The Effects of Health Shocks on Time Spent in Home Production

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Abstract

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

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1 Introduction

People spend around 12% of their non-sleeping time in home production, with even higher number for retirees, 17%.[1] Home production includes activities such as meal preparation, house cleaning, laundry, shopping, yard work, etc. In monetary terms, buying these services is equivalent to 26% of median retirement income.[2] An important feature of home production is that it directly affects people's effective consumption, 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; 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 on home production. I focus on retired people to rule out the confounding effects of labor supply. Retirees also spend more time in home production and are more likely to experience health shocks compared to working-age people.

Specifically, I focus on the following two effects that health shocks can trigger. First, health shocks increase out-of-pocket medical spending (e.g., Dobkin, Finkelstein, Kluender, and Notowidigdo, 2018; Poterba, Venti, and Wise, 2017; Cheng, Li, and Vaithianathan, 2018). Increased medical spending tightens the budget constraints of people and may lead them to shift their consumption away from market-purchased goods and towards home-produced goods, which are cheaper but require more time to produce. I refer to this mechanism as the income effect. Second, health shocks may increase the difficulty of performing physical activity, which may reduce the time spent in home production. I refer to this mechanism as the 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 their monetary effects, specifically, the decline in income and the increase in medical spending (Dobkin, Finkelstein, Kluender, and Notowidigdo, 2018). However, taking home production into account can change the conclusions based on monetary calculations alone. If the income effect is important, (1) home production partially insures against health risks, mitigating the losses measured in monetary terms, and (2) health shocks are more damaging than only monetary measures would suggest. In the latter case, further consideration should be given to policies that provide non-pecuniary support to people with poor health, such as home- and community-based care designed to substitute home production.

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

[1] American Time Use Survey (ATUS) Data

[2] 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.

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

To understand the importance of income and impairing effects on time spent in home production, I use a two-step strategy. In the first step, I divide different health shocks into three groups. Group 1 comprises health shocks that are costly but are less physically impairing than other health shocks; I refer to these shocks as costly shocks. Group 2 comprises 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)[3] 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.[4] In the second step, I exploit the 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 time spent in home production to these health shocks. If there is an income effect in response to health deterioration, this effect is more likely to be observed in response to costly shocks, whereas the impairing effect is more likely to be observed after impairing shocks.

My analysis yields several findings. First, I find strong evidence for the impairing effect, because impairing shocks significantly decrease the total time spent in home production. The impact can be as high as 16% of the average home production time in the immediate period after the shock. These effects are concentrated on 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 task, respectively. Additionally, the effects of CES-D depression and self-reported health shocks persist in the long run, whereas the effects of psychiatric shocks increase in the subsequent periods and dissipate in the long run.

I perform several robustness checks to test the sensitivity of these results: (1) I examine whether the decrease in home production is a mechanical function of a deteriorating memory, given the possibility of a decline in cognition upon a health shock; (2) to ensure that the impact of a health shock on home production is not driven predominantly by people who are severely debilitated, I exclude from my analysis the people who reside in a nursing home at the time of the interview or report an overnight nursing home stay; (3) 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; (4) I present the 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 after an impairing shock is robust to all these tests.

Second, I do not find strong evidence to support that costly shocks (i.e., cancer, heart condition, hypertension, and lung condition) have an income effect as expressed by an increase

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

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

in home production. Being diagnosed with 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 relative to the average home production time. The impact of a heart condition on home production is trivial, whereas the impact of hypertension and that of a lung condition are negative. Additionally, costly shocks do not increase home production in the long run. Therefore, I do not find evidence that home production plays an essential role in insuring people against the monetary costs of a health shock, or that mixed shocks significantly impact home production.

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

I do not find compelling evidence that suggests an increase in consumption spending following impairing shocks. Upon examining consumption spending categories correlated to the home production tasks, I find only self-reported health shocks induce increased spending on purchasing housekeeping and yard services. My results suggest important policy implications for structuring supports for home- and community-based services (HCBS). HCBS include services such as personal care, chore services, and meal delivery along with home health care services (health care by a skilled professional). Although Medicaid expansion of the HCBS program is a priority for federal policy, as is evident from President Biden's proposed Build Back Better bill. However, currently, Medicare only covers health care services provided by a skilled professional and for a limited period of time.

