and De Nardi, 2020; Dalton and LaFave, 2017), out-of-pocket medical expenditure, and increased probability of bankruptcy (Dobkin, Finkelstein, Kluender, and Notowidigdo, 2018). The findings of these studies are that bad health shocks have significant and adverse effects on important economic outcomes. For example, De Nardi, Pashchenko, and Porapakkarm (2022) quantify the lifetime cost of bad health accrued by out-of-pocket medical spending and income losses to about \$1,500 per year. Compared to these papers, my work finds evidence that health affects another important yet understudied outcome – the time spent in home production activities.

The second strand of literature studies the role of home production in peoples' lives. Several papers have explored the role of home production in mitigating the economic consequences of income changes. Aguiar and Hurst (2005) show that a drop in food expenditure after retirement is accompanied by increased time spent shopping for and preparing meals to keep consumption stable. The role of home production is not only limited to attenuating the consequences of anticipated income changes but also unanticipated income shocks such as unemployment (Burda and Hamermesh, 2010; Guler and Taskin, 2013) Additionally, the literature has also

documented that home production may not be able to mitigate the consequences of some economic shocks fully. Been, Rohwedder, and Hurd (2020) use the Great Recession to find that the housing wealth shock decreased consumption spending in a sizeable way, but only 11% of total consumption spending was replaceble by the corresponding home production tasks. My paper contributes to this literature by testing the role of home production as a coping mechanism in mitigating monetary consequences of a health shock. The detailed health information in the HRS enables me to categorize various health shocks into two groups, allowing me to identify and test the income effect and the impairing effect.

The third strand of literature I relate to studies the relationship between health and home production, and the overall findings are ambiguous. Focussing on the association between health and time use, Podor and Halliday (2012) develop a model where health affects decisions regarding time spent in market and non-market activities through productivity. Using the American Time Use Survey data, they find that healthier people work more at home and in the market, but at the cost of leisure time. Gimenez-Nadal and Ortega-Lapiedra (2013) and Gimenez-Nadal and Molina (2015) instead find a negative association. These studies use time use survey data from various European countries and find that better 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 unique to the US. However, this may not be the case, as a few other studies using European data find mixed evidence – extreme deterioration in self-perceived health decreases home production time, but mild deterioration increases it (Leopold and Schulz, 2020; Ozturk and Kose, 2019). All these papers study working-age population. Focussing on retired couples, Leopold and Schulz (2020) use German Socio-Economic Panel data to find mixed evidence, where home production declines only for serious deterioration in self-reported health.

The results of all the aforementioned studies are based on self-reported health. This is because most of these studies utilize cross-section time-use surveys.[6] These datasets offer very limited health information – only self-reported health information, in some waves. My work contributes to this literature in two ways. First, while all the studies mentioned above are descriptive in nature, I use panel data and exploit variation within individuals and across time to understand the causal impact on home production. Secondly, I complement these studies by using detailed health information in HRS on subjective and objective health measures to construct potentially exogenous health shocks. My results show important heterogeneity of effects by health condition.

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

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

# 2 Simple Model

In this section, I construct a simple static model to illustrate the two mechanisms I study: impairing effect and income effect.

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 (for example, processed food) while home-produced goods require some time input but are also less costly (for example, home cooked food). These two types of consumption goods can be partially substituted[7]. Individuals derive disutility $\phi$ from hours spent in home production ($h$).

Home produced good is in turn a function of market input, $d$ required for home produced good and home production time. Individuals spend out of their non-labor income $I$ (eg., retirement income). Apart from spending on consumption, individuals also incur out-of-pocket medical expenditure, $X$. The disutility from home production time ($\phi$) and out-of-pocket medical expenditure depend on the state of health condition, $s$, where $s \in \{healthy, unhealthy\}$. Unhealthy state implies higher disutility, $\phi$, and higher out-of-pocket medical cost, $X$. Individual maximization problem can be stated as follows::

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

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

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

Consider a possible effect of health shock. An adverse health shock increases disutility associated with home production tasks which can decrease time spent in home production. Home production can be pinned down by equation (5) which shows that higher $\phi$ can decrease $h$. Another possible effect of health shock can be though medical expenses. An adverse health shock implies higher out-of-pocket medical cost ($X$) thereby decreasing the available resources in Equation (4). Tightening of budget constraint can induce a substutution from $c_m$ to $c_h$ which can therefore increase $h$. Given this theoretical ambiguity, the impact of health on home production is, eventually, an empirical question.

[7]Becker (1965) predicts an elasticity of substitution between market spending and home production as -1, in other words, full substitution. However papers such as Been, Rohwedder, and Hurst (2020) argue for an existence of partial substitutability.

# 3 Data

The data comes from the Health and Retirement Study (HRS), a nationally representative longitudinal survey of the US population over the age of 50 and their spouses. It conducts interviews with about 20,000 individuals every two years. In addition, the HRS conducts supplementary studies to collect information on several other specific topics. The time use and expenditure data I use in this paper are collected as a part of a supplementary study, the Consumption and Activities Mail Survey (CAMS). I merge information from the HRS core interviews and the CAMS, which is administered to a subset of HRS respondents.

*A. Health and Retirement Study* – The HRS collects information on labor force participation, income, household wealth, and social well-being, along with information on health, and health spending, including out-of-pocket (OoP) medical expenditure.[8] The data on health conditions are described in detail below. HRS collates spending information for the following medical cost categories: hospitalization, nursing home, clinic visits, dental care, outpatient surgery, prescription drugs, home health care, and community care. The recall period for OoP medical expenditure is last two years. Detailed information on functional limitations such as difficulty in activities of daily living (ADLs) and instrumental ADLs is also gathered.[9] I use these functional limitations to measure impairement. HRS also collects comprehensive information on cognition and formal and informal help utilization.

*B. 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. Both HRS and CAMS are biennial. The CAMS is conducted in the HRS off-years, but the information mostly overlaps because health questions refer to the last two years, whereas time use refers to the last week or month, and consumption spending refers to the last month or past year. The variables in CAMS are merged to the preceding HRS wave, for example, CAMS 2001 to HRS 2000. Around 4666 individuals completed CAMS in 2019. Item response rates related to more than 30 time-use categories questions in CAMS are very high. Collectively among all waves, figure A5 shows that 71% have 0 missing item response, 17% have only 1 item missing, and only 6% have two items missing.[10] To further assess the data quality, in Appendix A.2 , I compare the summary statistics and distribution of various categories of time-use in CAMS with the American-Time Use Study (ATUS). ATUS is collected by the Bureau of Labor Statistics (BLS) and is the only survey that collects comprehensive data on time-use and is representative of the US population. Overall the summary statistics and distribution of hours turn out to be very close in CAMS and ATUS.

[8] French, Jones, and McCauley (2017) find that the HRS data are of high quality.

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

[10] Author's calculations.

## 3.1 Time-Use

Respondents were asked about 31 time-use categories in wave 1 (the year 2001). More categories were added in the subsequent waves. I use time-use activities that are available in all the waves. For most categories, respondents are asked how many hours they spent on this task "last week". For less frequent categories, respondents are asked about hours spent "last month". I convert the variables with monthly frequency into weekly by dividing the response by 4.3 (number of weeks in a month). CAMS asks about time spent on various home production tasks. Following the definition of home production used by Been, Rohwedder, and Hurd (2020) and Aguiar, Hurst, and Karabarbounis (2012)[11], time spent in home production is the sum of the following time use activities:

- House Cleaning
- Washing, ironing, or mending clothes
- 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, this information is not collected in the first six waves. Therefore, I do not include them in my definition of home production.

On average, people spend more than 20 hours per week on home production, which is about 20% of total non-sleeping hours. Appendix A discusses further the summary statistics and distribution of home production hours, various tasks under home production, and total hours in detail.

## 3.2 Health Indicators

The HRS gathers information on a set of doctor-diagnosed chronic health problems, including cancer, heart disease, stroke, diabetes, lung disease, hypertension, arthritis, and major psychiatric problems.[12] Psychiatric condition includes emotional or nervous problems. In Appendix D, I test whether psychiatric condition is related to death of a spouse, falling, and wealth

[11] Been, Rohwedder, and Hurd (2020) also use CAMS to define home production. I differ slightly from them as they include information on time spent on maintaining vehicles in home production. However, this information is not collected in the first wave of CAMS; therefore, I exclude it.

[12] 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.

shock. 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 meausres, comprehensive data on self-reported health and self-reported mental health are also collected. HRS collates information on several indicators to derive a mental health index using a score on the Center for Epidemiologic 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 screen. Additionally, a five-point scale is used to measure self-reported health – "excellent, very good, good, fair, and poor". I group together the first three responses as good health and the latter two as bad health.

## 3.3 Sample Selection

My merged sample covers the years 2000 to 2019 and individuals who responded to both CAMS and HRS. My analysis focuses on retired elderly aged 65 to 85. To obtain a cleaner sample of retirees, for whom the impact on time use that operate via changes in labor supply and earnings are non-salient, I exclude individual-year observations of the elderly who earn more than $3,000 per annum in labor earnings, following De Nardi, French, and Jones (2010).[13] I further restrict my sample to the individuals observed for at least two consecutive waves. This brings the sample down to 19,797 individual-year observations. All financial variables are converted into real variables using CPI with 2015 as the base year.

To focus on health shocks, I restrict the sample to individuals with a new diagnosis by excluding those who enter the sample with a pre-existing condition. For example, to understand the impact of cancer, I exclude people who enter the sample with a pre-existing cancer diagnosis. Then I identify the survey wave in which the individual first reports having being diagnosed with a given condition over the last two years. A person is considered to have undergone a particular doctor-diagnosed health shock if they report getting diagnosed with a given condition after not being diagnosed in the previous wave. Subjective health shocks are also defined likewise. A person is considered to face a depression shock if their CES-D score is $\geq 3$ in the current wave but less than 3 in the previous wave. Similarly, a person faces a self-reported health shock when they report bad health in the current wave after reporting good health in the previous wave. After imposing all the sample restrictions, the individual-year observations in treatment groups range between 1,367 and 5,153, depending on the type of shock. The never-treated sample ranges between 4,800 and 16,292 individual-year observations.

Table 1 presents some basic summary statistics. The average age in the sample is 74, with 60% being women. Median number of doctor diagnosed conditions is 2, with 0 ADLs and IADLs. Additionally, only 6% of the sample has missing value for atleast one task under home

[13] I include their individual-year observations once their labor earnings turn to 0 or less than $3,000 per annum and does not go over $3,000 again for the remaining sample period observed.

production. Noticeably, only 9% of the entire sample is covered by Medicaid and 15% by long-term care insurance.

Table 4 and Table 5 shows differences in the characteristics of the treated and never-treated groups for the two subjective and 8 objective health shocks. There is no noticeable age difference between the treated and never treated samples. Individuals in the treated samples have more ADLs and IADLs and are more likely to have relatively poor cognition except for cancer and arthritis. Not surprisingly, treated samples are more likely to be hospitalized, stay overnight in a nursing home, and have higher out-of-pocket medical expenditures. The most noticeable difference is in the utilization of help. On the one hand, the treated and never-treated samples for cancer, heart, hypertension, and lung do not differ much in the utilization of formal help, informal help, and hours of help received. On the other hand, the utilization of help is strikingly higher for the treated samples under psychiatric shock, CES-D depression, and self-reported health. In the Table A2, Appendix A, I show the correlation between various health conditions.

### 3.4 Preliminary Analysis

I start by exploring the links between current health status and time spent in home production in cross-section. Using ordinary least square (OLS), I regress the weekly time spent in home production on a health indicator such as a given doctor-diagnosed disease or indicator for depression as obtained from the CES-D score or an indicator of self-reported health. Each regression controls for age, polynomial of age, gender, marital status, number of members in the household, race, education, and year dummies. Standard errors are clustered at individual level.

Figure 1 displays the results with 95% confidence intervals. It documents that fact that, on average, people with worse health status spend less time in home production. However, the magnitude of this difference varies by the type of health condition and ranges from 0 to 24% of the average home production time in a week. The highest difference of 4 hours is observed in the case individuals with and without stroke. A significant difference is observed for all other health conditions, except for cancer and arthritis, for which the difference in home production time is not significant. This indicates that healthy and unhealthy individuals engage differently in home production.

## 4 Empirical Methodology

I am interested in the causal effect of health shocks on home production time. I leverage the fact that different individuals face health shocks at different times. In this case, the usual approach is to estimate Ordinary Least Square (OLS) regression with dynamic two-way fixed effects (TWFE) event study model:

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

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 | |

Note: ADLs and IADLs range from 0 to 5. Doctor 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. Ratio of medical cost to income is calculated by taking fraction of out-of-pocket medical spending over total retirement income.

where $y_{it}$ is the time spent in home production for individual $i$ who faces a health shock in year $t$. $\beta_i$ and $\gamma_t$ are the coefficients on individual fixed effects and calendar time fixed effects, respectively. $X_{it}$ represents a vector a potential control variables and $\mu_r$ are coefficients on indicators of time periods relative to the onset of the shock.

However, recent econometric research casts doubt on the validity of the causal interpretation of TWFE DiD estimator when it is applied to settings with staggered timing of treatment. This is due to the presence of heterogeneity in treatment effects within units over time or between different treated groups at different times (Borusyak and Jaravel, 2018; de Chaisemartin and D'Haultfoeuille 2020; and Goodman-Bacon, 2021; Sun and Abraham, 2021). The latter case creates "forbidden comparisons" – when earlier treated units are treated as control groups for the later treated units. This may give biased estimates of the effects.