My paper is related to three strands of literature. The first is the literature studying the effects of health shocks on economic outcomes. Several studies have documented the impact of health shocks on their 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 negative 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 shocks affect another important yet understudied outcome: the time spent in home production activities.

The second strand of literature that my paper is related to 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 limited to attenuating only the consequences of anticipated income changes but also those of 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 fully mitigate the consequences of some economic shocks. For instance, Been, Rohwedder, and Hurd (2020) find that the housing wealth shock following the Great Recession decreased consumption spending in a sizeable way, but only 11% of total consumption spending was replaced 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 the monetary consequences of a health shock. The detailed health information in the HRS enables me to categorize various health shocks into groups, in order to identify and test the income effect and the impairing effect.

The third strand of literature that my paper is related to studies the relationship between health and home production. The overall findings of this literature strand are ambiguous. Focusing 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 their leisure time. These authors' results are in contrast to those of Gimenez-Nadal and Ortega-Lapiedra (2013) and Gimenez-Nadal and Molina (2015), who find a negative association. These studies employ 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 spent on home production tasks. Gimenez-Nadal and Molina (2015) argue that the positive association between health and home production time may be unique to the United States. 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 the working-age population. Leopold and Schulz (2020) use German Socio-Economic Panel data on retired couples to find mixed evidence: home production declines only for serious deterioration in self-reported health.

The results of all the aforementioned studies are based on self-reported health data, because most of these studies use cross-section time-use surveys.[5] These data sets offer very limited health data, only self-reported health data, in some waves. My work contributes to this litera-

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

ture in two ways. Firstly, whereas 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 of health shocks on home production. Secondly, I complement these studies by using detailed information derived from HRS health data 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 presents descriptive statistics. Section 4 presents the empirical framework. Section 5 shows the estimation results and the implications of the findings. The last section presents the conclusions of the paper.

2 Simple Model

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

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

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

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

where

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

with

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

such that,

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

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

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

3 Data

The data I use in this study come from the Health and Retirement Study (HRS), a nationally representative longitudinal survey of the U.S. population older than 50 years and their spouses. For HRS, the National Institute on Aging and the University of Michigan conduct interviews with about 20,000 people every two years, in addition to conducting supplementary studies to collect information on several other specific topics. The time use and expenditure data I employ in this paper were collected as part of a supplementary study, the Consumption and Activities Mail Survey (CAMS). I merge the data from the HRS core interviews and the data from the CAMS, which is administered to a subset of HRS respondents.

A. The Health and Retirement Study. The HRS collects data on labor force participation, income, household wealth, and social well-being, along with data on health and health spending, including out-of-pocket (OoP) medical expenditure.[7] The data on health conditions are described in detail below. The HRS collates spending data 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 the last two years. Detailed data on functional limitations such as difficulty in activities of daily living (ADL) and instrumental ADL (IADL) are also gathered.[8] I use these functional limitations to measure impairment. The HRS also collects comprehensive data on cognition and the use of formal and informal help.

B. The Consumption and Activities Mail Survey: The CAMS collects detailed measures of time use on more than 31 categories and household spending on around 38 items. The

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

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

HRS and CAMS are biennial. The CAMS is conducted in the HRS off-years, but the health data in the two surveys mostly overlap because health questions refer to the last two years, whereas time-use questions refer to last week or month, and consumption-spending questions refer to 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 the CAMS in 2019. The item response rates related to questions about more than 30 time-use categories in the CAMS are very high. Figure A5 shows that collectively among all waves, 71% have 0 missing item responses, 17% have only 1 item missing, and only 6% have two items missing.[9] To further assess the data quality, in Appendix A.2, I compare the summary statistics and the distribution of various time-use categories in the CAMS with the data in the American-Time Use Study (ATUS). The 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 U.S. population. Overall, the summary statistics and distribution of hours are very close in both the CAMS and ATUS.

3.1 Time Use

Respondents were asked about 31 time-use categories in wave 1 of the CAMS (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 that task "last week". For less frequent categories, respondents are asked about hours spent "last month". I convert the variables with monthly frequency into weekly frequency by dividing the response by 4.3 (number of weeks in a month). The 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),[10] I consider that time spent in home production is the sum of the following time-use activities:

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

[9] According to my calculations.