The effect of a health shock on home production is potentially heterogeneous across individuals hit with the shock in different waves. Individuals who face a health shock at a later period tend to be mechanically older. Suppose we assume that, to some extent, the effect of health on home production is determined by out-of-pocket medical cost and, therefore, the generosity of health insurance, which may increase as individuals age and become eligible for various healthcare schemes. Then, if the impact of a health shock varies over time, the estimate of $\mu_r$ can be biased due to "forbidden comparisons". For example, for individuals just hit with a health shock, the home production may not increase much (perhaps because the income channel is

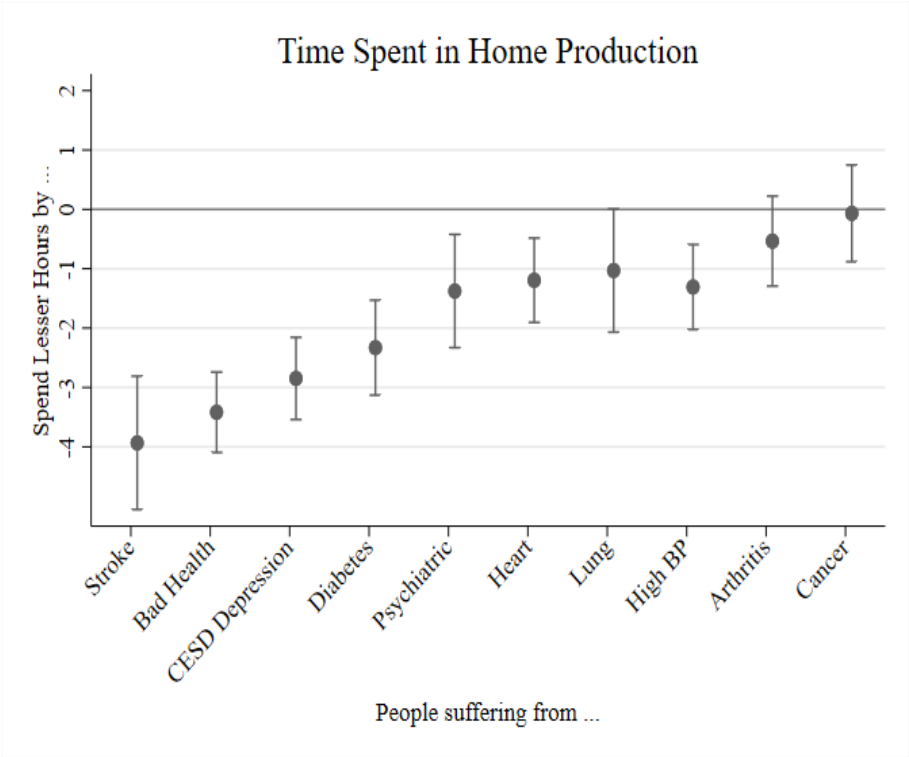



Figure 1: Home production by current health status

Note: Estimates with 95% confidence intervals displayed after controlling for age, age polynomial, gender, marital status, number of household members, race, education, time fixed-effects.

too weak), while the control (earlier treated) group may increase home production (perhaps because of lack of insurance against increased medical cost). Thus compared to the individuals treated early, home production increases for the individuals that just faced the health shock.

To account for these issues, I use the DiD estimator proposed by Callaway and Sant'anna (2021), hereafter CS. This estimator gives zero weightage to "forbidden comparisons". I leverage 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 HRS and CAMS. Every wave has individuals that receive their first shock in that wave, except for the first wave (where by construction no individual is treated). As mentioned in the previous section, I exclude people who enter the sample with pre-diagnosed health conditions. Therefore, the variation in treatment timing yields 9 "timing groups", denoted by $g$. I estimate the group-time average treatment effect for each group $g$ in each time period $t$ by comparing individuals in $g$ to individuals that were not yet treated in time period $t$ (including never treated individuals). I then aggregate these group-time average treatment effects together to estimate the impact of health shocks on home production. In Appendix B.4, I estimate CS using the control group as a. strictly not-yet (but eventually) treated and; b. never treated.

For these average treatment effects to be causally identified, parallel trends assumption must hold. To do so, I must assume that in the absence of a health shock, the average potential outcomes for the treatment group $g$ after the year $g$ would have evolved parallelly with the individuals that never faced a given health shock or faced it later. Thus, ATT(g, t) can be

identified by comparing the 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 one for units in treatment group $g$ and $C_t$ 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 average outcome the year before the treatment.[14]

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:

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

In this paper, I present and plot the estimates of $\theta_D(e)$ for each outcome.[15] In Appendix B.4, I also explore two other approaches to estimate the impacts and provide a comparison with the CS approach described above. The first is the standard TWFE. In the second approach, I make treatment groups based on the first age they are treated, as opposed to the first wave.[16] These estimators yield qualitatively similar results.

## 4.1 Threats to Identification

There are two primary concerns that could be a threat to the identification strategy. First and more worrisome is the exogeneity of health shocks. Causal interpretation of $\theta_D(e)$ in the post-treatment period requires strict exogeneity of health conditions. In other words, prior periods' health cannot affect contemporaneous home production time. To address this concern, as a first step, I limit my sample to people with a new diagnosis of a given health shock. As mentioned previously, I exclude people with pre-existing conditions. Furthermore, in the robustness checks below, I test if the impact on home production is a marginal impact of an additional shock. Additionally, I illustrate that the evolution of difficulties in daily living (which can be thought of as a measure of general health) prior to the health shock does not show any trends in the worsening of general health.

An additional concern related to the above threat is that the timing of the shock may be endogenous. Individuals getting diagnosed with a condition for the first time in old age may be relatively sturdy. This might weaken the impact on home production. To address this

[14] At first, $Y_t$ is out-of-pocket medical cost and difficulties in daily living. I use the aggregated ATT to arrive at relative ranking that categorizes the shocks into "costly" and "impairing" shocks. In the second step, to arrive at my main results, $Y_t$ is the weekly time spent in home production and its various tasks.

[15] Based on the total relative time periods, my event study graphs will have 9 post treatment periods, however, due to noisy estimates in the later post-treatment periods, I show event study estimates for only 4 post-treatment periods. It is also worthwhile to note that one period is equivalent to two years, given the structure of HRS and CAMS.

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

concern, in Appendix B.4, I consider only the not-yet-treated individuals as a control group. Additionally, as mentioned above, I also created treatment groups based on the age at which they first faced the shock. This allows me to compare individuals hit with a shock for the first time at a similar age. The results are presented in Appendix B.4. Finally, I use the procedure described by Roth and Rambachan (2021) to test the sensitivity of my estimates to the potential violations of the parallel trends assumption. This has been discussed in detail in the results section.

## 4.2 Categorization of Health Shocks

I use Callaway and Sant'Anna (2021) to compute changes in out-of-pocket medical spending and difficulties of daily living after a health shock. Table 2 shows the increase in medical cost and daily limitations in the first period following a given health shock and their relative rankings in terms of severity. These rankings are then used to classify the shocks into three groups: costly, impairing, and mixed shocks.

Cancer, heart condition, hypertension, and lung condition fall into the group of costly shocks. Columns (1) and (2) show that a significant and large increase in medical expenditure is brought about by cancer, followed by heart problems, stroke, hypertension, and lung condition, respectively. The significant increase in medical cost in the first period observed after facing these shocks ranges between \$1038 (cancer) and \$629 (lung condition). There is a visible break in the magnitude of the increase for other shocks.[17]

Column (3)-(6) show that among the costly shocks, hypertension is the least impairing in terms of ADLs and IADLs. Cancer, heart, and lung condition also stand among the bottom three shocks in terms of difficulty in daily living. Since stroke induces the highest increase in daily living limitations despite being highly costly, I exclude it from Costly shocks.

Second group – impairing shocks – consists of shocks with a lower increase in out-of-pocket medical expenditure but a higher increase in difficulties of daily living. Table 2 shows that psychiatric conditions, CES-D depression, and self-reported health induce high increases in activities of daily living limitations and are the least costly shocks. Psychiatric shocks are associated with a significant increase of 0.27 ADLs and 0.3 IADLs in the first period observed after the shock. CES-D depression and self-reported health also affect daily limitations within a similar range.

The data-driven two-way classification of the health shocks into two groups is quite stark. The lowest increase in ADLs and IADLs among the Impairing shocks (self-reported health and CES-D depression, respectively) is twice that of the highest increase in costly shocks (cancer and heart, respectively). Similarly, the lowest increase in oop medical cost among the costly shocks (lung condition) is more than twice in the magnitude of the highest increase among impairing shocks (self-reported health).[18] Finally, stroke, diabetes, and arthritis do not fit any

[17]Papers studying the out-of-pocket medical cost of health shocks such as Fong (2019), Cheng, Li, and Vaithianathan (2018) also find cancer, hypertension, and heart diseases to be among the costly shocks.

[18]I use two other measures of increase in medical cost as shown in Table A4 in Appendix B.1. The first is the log of out-of-pocket medical expenditures. Second is the ratio of out-of-pocket medical expenditure to the

Table 2: Impact on Medical Cost, ADLs, and IADLs

| | 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) | |

Note: Coefficients represent the impact in the first period after the shock. Top 1 pctile of real out-of-pocket medical cost is excluded. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

of the above two criteria. Stroke leads to higher medical expenses and greater daily living difficulty. Diabetes and arthritis are neither costly nor highly impairing. I categorize these three conditions as mixed shocks and show the effects of these shocks on home production in the results section.

# 5 Results

I now use these three groups to test the channels through which health shocks impact home production. Estimation results are presented in Table 3. For each shock, the coefficients represent the impact in the first period after the shock. Recall that the time-use variables in CAMS are merged to the health variables in the preceding HRS wave. Therefore, these coefficients indicate the impact at least 1 year after the shock. I begin by illustrating the impact of Costly shocks on home production time.

sum of social security income and pension of an individual. The ranking of shocks with higher monetary costs does not change. Additionally, I also compare the distribution of the change in out-of-pocket medical cost for the treated vs. never treated for all the shocks. In figure A9, costly shocks show a visible distribution shift towards high cost for the treated. In contrast, impairing shocks have very similar distribution for treated and never treated.

## 5.1 Effects of Costly Shocks

In this section, I present results whether individuals increase their home production in response to costly shocks through income effect. Panel A in Table 3 shows the impact of costly shocks on total home production and its various tasks. Column (1) highlights that the total home production does not increase significantly. Cancer is the only shock to increase home production. It increases home production time by 0.4 hours (standard error = 0.78) in the first period after the diagnosis. This represents a small and statistically insignificant 2% increase relative to the average home production time. The impact of a heart condition is insignificant. While the costly shocks are more likely to see income effect (shift towards consumption with more home-produced goods), I find the opposite for high blood pressure and lung condition.

Column (2)-(7) provide more detail on the various tasks of home production. Individual tasks of home production also do not display any strong evidence for income effect. Except for a significant increase of 0.41 hours in yard work and gardening (standard error = 0.15) after a cancer shock (20% increase relative to the average time spent in gardening and yard work), I do not find any signficant increase in hours alotted to the tasks.

To further understand the impact in the longer run, figure 2 shows the event study plots. It is important to note that the decrease in home production after lung condition and high blood pressure, discussed previously, is only short-lived, as seen in the event study plots. Overall, I do not find any evidence of an increase in home production in the short run and long run for any shocks in the Costly Shocks group.[19]

Furthermore, decline in ability to carry out home production can cancel out the income effect even for costly shocks. To restrict the non-monetary cost of these health shocks, as an additional check, I exclude individuals who ever report any ADLs or IADLs in the entire sample. Results are presented in table A5 (Appendix B.1). The impact of cancer and heart condition on home production is positive. However, despite an increase in the magnitude compared to the baseline results, the effects are not statistically significant. The impact of high blood pressure and lung condition is in accordance with baseline results.

## 5.2 Effects of Impairing Shocks

I next consider the effects of Impairing Shocks. In this section, I present results whether individuals decrease the time spent in home production due to impairing effects of health shocks. Column (1) in Panel B in table 3 indicates that all the shocks categorized as Impairing Shocks significantly decrease home production time in the immediate period after the shock. The highest impact is observed after a psychiatric shock. Diagnosis of a psychiatric condition significantly decreases home production time by 3.2 hours in a week (standard error = 1.61). This represents a decline of 16% relative to the average time spent in home production.

The other two Impairing shocks also induce a sizeable decline in home production. The onset of depression, as measured by the CES-D score, decreases average home production time

[19]The time gap between two periods in the event study plots is two years, as HRS surveys are conducted once every two years.

by 1.12 hours in the first period (standard error = 0.56). An adverse health shock defined by self-reported health also decreases the average time spent in home production by an hour (standard error = 0.53).

The decline in total home production is being driven mostly by the biggest components of home production – time spent in meal preparation and housekeeping. A psychiatric shocks decreases time spent in these two tasks by 0.7 (standard error = 0.42) and 1.4 hours (standard error = 0.45), respectively. Given the underlying means, these estimates reflect a decline of 12% in the meal preparation and 22% in housekeeping time. Similarly, CES-D depression and self-reported health decrease meal preparation time significantly by around half an hour each, followed by time spent in housekeeping and gardening.

Given the significant decline in home production and its various activities in the first period, it is important to further look at the extent of these effects in the longer run. Event study graphs in figure 2 show that the effects are not short-lived and persist in the longer run. The impact of a psychiatric shock that is visually apparent immediately persists for two more subsequent periods before returning to a smaller, statistically insignificant estimate. Whereas the impact of CES-D depression and self-reported health persists for many more periods in the longer run. Similarly, the event study graphs for meal preparation and housekeeping tasks in figures 4 - 5 show that the impact is not restricted to the immediate period after the shocks. In Appendix E I explore the heterogeneity in the effects by gender and marital status. Resuklts are presented in tables A11 - A13

## 5.3 Effects of Mixed Shocks

Finally, I present the impact of mixed shocks. Panel C in Table 3 shows the short run results for stroke, diabetes, arthritis. Column (1) shows that total home production decreases for all these shocks, but none of the effects are statistically significant. Arthritis decreases home production by 1 hour (standard error = 0.78), which is comparable to the impairing shocks. Columns (2)-(7) display the results for individual tasks of home production and highlight two points. First, the direction of the impact of all these shocks is mixed. For example, while meal preparation time increases after diabetes and arthritis but decreases after stroke, housekeeping time responds in the opposite way. Second, the effects are not statistically significant. The only exception is stroke, which decreases meal preparation time by 0.7 hours (standard error = 0.34) – an 11% decline relative to the average meal preparation time.

Figure A15 in Appendix B.3 shows the event study plots for the mixed shocks. Total home production shows a downward trend in the long run after stroke and arthritis. However, the impacts are not statistically significant. While home production shows a downward trend prior to the onset of diabetes, there is no significant impact after the shock. Among other unexplored reasons, the absence of any impact for mixed shocks could be a result of income effect and impairing effect canceling each other.

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 |

Note: Coefficients represent the impact (hours per week) in the first period after the shock. Top 1 pctile of all time-use is excluded. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

### 5.3.1 Identifying Assumptions and Robustness

If we were to interpret the coefficients from the event study as the causal effect of a given impairing shock, this would require the identifying assumption that if a given health shock had not occurred, the average home production would have evolved parallelly for the treated and the not treated groups. An implication is that there should be no downward trends in home production time in the periods leading up to the shock. While figure 2 may visually indicate this to be the case for all the impairing shocks, I further test the sensitivity of my estimates to potential violations of parallel trends assumption. Following the procedures described by Rambachan and Roth (2022), I compare 95% confidence intervals obtained by my primary Callaway and Sant'Anna (2021) DiD model against those obtained after allowing for deviations from a linear trend of up to an arbitrary amount, $M$. Figure A14 in Appendix B.2 displays the plots for the first period estimates after the shock. In the remainder of this section, I demonstrate the robustness of the main results (for impairing shocks) to a host of alternative specifications. The main results are overall robust.

#### Nursing Home Utilization

To test whether the impact on home production is driven predominantly by severely impaired individuals, I design two specifications that exclude individuals who a. reside in a nursing home at the time of the interview, b. report an overnight nursing home stay since the previous wave but did not report any stay in the previous wave. Column (1) in Table A6, Appendix B.2, shows that despite excluding those in nursing home institutions during the interview, average home production declines in the first period after the shock. The magnitude of the decline is comparable to the baseline results for all the impairing shocks. People who are in nursing homes at the time of the interview mechanically carry out less home production than those staying at home.[20] Therefore, the decrease in home production, despite excluding nursing home utilization, additionally informs that the decline in the baseline specification is not a trivial observation. Upon excluding those whose timing of nursing home stay is concurrent with the shock, baseline results not only hold but also strengthen in magnitude (see Column (2) in Table A6). This sheds light on an important point – the baseline results are not driven by only the severely impaired individuals.

#### 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 – diagnosis of psychiatric condition and CES-D depression – are commonly associated with cognitive impairment (Lee et al., 2012; CDC, 2020). This may lead to short-

[20] Oftentimes, information from proxy respondents is recorded for the respondents who are in a nursing home at the time of the interview.

term forgetfulness and impact the recall of time-use responses in the survey. From 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 all those 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., 2022) is a researcher-contributed dataset that provides a summary score for cognition using measures[21] from the core HRS interview.[22] This score is used to categorize respondents into three Langa-Weir classifications: Normal, Cognitively Impaired but not Demented (CIND), and Demented. Information on self-reported memory is obtained by asking respondents to rate their memory at present. I categorize "excellent", "very good", and "good" responses as a good memory. "Fair" and "poor" are categorized as bad/impaired memory. In Table A7, I exclude all those whose memory state worsens after the shock. For example, people who move from Langa-Weir category Normal to CIND or from CIND to Demented, etc., are excluded in 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 respondents suffering from health shocks. In column (1), which displays results with Langa-Weir restriction, the impact of psychiatric condition and CES-D depression is moderately weaker in magnitude and statistical significance compared to the baseline results but the impact of self-reported health does not change much. The impact in column (2), 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 10%) after a psychiatric shock and CES-D depression, respectively. The impact of self-reported health weakens relative to the baseline results.

**Marginal effect of an additional shock**

The impact of a health shock in the baseline result could reflect not the plain effect of one shock but a marginal effect of an additional shock. I address and inspect this concern in three ways. First, I condition the baseline specification on the presence of a given number of total doctor-diagnosed conditions. For example, from the summary statistics, it is known that people with and without psychiatric conditions have, on average, 2 other doctor-diagnosed conditions. Therefore, in one specification, I exclude people who reported being diagnosed with more than 2 doctor-diagnosed conditions (other than the shock itself) in the observed sample period. Second, since Callaway and Sant'anna's (2021) specification allows for parallel trends assumption to hold after controlling for covariates, I control for the total number of doctor-

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

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

diagnosed conditions (other than the shock itself). Third, I examine the evolution of the number of ADLs and the number of other (than the shock itself) doctor-diagnosed conditions pre and post-shock. Significant pre-trends in any of these variables would indicate a gradual health degradation even prior to the shock in question. However, an absence of significant pre-trends would reassure us 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 doctor-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 2 and 1 other doctor-diagnosed diseases, respectively. First-period impact of psychiatric condition and self-reported health shock is in accordance with the baseline results.

Figure A11 charts the evolution of ADLs and the number of other doctor-diagnosed conditions before and after the shock. A discernible jump in ADLs can be observed before and after the impairing shocks. Moreover, no noticeable pre-trends seem to exist in the number of doctor-diagnosed diseases as well.

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.[23] The impact of the psychiatric shock on time spent in home production is super robust to all these specifications. In all the specifications, the impact is around 3 hours weekly and is statistically significant at the 5% level. Similarly, the impact of CES-D depression and self-reported health is robust for most of the specifications, and the magnitude is similar to that in the main specification.

# 6 Possible Adjustments to Decrease in Home Production

Thus far, my findings in the previous section show that while costly shocks and mixed shocks do not have significant effects, home production decreases when individuals face impairing shocks.

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

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 indivdividuals seek inter- and intrahousehold help or buy home production equivalent services from the market.

### 6.0.1 Utilization of Help

I first examine whether people who face shocks rely more on formal and informal help with home production-related tasks? HRS collects information on the use of help received by the respondents and the helpers who helped them with ADLs and IADLs, their relationship with the helpers, total hours of help received, and the type of difficulty in living for which the help was required. I use this information to categorize the nature of help into formal and informal. Formal help is categorized as any help provided by an organization, employee of an institution, paid helper, or professional in the last month. Informal help is provided by a spouse, children, grandchildren, or other relatives in the last month. These measure of formal help and informal help are not mutually exclusive as various kinds of helpers may assist people at a given time.

Column (1) in Table A9 shows that the likelihood of receiving formal help in the short run (first period after the shock) increases by 6, 4, and 2.3 percentage points for a psychiatric condition, CES-D depression, and self-reported health, respectively. Although larger in magnitude than formal help, the likelihood of using informal help in Column (2) exhibits a similar result. Informal help received increases by 10, 6, and 7 percentage points for a psychiatric condition, CES-D depression, and self-reported health, respectively. Among the specific home production-related tasks, the most significant increase is observed in the reliance on help related to work around the house and yard for all the impairing shocks (Column (3)-(7)). The increase in the likelihood of utilization of help continues in the longer run. The increase persists for more periods for CES-D depression and self-reported health as compared to psychiatric shock.

For comparison, I also show the impact of costly shocks (cancer, heart condition, high blood pressure, and lung condition) on the likelihood of utilization of help. The magnitude of impact on formal and informal help received is much smaller than impairing shocks, with the impact being not significant for most shocks, as shown in Table A9. Likewise, in the long run, the impact on both formal and informal help availed is minimal in magnitude and statistically insignificant.

I next investigate whether the help provided compensates for the home production time lost. Column (8) in Table A9 shows that the number of hours of help received per week increases significantly. The increase is comparable to the decline in the total hours of home production, followed by depression and self-reported health shock. Hours of help increased by 1.7 hours (half the amount of decrease in home production) followed by a psychiatric shock. This might suggest that the loss in home production is partially recovered by the increase in the amount of help. However, the hours of help are asked for those who report and need help with functional limitations. Therefore, hours of help may not strictly include assistance with home production

tasks. [24]

The reseults above are about extensive margin. To study the help received on the intensive margin, I further investigate the nature of informal help rceived. I look at the impact of a spouse's health shock on their own time spent in home production. Table A14 shows that husbands significantly increase their time spent in total home production by 2.3 hours (standard error = 0.9) when the wife faces a shock in self-reported health. Most of the increase comes from meal preparation and housekeeping time (around an hour each). The event study graph for the husband's total home production upon the wife's self-reported health shock shows a significant positive shift in coefficients post shock. However, no significant change in the husband's time for the wife's psychiatric and CES-D depression shock is observed. Similarly, I do not find that wives significantly change their home production time when their husbands face any impairing shock (see Table A15). This may be due to the larger margin men have, as opposed to wives who, on average, work 40% more in home production tasks. Consistent with such gendered response of home production to spouse's illness, in a relatively younger sample (with a mean age of 47 years), Dalton and LaFave (2017) also find that husbands increase their home production by around 1.9 hours per week in response to wife's severe limitations in daily activities. Overall, these results suggest an increase in the utilization of help on the extensive margin. However, given the limitations in the data on utilization of help, it is unclear if this increase offsets the decrease in home production.

### 6.0.2 Consumption Spending

I next investigate whether individuals respond to a decrease in home production by increasing consumption spending. Respondents were asked about 39 spending categories in the CAMS waves. Information on consumption spending is collected at the household level. I examine the effect on total non-medical consumption spending as well as spending on categories corresponding to different home production tasks. The CAMS data allow for mapping home production categories to such spending categories. The following shows the mapping between market spending on the left and the home production time categories on the right.

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

I combined expenditure on housekeeping services and gardening services because, in the first wave (2001), respondents were asked jointly about the expenditure on these two categories. All

[24] In HRS, hours of help received cannot be directly mapped with total home production or its various tasks. Moreover, the available information does not allow for separating hours of help received into formal and informal types.

spending has been converted into log of monthly figures.[25]

Table A10 shows the impact on consumption spending for the first two periods after the shock for impairing shocks.[26] Spending on purchasing house and yard services seems to be the most responsive to health shocks. Expenditure on other services does not increase. While the purchase of housekeeping and yard services decreases by around 30 percent for psychiatric shocks, it significantly increases by around 20 percent for CES-D depression and self-reported health shock. However, the event study graphs show an increasing trend prior to the depression and self-reported health shock.This could potentially violate the identifying assumption of no pre-trends. Hence I am cautious in interpreting these results as a causal effect of health shock and evidence towards a reverse substitution – away from home production towards market spending. The lack of strong evidence for reverse substitution may be due to a decline in the utility of consumption itself after a health shock.[27] A decline in utility derived from consumption might reduce the need to compensate the decrease in home production with increased market spending. However, it is beyond the scope of this paper to investigate the utility channel.

# 7 Summary and Concluding Remarks

People can use home production protect consumption against income changes

People can substitute consumption spending with home production to protect overall consumption when they face a negative shock to their monetary resources. Prior research has confirmed an increase in home production in the face of income changes such as retirement and unemployment. However, home production requires the ability to exert efforts. If individuals face a negative shock to this ability, home production can become an additional burden. Since health shocks can impact the monetary resources and the ability to exert effort at the same time, in this paper, I examine the effects of health shocks affect time spent in home production. I study two channels – income effect and impairing effect – where the former is likely to induce an increase in home production, and the latter can reduce home production. However, studying the impact of health shock on home production,

I find that home production declines significantly for impairing health shocks. Most of this decline comes from tasks essential for welfare, such as meal preparation and housekeeping. The decrease in home production is not short-lived. Though the effect dissipates for psychiatric

[25]Even though CAMS is designed to map time-use and spending categories, such a mapping may have missed some relevant categories of home production or spending. For example, even though time spent in managing money is a time use category, its counterpart spending category is not inquired in the CAMS. Similarly, money spent on buying meal preparation services may be mapped better to time spent cooking meals and cleaning afterward than dining out. Dining out may be impacted (increase) not only as a part of substitution away from home production but also might decrease as a consequence of bad health, as food away from home is higher in fat, cholesterol, and calories (Soni and Morrissey, 2021). Therefore, it is likely that my estimated substitution of consumption spending may be a lower bound.

[26]Unlike time use information collected for the previous week, spending information has a different look-back period. Most categories allow one to report the consumption expenditure over the last year. This may lead to only a partial overlap where the health shock was hit within the same 12-month window as the reference period for consumption spending.

[27]See, for example, Blundell, Commault, Borella, and De Nardi (2020).

shock after a few periods, it persists in the long run for depression measured through CES-D score and self-reported health shock. I employ several robustness checks to test the sensitivity of the results and understand the nature of the shocks. In addition to various alternate econometric specifications, I explore the role of decline in cognition in driving the results. However, I do not find strong evidence in favor of income effect. I find that home production does not increase for the health shock that brings about a more significant increase in out-of-pocket medical costs (costly shocks). I also do not find evidence for any impact of mixed shocks on home production. Taken together, my findings underscore the nature of cushioning provided by home production in the face of a health shock.

I further examine some plausible ways individuals use to offset the decline in home production – utilization of inter- and intrahousehold help, and increase in consumption spending. On the extensive margin, I find a significant increase in the likelihood of utilization of formal and informal help for the impairing shocks. The likelihood of help required with housekeeping and yard work increases the most. However, it is challenging to examine if the increased hours of help provided compensate for the loss of home production. My results also find weak evidence of spouses increasing their home production time when their partners face health shocks. While I do find that husbands increase their time spent in home production when their wives face a shock to self-reported health, this does not hold for other shocks or wives' home production when their husbands face any health shocks. I also find weak evidence of substitution towards consumption spending. Except for an increase in the purchase of housekeeping and yard services after CES-D depression and self-reported health shock, spending on other consumption categories mapped to time-use does not increase despite a decrease in home production.

There are some limitations of my work that may hinder our ability to detect the impact of health on home production. One limitation is the time lag between reporting information on health and time use. As mentioned earlier, time use information in CAMS is merged with the health information in the preceding wave of HRS. This could lead to a maximum time lag of around three years, which limits our ability to capture short term change in home production in response to the shock. This may be the case especially for costly shocks that do not lead to high ADLs, to begin with. The impact of such shocks on home production may be short lived and therefore, not captured by my estimates. Overall, such a time lag means that my results may be underestimating the actual impact.

Another limitation is that even though the number of time use activities reported in CAMS may be high enough to give us a picture of overall time use in a typical week, data on certain categories where healthy and unhealthy may be spending time differently are not collected for example, time spent in resting which may be different from sleeping. Finally, I use ADLs and IADLs to capture the disutility induced by health shocks. These measures may not fully capture the disutility cost of health shocks. For example, even though a lung condition does not induce significant iincrease in ADLs and IADLs, however, cleaning house involves the use of aerosols to clean dust. This could inhibit people suffering from lung conditions to undertake various types of 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 the American Association of Retired Persons, 77% of individuals aged 50 and above want to remain in their homes in the long run (AARP, 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 time spent in home production differentially and whether reliance on help with home production-related tasks changes in response to these shocks. This has important policy implications for structuring supports for home- and community-based services (HCBS) – a recent topic of discussion in President Biden's proposed Build Back Better bill. HCBS include services such as personal care, chore services, and meal delivery along with home health care services (health care by a skilled professional). Currently, Medicare only covers a subset of these services (mostly home health care) and for a limited period of time.