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

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

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

3.2 Health Indicators

The HRS gathers information on a set of medically diagnosed chronic health problems, including cancer, heart disease, stroke, diabetes, lung disease, hypertension, arthritis, and major psychiatric problems.[11] "Psychiatric condition" includes emotional or nervous problems. In Appendix D, I test whether the psychiatric condition is related to the death of a spouse, falling, or a wealth shock. In the HRS, respondents are asked whether they have been diagnosed with a given condition by a medical specialist since the last interview. In addition to these objective health measures, comprehensive data on self-reported health and self-reported mental health are also collected. The HRS collates data on several indicators to derive a mental health index using a score on the Center for 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 screening. Additionally, a five-point scale is used to measure self-reported health: "excellent", "very good", "good", "fair", and "poor". I group the first three responses as good health, and the latter two as bad health.

3.3 Sample Selection

My merged sample covers the years 2000 to 2019 and includes respondents to both the CAMS and HRS. My analysis focuses on retired people aged 65 to 85 years. To obtain a cleaner sample of retirees for whom the impacts on time use that operate via changes in labor supply and earnings are non-salient, I exclude individual-year observations of the people with more than $3,000 per annum in labor earnings, following De Nardi, French, and Jones (2010).[12] I further restrict my sample to the people observed for at least two consecutive waves. These constraints reduce the sample to 19,797 individual-year observations. All financial variables are converted into real variables using the Consumer Price Index (CPI) with 2015 as the base year.

[11] "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.

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

To focus on health shocks, I restrict the sample to people with a new diagnosis by excluding those who enter the sample with a preexisting condition. For example, to understand the impact of cancer, I exclude people who enter the sample with a preexisting cancer diagnosis. Then I identify the survey wave in which the person first reports having being diagnosed with a given condition over the last two years. A person is considered to have suffered a particular medically diagnosed health shock if that person reports getting diagnosed with a given condition after not being diagnosed with the same condition in the previous wave. Subjective health shocks are also defined likewise. A person is considered to face a depression shock if that person's CES-D score is greater than or equal to 3 in the current wave but less than 3 in the previous wave. Similarly, a person is considered to face a self-reported health shock when that person reports bad health in the current wave after reporting good health in the previous wave. After I impose all the sample restrictions, the individual-year observations in the 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 the basic summary statistics. The average age of the people in the sample is 74, and women comprise 60% of the sample. The median number of medically diagnosed conditions is 2, with 0 ADL and 0 IADL. Additionally, only 6% of the sample has a missing value for at least one task under home production. Noticeably, only 9% of the entire sample is covered by Medicaid, and 15%, by long-term care insurance.

Table 4 and Table 5 show differences in the characteristics of the treated and never treated groups for the two subjective and eight objective health shocks. There is no noticeable age difference between the treated and never treated samples. Compared to the non-treated sample, the people in the treated sample have more ADL and IADL, and except for those with cancer or arthritis, are also more likely to have relatively poor cognition. Not surprisingly, the people in the 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 between the treated and never treated samples is in the use of help. On the one hand, the treated and never treated samples for cancer, heart disease, hypertension, and lung disease do not differ much in the use of formal help, use of informal help, and hours of help received. On the other hand, the use of help is strikingly higher for the treated samples for psychiatric shock, CES-D depression, and adverse health shock defined by self-reported health. In Table A2 in 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 the ordinary least squares (OLS) technique, I regress the weekly time spent in home production on a health indicator such as a given medically diagnosed disease, an indicator for depression based on the CES-D score, or an indicator of self-reported health. In each regression I control for age, polynomial of age, gender, marital status, number of members in the household, race, and education, and I use year dummies. Standard errors are clustered

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

at individual level.