Future work should explore other channels through which health shocks can impact home production. One such mechanism is a change in marginal utility of consumption upon a health shock. Another channel can be a adjustments in life expectancy. Suppose people expect to live shorter after a health shock, for example, cancer. A shortened life span can increase monetary resources available in every period which can have an impact opposite to that of income effect considered in this paper. Another avenue for future research is to study how health shocks induce re-entry in the labor force of oneself and their spouse, especially for retired individuals.

## Main Figures and Tables

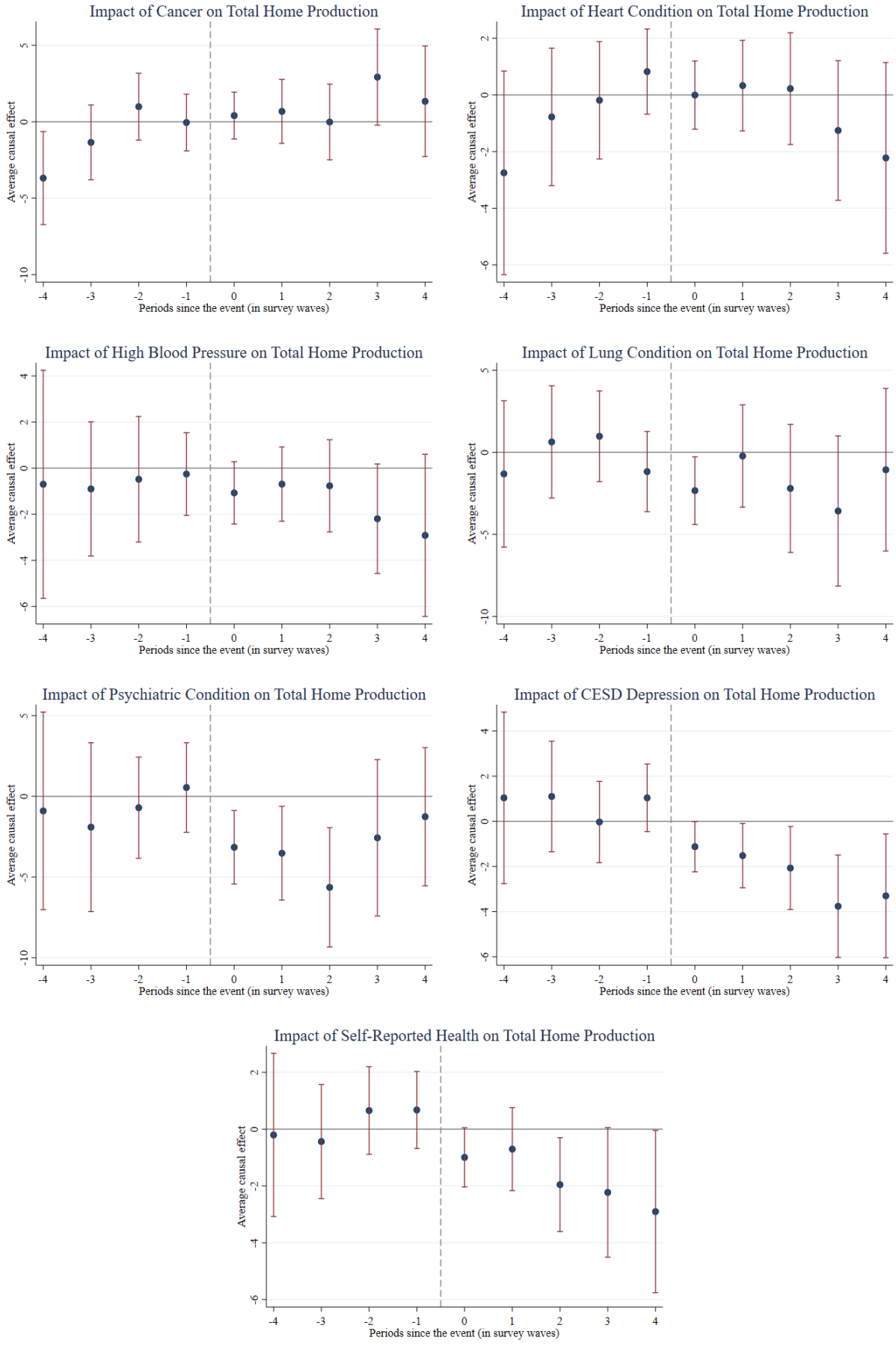



Figure 2: Impact of Health Shocks on Time Spent in Home Production

Note: These event study graphs show the expanded results of Column (1) in Table 3. The points in each figure represent the estimated effects in time period relative to the treatment period, with period 0 being the first wave observed after the treatment started. Survey waves are biannual, hence there is a two year gap between two periods on the x-axis. The vertical lines represent 95% confidence intervals.

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 |

Note: Attrition from sample is the percent of individuals that eventually stop responding to the surveys due to death or other reasons. Other diagnosed conditions refer to the total number of doctor-diagnosed conditions other than the disease in the column head. The three categories of to measure cognition are taken from Langa-Weir cognition classification (Langa et al, 2022)

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 |

Note: Attrition from sample is the percent of individuals that eventually stop responding to the surveys due to death or other reasons. Other diagnosed conditions refer to the total number of doctor-diagnosed conditions other than the disease in the column head. The three categories of to measure cognition are taken from Langa-Weir cognition classification (Langa et al, 2022)

## Impact of Health Shocks on Tasks of Home Production

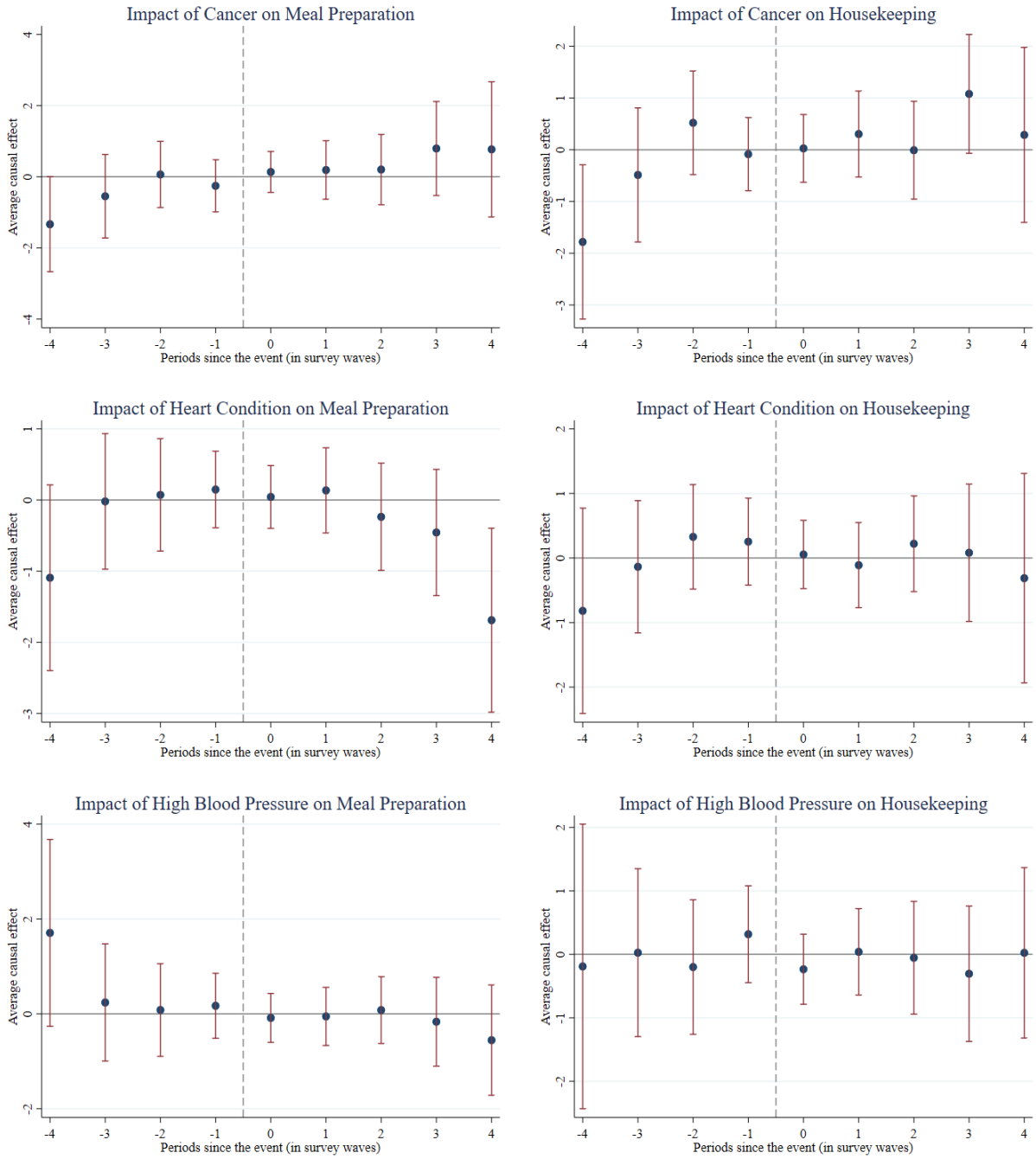



Figure 3: Impact of Health Shocks on Tasks of Home Production

Note: These event study graphs show the expanded results of Column (2) and (3) in Table 3 for cancer, heart, and high blood pressure. The points in each figure represent the estimated effects in time period relative to the treatment period, with period 0 being the first wave observed after the treatment started. Survey waves are biannual, hence there is a two year gap between two periods on the x-axis. The vertical lines represent 95% confidence intervals.

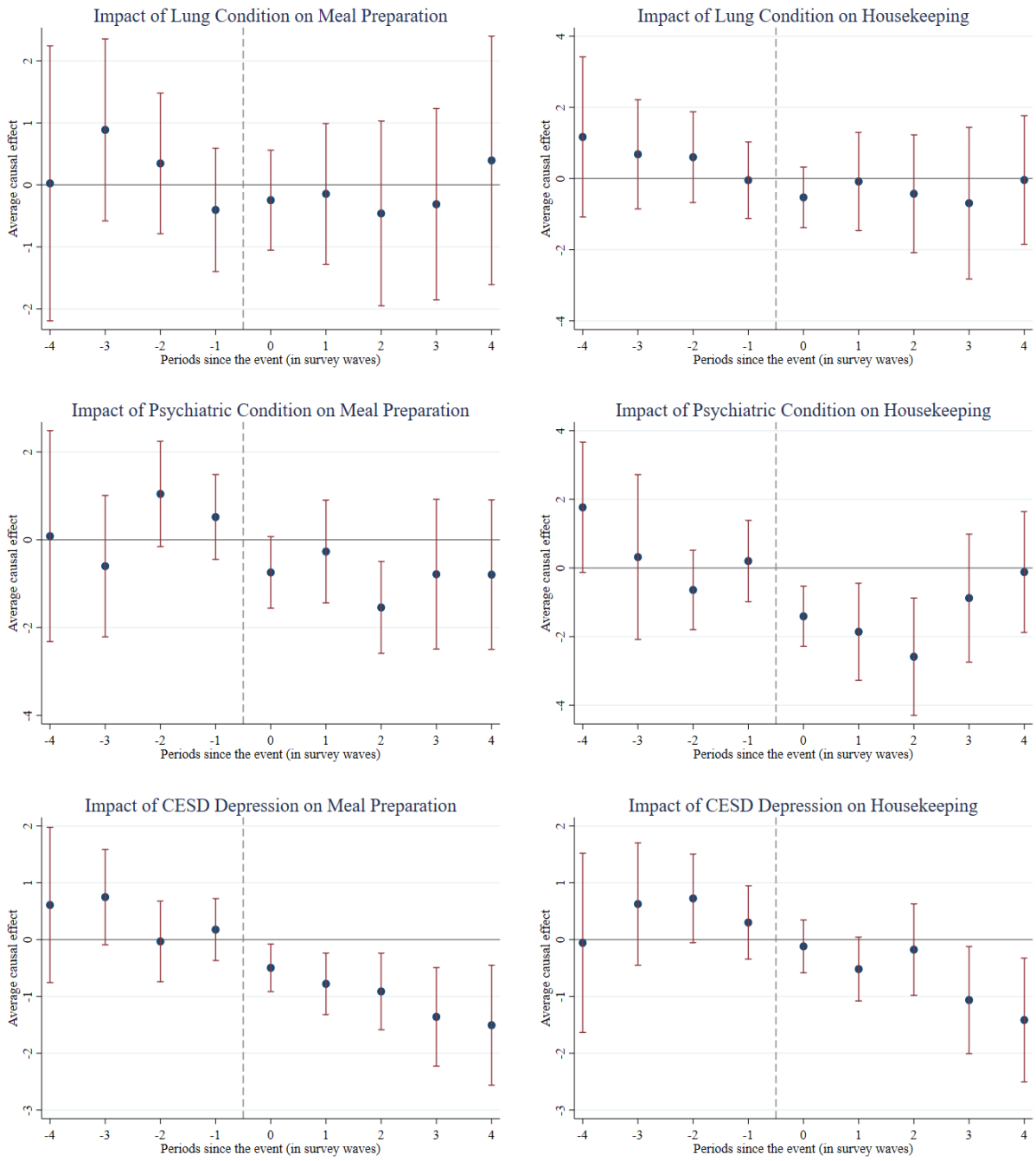



Figure 4: Impact of Health Shocks on Tasks of Home Production

Note: These event study graphs show the expanded results of Column (2) and (3) in Table 3 for lung condition, psychiatric condition, and CES-D depression. The points in each figure represent the estimated effects in time period relative to the treatment period, with period 0 being the first wave observed after the treatment started. Survey waves are biannual, hence there is a two year gap between two periods on the x-axis. The vertical lines represent 95% confidence intervals.

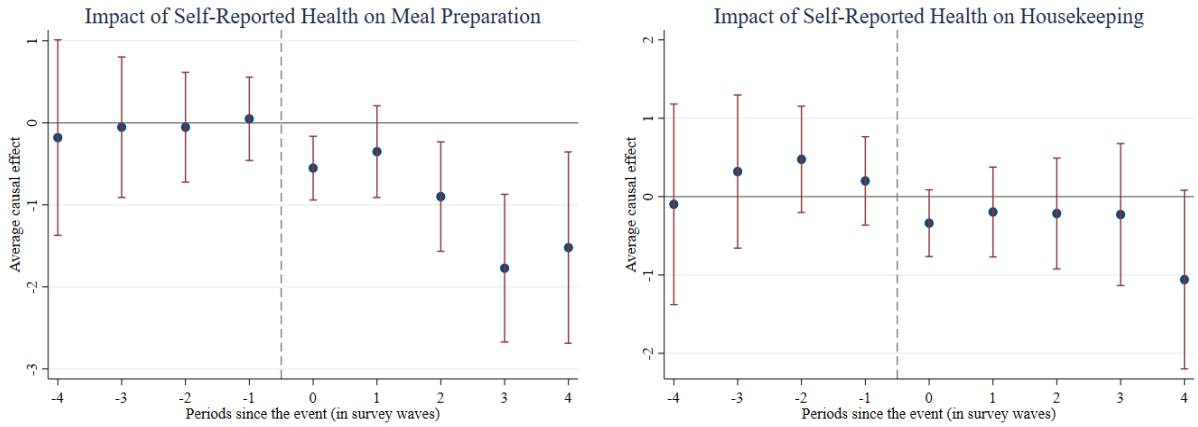



Figure 5: Impact of Health Shocks on Tasks of Home Production

Note: These event study graphs show the expanded results of Column (2) and (3) in Table 3 for self-reported health. The points in each figure represent the estimated effects in time period relative to the treatment period, with period 0 being the first wave observed after the treatment started. Survey waves are biannual, hence there is a two year gap between two periods on the x-axis. The vertical lines represent 95% confidence intervals.

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# A Appendix – Data

Figure A1 shows total home production as a fraction of total non-sleeping hours. Home production takes up the most time (20%) after leisure (39%). Table A1 shows the summary stats for total home production hours as well as its separate components. On average, home production takes more than 20 hours per week. The biggest time-consuming task of home production is meal preparation and cleaning afterward. Figure A3 further shows the distribution of total home production hours. Around 7% of the sample reports no hours spent in home production. This is not unusual when compared to ATUS in the later section.

Figure A2 shows the distribution of total hours. Since CAMS has added additional time-use categories in later waves, I incorporate that information in calculating total hours for every wave and then sum all across all the waves. Although the distribution peak is around 168 hours, a wide distribution around the mean can be observed. The survey instrument allows for double counting of hours, which could result from individuals engaging in different tasks simultaneously or as a result of certain tasks fitting the description of more than 1 time-use activity surveyed in CAMS. This could be a reason behind the over-reporting of hours. The recall method in CAMS may result in under-reporting of total hours because respondents are likely to forget some tasks over the last month or week.[28]

The other reasons for under or over-reporting could be a misinterpretation of the recall period by the respondent. For example, some frequent tasks have a weekly recall period, but less frequent activities have a monthly recall period. This may lead some respondents to respond with a different recall period mistakenly. To examine this, I plot the distribution of hours of sleep in a week for those whose total hours reported are less than 100 hours per week. It is a documented biological fact that adults require 7-8 hours of sleep per day (Centers for Disease Control and Prevention, 2017) I plot the sleep distribution since no other time-use activity commands some definitive number of hours. FigureA4 fairly confirms the confusion between recall periods. Among those under-reporting weekly total hours, around 30% report sleeping between 7-8 hours, which is a reasonable sleeping time in a day and not a week.

To make sure the main results are not being driven by the mechanical under-reporting of hours, as a robustness check, I report the results for those who report sensible seeping hours.The results are shown in .

[28]For more information, see Hurd and Rohwedder, 2007.

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 |

All variables have been trimmed by top 1 percentile.

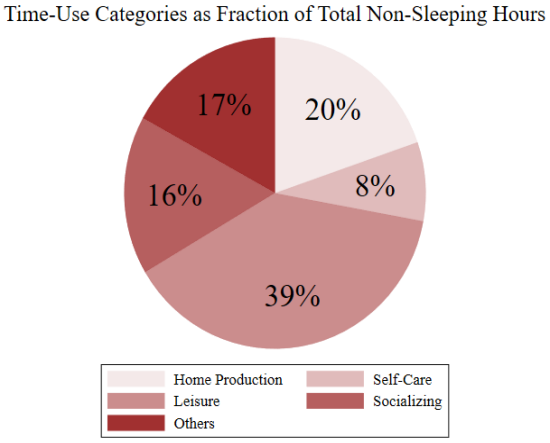



Figure A1

Note: "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.

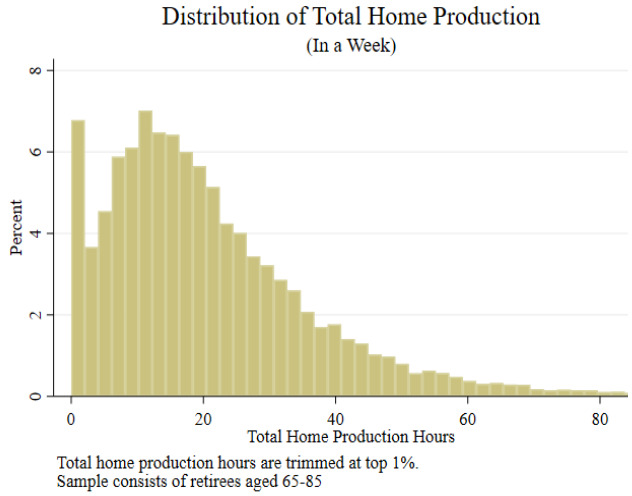



Figure A2

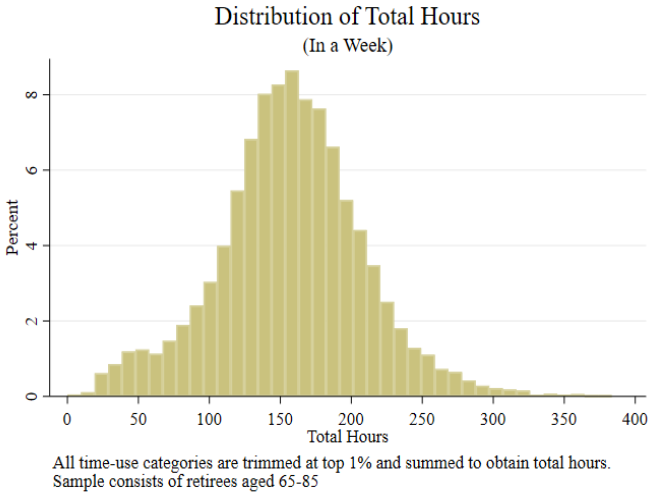



Figure A3

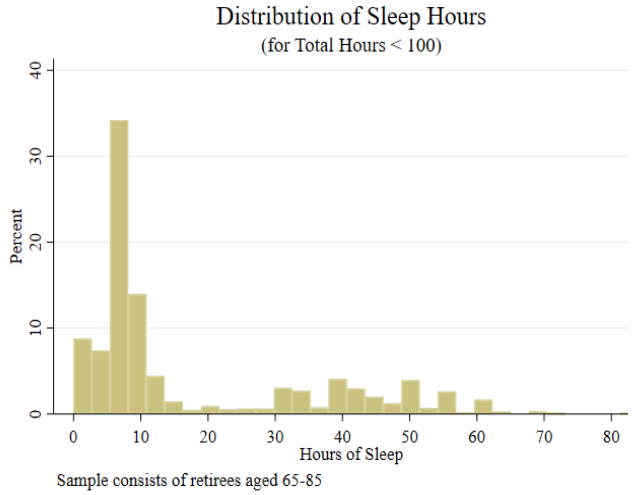



Figure A4

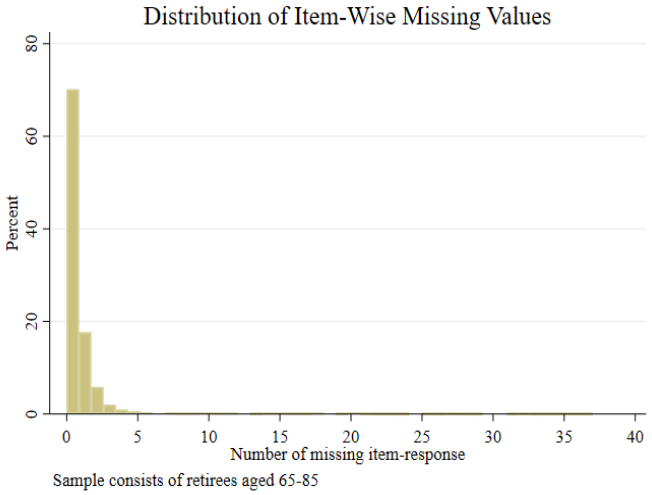



Figure A5

## 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

## A.2 Data Quality

In this section, I compare CAMS and ATUS. However, such a comparison has limitations because of the differences in sampling, interview mode, and recall period. While CAMS uses a paper and pencil questionnaire that asks respondents to recall the time used in various tasks last month or last week, ATUS interviews are conducted via computer-assisted telephone technology and use the diary method to cover 24 hours of the previous day. These methodological differences are bound to bring some differences in the summary statistics. Despite these differences, CAMS and ATUS turn out reasonably close to each other.

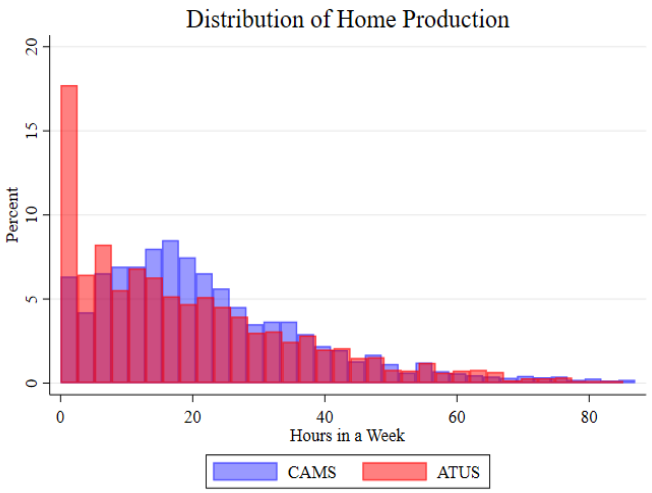
I use the 2015 survey wave of CAMS to compare the time use of healthy and unhealthy respondents to those in ATUS. While health information for CAMS respondents is available for every wave (through corresponding HRS), ATUS does not collect health information regularly. The most recent health module in ATUS was carried out between 2014 and 2016. The Eating and Health Module in ATUS only collects information about self-reported health, which is then used to categorize healthy and unhealthy[29] respondents in the following table.

Table A3 shows the weighted averages by health status for selected categories. CAMS records somewhat higher home production by 2 hours a week. This is because more ATUS respondents report 0 home production hours, as is evident from the distribution comparison in Figure A6. CAMS also records higher time in personal care and caring for others by around 2 hours. ATUS records a higher time for watching TV. Time spent in voluntary and organizational meetings, and eating and drinking are similar. Time spent using phones and email, listening to music, and leisure is higher in CAMS. The inclusion of secondary activity in CAMS is likely to give rise to these differences. These descriptive facts are consistent with Hurd and Rohwedder (2007). The statistics by health categorization follow similar patterns, with healthy people spending significantly more time in home production and leisure. Figure A6 to A8 compare the distribution of these categories. ATUS reports a higher proportion of 0 hours in various categories. Overall, the distributions of all categories seem to be very similar, especially for home production, leisure, eating, and drinking.

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

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 |



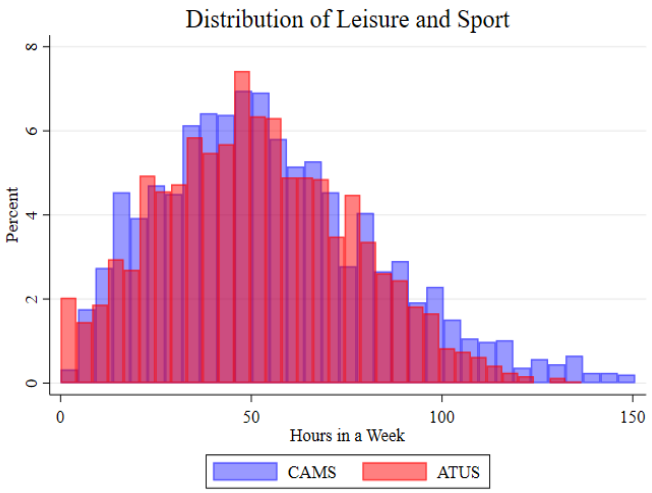
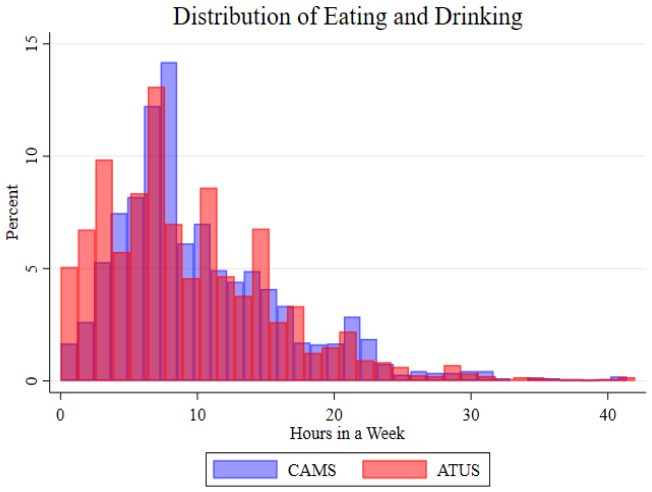




Figure A6



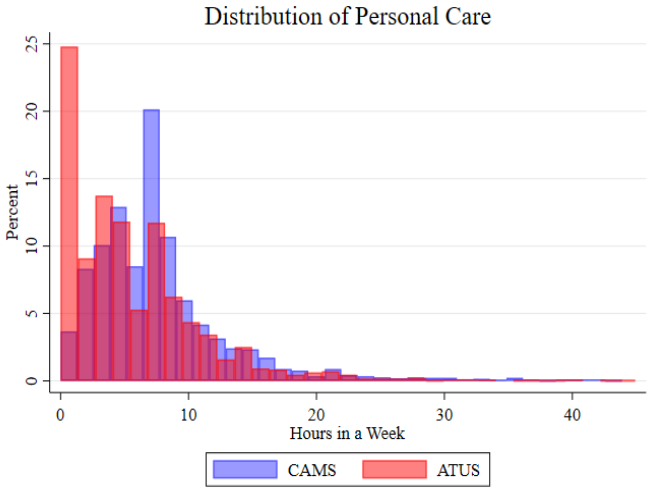
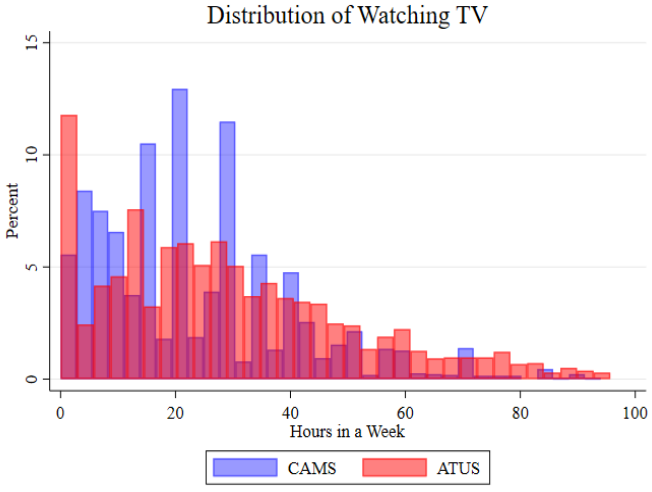




Figure A7



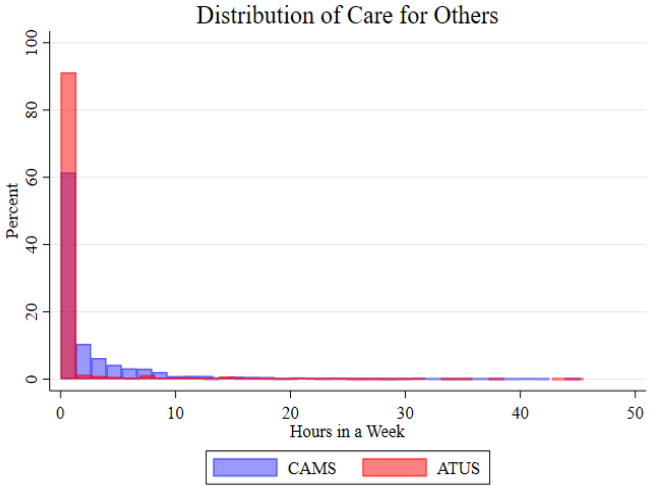




Figure A8

# B Robustness Checks

## B.1 Income Effect

Table A4: Impact on Medical Cost

| | (1)<br>Ln OOPMX | (2)<br>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

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

Table A5: Impact on Home Production (No Limitations)

| | (1)<br>Home Production<br>(No ADLs) | (2)<br>Home Production<br>(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

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

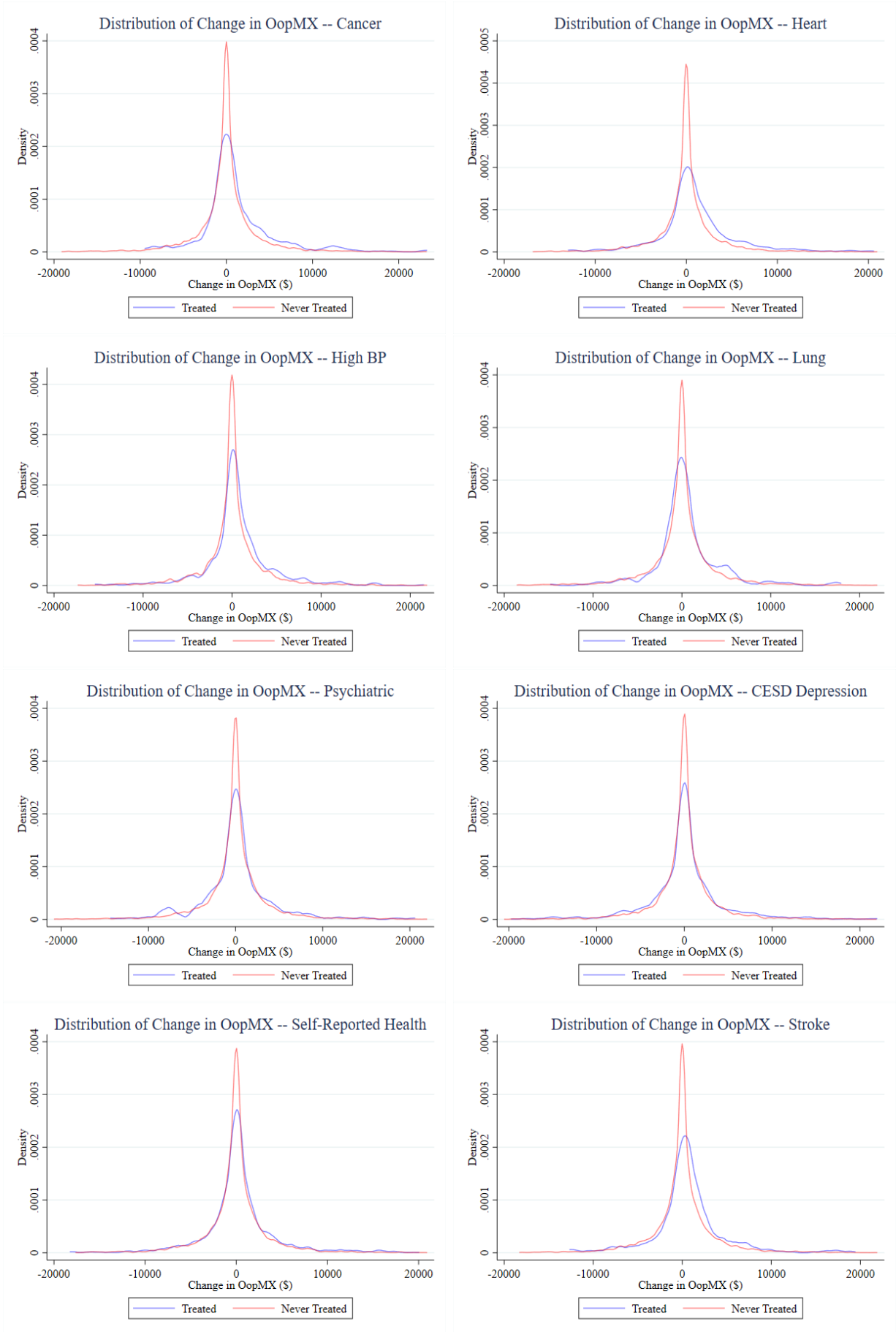

Distribution of Change in OopMX -- Cancer
Distribution of Change in OopMX -- Heart
Distribution of Change in OopMX -- High BP
Distribution of Change in OopMX -- Lung
Distribution of Change in OopMX -- Psychiatric
Distribution of Change in OopMX -- CESD Depression
Distribution of Change in OopMX -- Self-Reported Health
Distribution of Change in OopMX -- Stroke
Density
Change in OopMX ($)
Treated
Never Treated

Figure A9

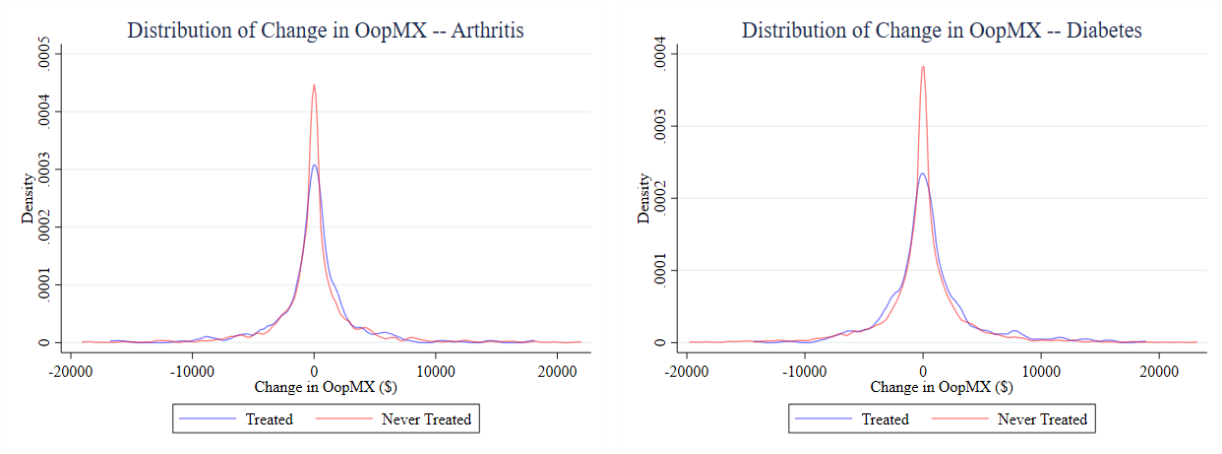

Distribution of Change in OopMX -- Arthritis
Density
0
.0001
.0002
.0003
.0004
.0005
-20000
-10000
0
10000
20000
Change in OopMX ($)
Treated
Never Treated
Distribution of Change in OopMX -- Diabetes
Density
0
.0001
.0002
.0003
.0004
-20000
-10000
0
10000
20000
Change in OopMX ($)
Treated
Never Treated

Figure A10

## 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) |

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

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) |

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

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.

**Evolution of Doctor-Diagnosed Conditions and ADLs (Graphs)**

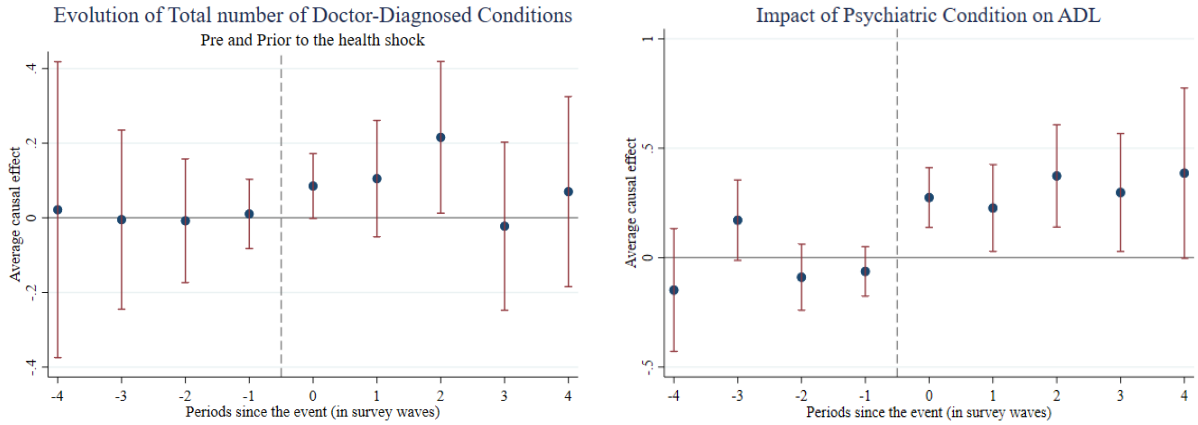



Figure A11: Psychiatric Shock

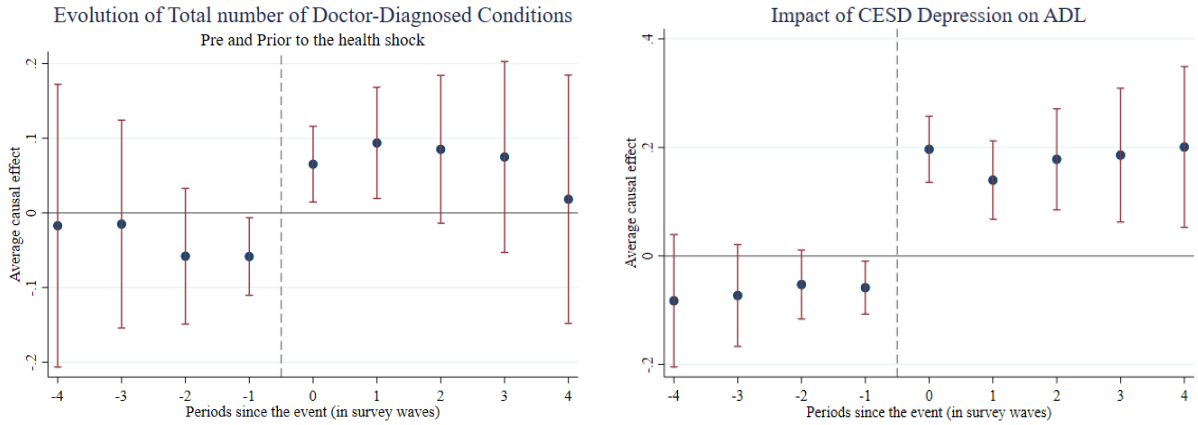



Figure A12: CES-D Depression Shock

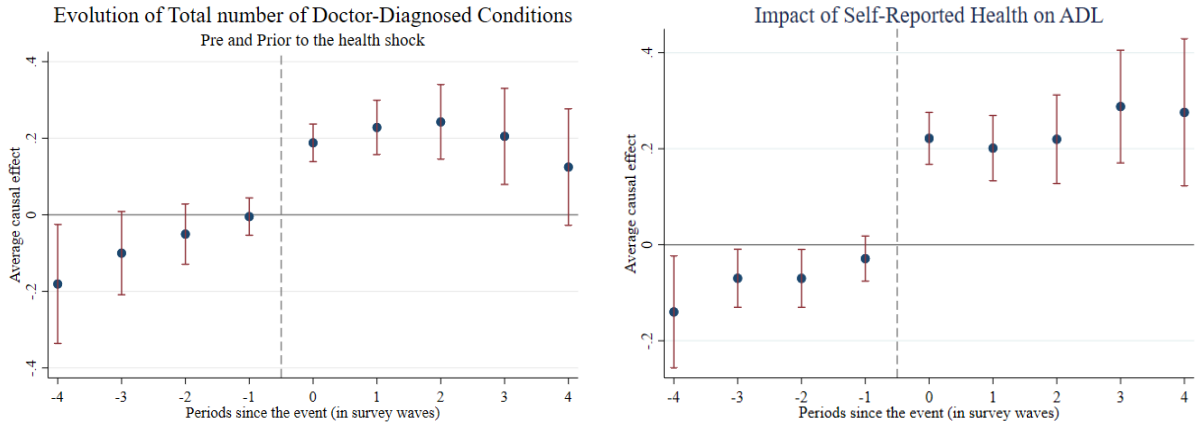
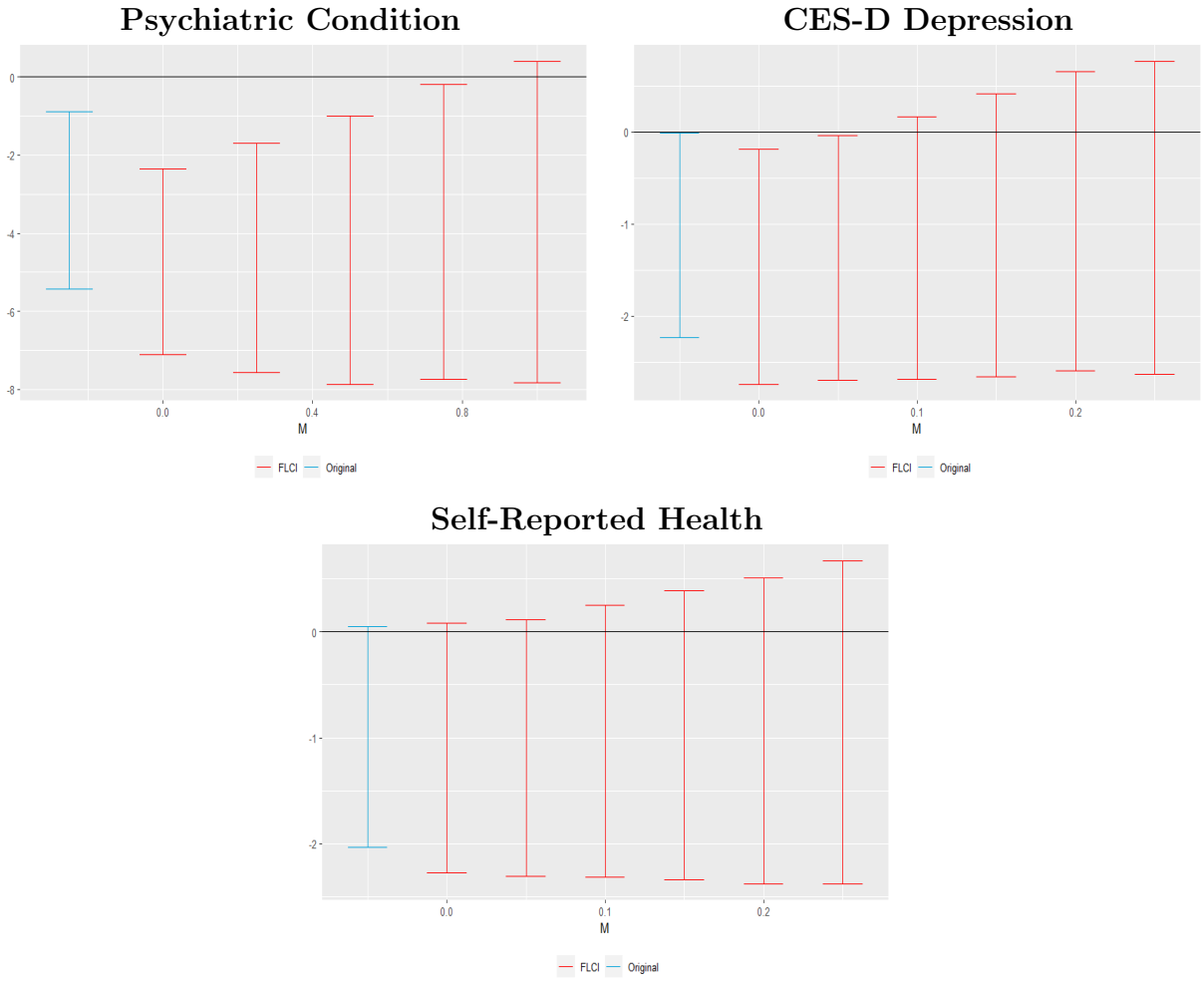



Figure A13: Self-Reported Health Shock

Note: These event study graphs show the evolution of doctor-diagnosed conditions and ADLs prior and post the shock. The points in each figure represent the estimated effects in time period relative to the treatment period, with period 0 being the first wave observed after the treatment started. Survey waves are biannual, hence there is a two year gap between two periods on the x-axis. The vertical lines represent 95% confidence intervals.

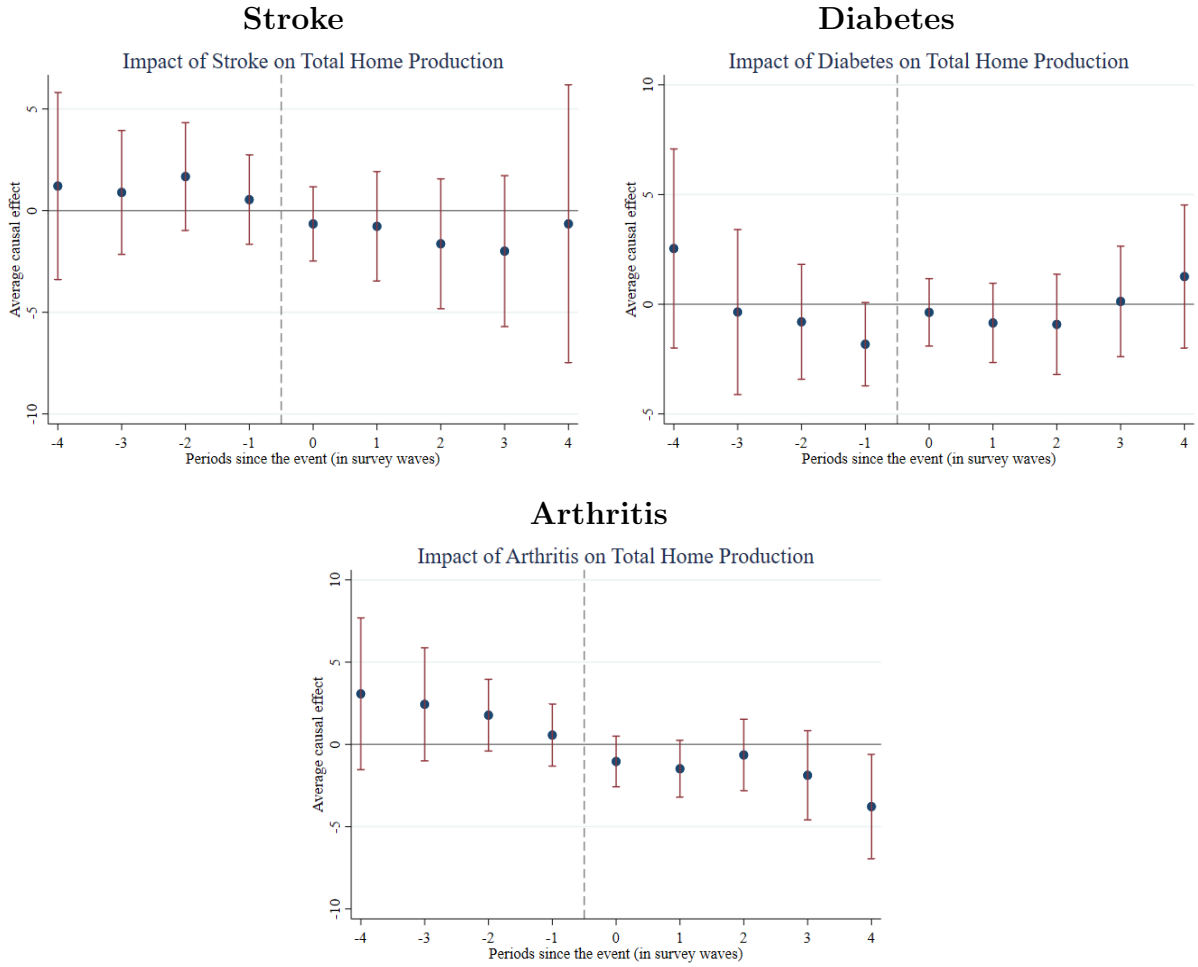
Figure A14: Effects on Home Production: Parallel Trends Test




Note: Figures show a test of parallel trends of the estimated effects on home production to potential violations of the parallel trends assumptions as per Roth and Rambachan (2022). The blue bar in each figure represents the 95% confidence interval of the primary DiD event study estimate for the first period after the shock. The red bars represent corresponding 95% confidence intervals when I allow violations of parallel trends of up to an arbitrary number $M$. In other words, $M$ respresents the largest permissible deviation in the slope of an inherent linear trend between two periods.

## B.3 Mixed Shocks

Figure A15: Event Study Plots: Mixed Shocks and Total Home Production




## 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.

In another specification, I use 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 HRS even though HRS is conducted biennially, some individuals may have an age gap of odd years between two waves, depending on the time of

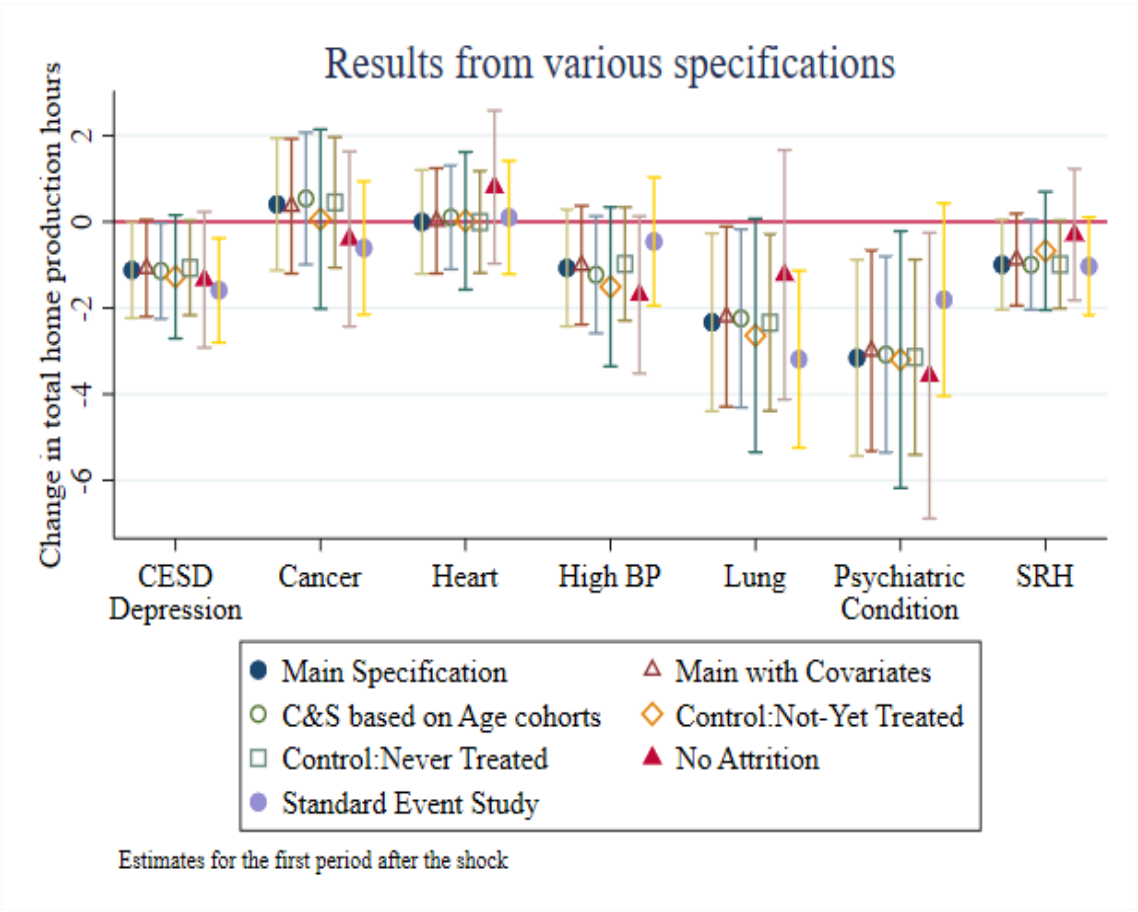



Figure A16

of interview. Therefore, I have to recode 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 consist of individuals who have not been treated yet but will be treated eventually at some later stage in the sample period pbserved. 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 comapred to the main results. However, the rersults 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 purple dot. While results for CES-D depression and self-reported health are robust, estimate for psychiatric shock are smaller in magnitude and not significant for this specification. Overall, the results for impairing shocks are robust to the various alternate 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 |

Standard errors in parentheses

Control group includes not yet and never treated individuals.

Top 1 pctile of hours of help has been trimmed.

Sample only consists of Individuals with non missing total HP info

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

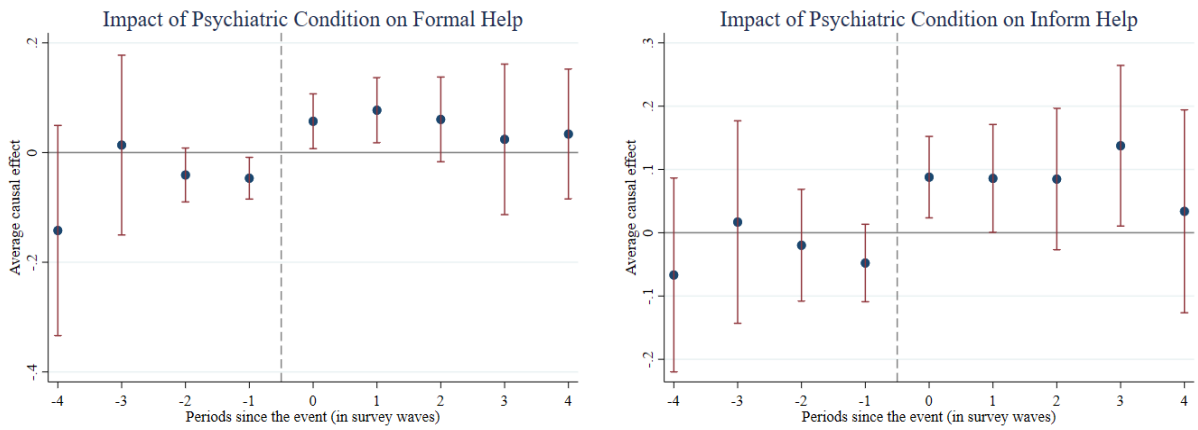



Figure A17: Psychiatric Shock

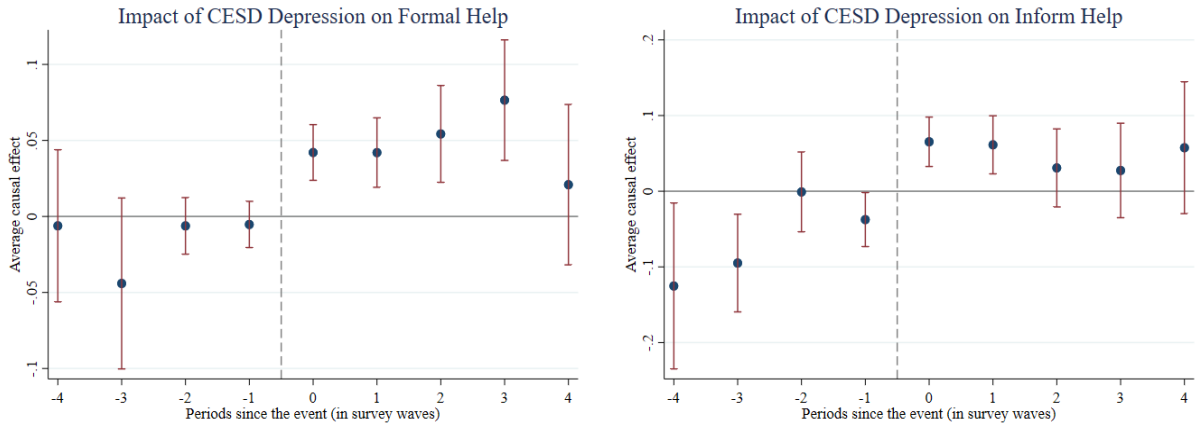



Figure A18: CES-D Depression Shock

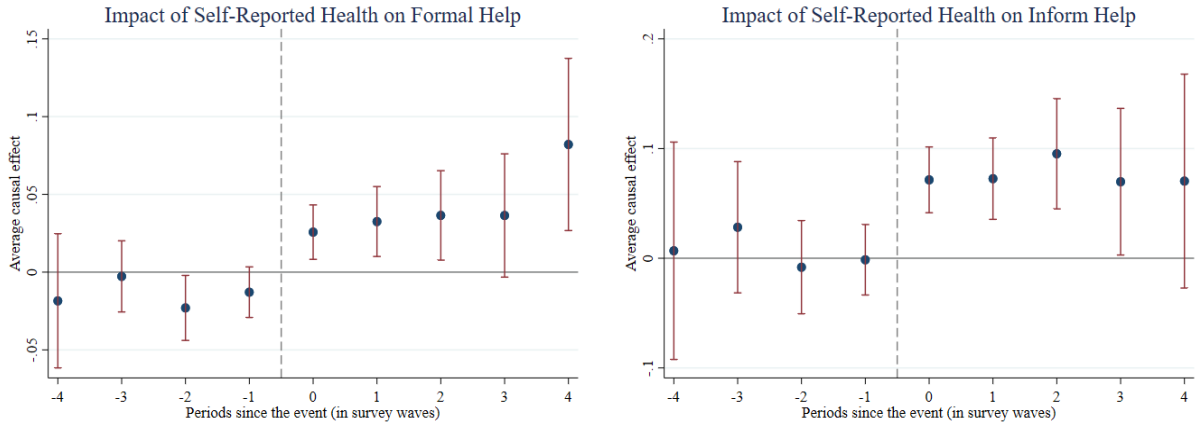



Figure A19: Self-Reported Health Shock

Note: These event study graphs show the the expanded results of column (1) and (2) from Table A9. The points in each figure represent the estimated effects in time period relative to the treatment period, with period 0 being the first wave observed after the treatment started. Survey waves are biannual, hence there is a two year gap between two periods on the x-axis. The vertical lines represent 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 |

Control Group: not yet+never treated.

Sample consists of individuals with non-missing home production values

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

# 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 are "psychiatric, emotional or nervous" conditions? I look at three events that may be coinciding with the diagnosis of a psychiatric condition and affecting time spent in home production at the same time. These events include falling down, death of a partner, and moving to a smaller house. I use housing wealth as proxy for the size of housing. Figure A20 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 the deathe 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 A21 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 worsenign 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.

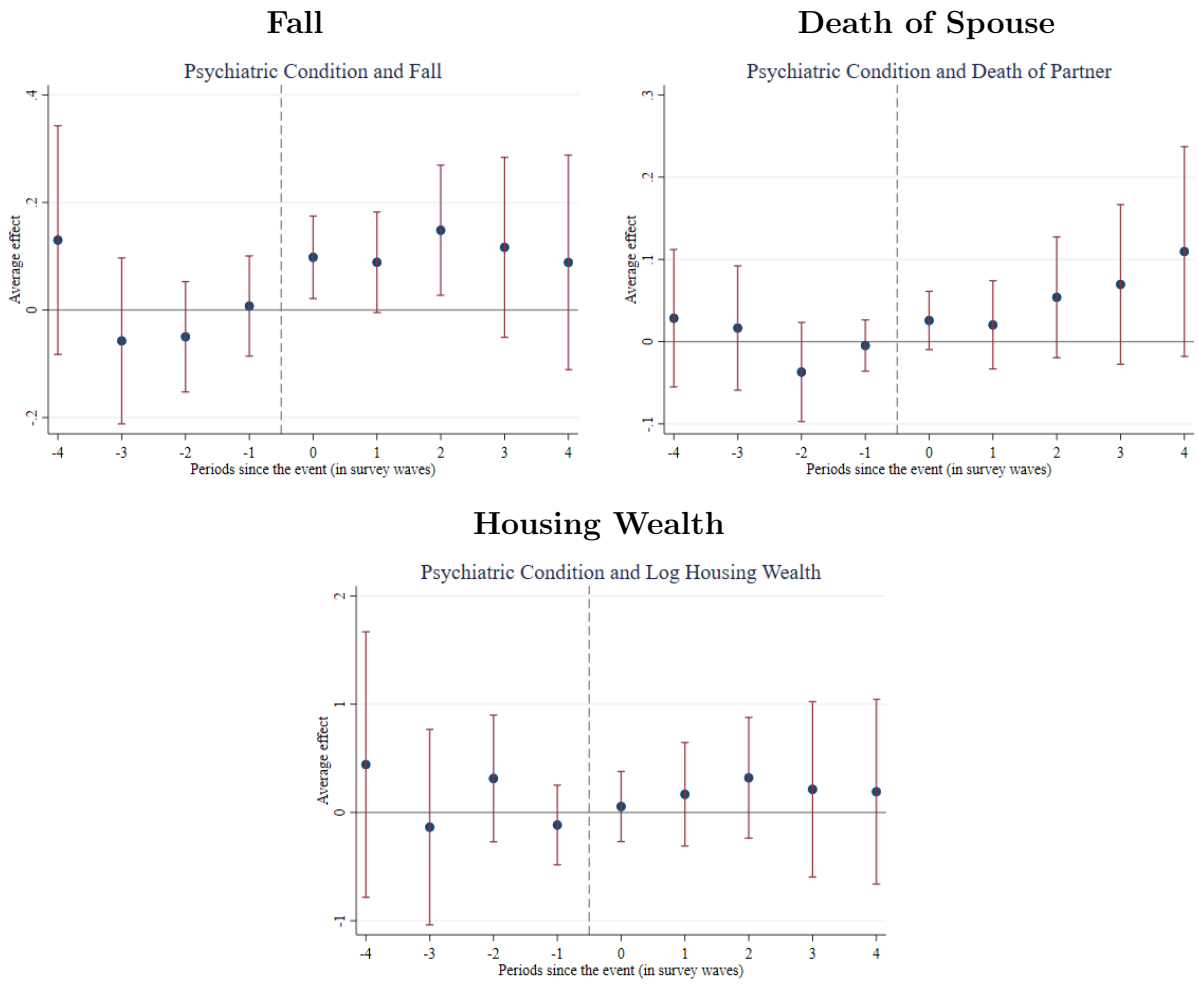



Figure A20: Events Coinciding with Psychiatric Shock

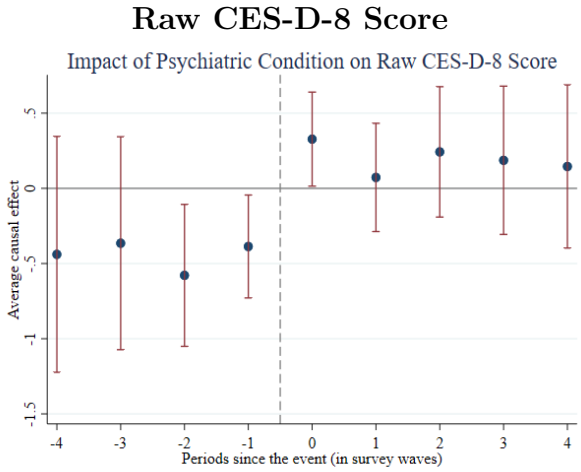



Figure A21: Psychiatric Shock and Depression

# 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 statuses.

**Main results conditioned on gender and marital status**

Table 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 people as they face a health shock. This result particularly holds for psychiatric condition and CES-D Depression. The converse holds for slef-reported health.

Table A11: Impact on Total Home Production

| | (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) |

Control Group: not yet+never treated.

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

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) |

Control Group: not yet+never treated.

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

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) |

Control Group: not yet+never treated.

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

**Impact on own home production follwing spouse's health shock**

Table A14 and A15 show that husbands significanlty increase the time spent in total HP 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 A22 show a significant positive shift in coefficients post shock. No significant change in husband's time for wife's psychiatric and CESD Dperession shock. On the other hand, wives decrease their total home production (including meal prep and housekeeping) when husband faces psyhiatric shock. For other shocks, her home production declines but is not statistically significant. Event study graphs in figure A22 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 looks like 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) |

Control group includes not yet + never treated.

$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

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

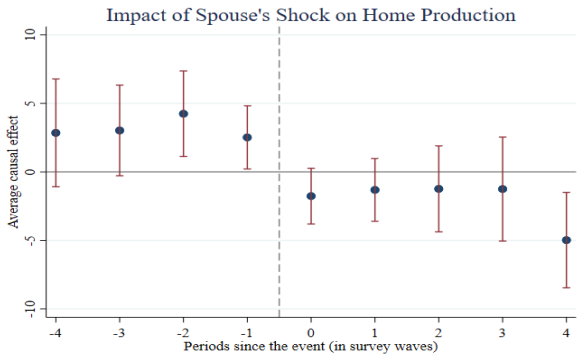
| | (1) HP | (2) Meal Prep | (3) Housekeeping | (4) Shopping | (5) Home Maint. | (6) Yard work |
|---|---|---|---|---|---|---|
| Psychiatric | -1.766$^{+}$ | -0.806$^{+}$ | -1.042$^{*}$ | -0.312 | 0.00428 | 0.00340 |
| | (1.038) | (0.429) | (0.473) | (0.205) | (0.0681) | (0.164) |
| CES-D Depression | -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) |

Control group includes not yet + never treated.

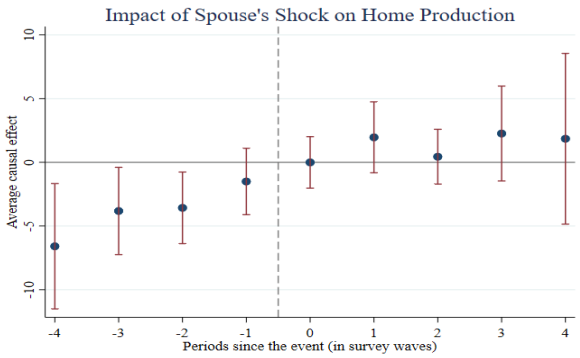
$^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

## Psychiatric Condition

Wife's HP

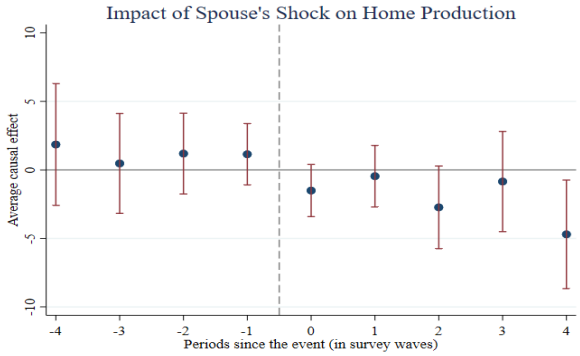



Husband's HP

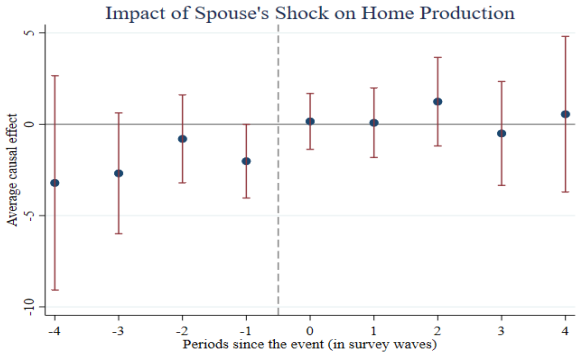



## CES-D Depression

Wife's HP

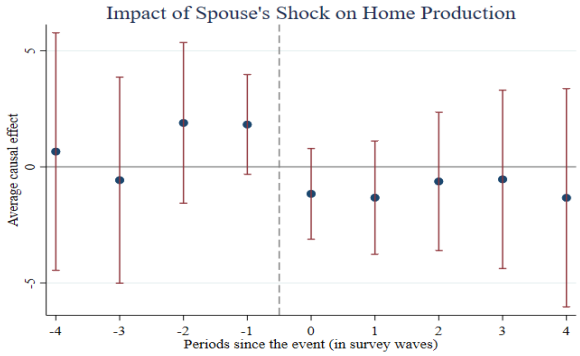



Husband's HP




## Self-Reported Health

Wife's HP




Husband's HP

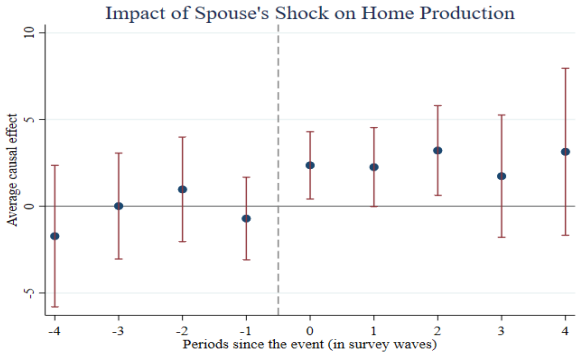



Figure A22

# F Other Categories of Time use

Table A16: Impact 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

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