Figure 1 displays the results with 95% confidence intervals. It documents 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, 4 hours, is observed in the case of people 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 observation indicates that people with good health and those with poor health 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:

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

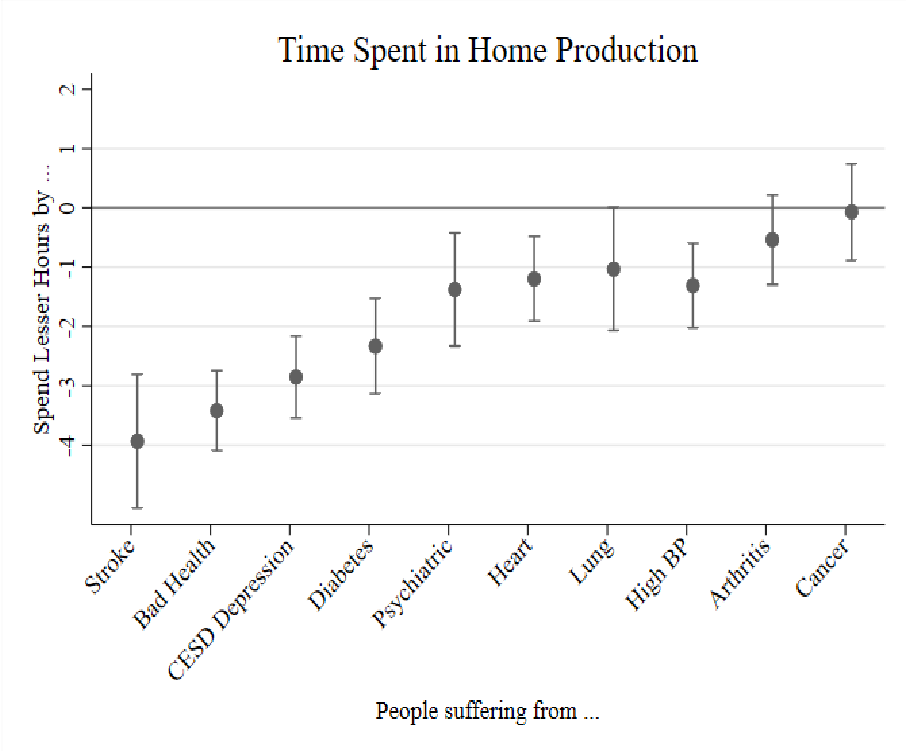

Figure 1: Home Production by Current Health Status

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

where y_{it} is the time spent in home production for individual i who faces a health shock in year t; β_i and γ_t are the coefficients on individual fixed effects and calendar time fixed effects, respectively; X_{it} represents a vector of potential control variables; and μ_r are coefficients on indicators of time periods relative to the onset of the shock. ϵ_{it} is the econometric error.

However, recent econometric research casts doubt on the validity of the causal interpretation of the TWFE difference-in-differences estimator when it is applied to settings with staggered timing of treatment. The reason is 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 become the control groups for the later treated units, therefore leading to biased estimates of the effects.

The effect of a health shock on home production is potentially heterogeneous across people faced with the shock in different waves. People who face a health shock at a later period tend to be mechanically older. Consider the following example. Suppose that to some extent, the effect of health on home production is determined by out-of-pocket medical costs and, therefore, the generosity of health insurance, which may increase as people age and become eligible for various health care schemes. Then, if the impact of a health shock varies over time, the estimate of μ_r can be biased because of the aforementioned forbidden comparisons. For example, for people just faced with a health shock, the home production may not increase much (perhaps because the income channel is too weak), while the home production of the control (earlier treated) group may increase, possibly because they lack insurance against increased medical cost. Thus, compared to the people treated early, home production decreases for those who just faced the health shock.

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

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

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

where G_g is a dummy variable that equals 1 for units in treatment group g; C_t is a dummy that equals 0 for individuals either not yet treated or never treated at time t; Y_t is the average outcome variable at time t; and Y_{g-1} is the average outcome the year before the treatment.[13]

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.[14] In Appendix B.4, I

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

[14]Based on the total relative time periods, the event study graphs have nine post-treatment periods; however, I show event study estimates for only four post-treatment periods, because there are noisy estimates in the later

also explore two other approaches to estimate the impact of health shocks on home production time and compare them with the CS approach described above. The first approach is the standard TWFE. In the second approach, I make treatment groups based on the first age they are treated, as opposed to the first wave.[15] These estimators yield qualitatively similar results.

In order to interpret $\theta_D(e)$ in the post-treatment period as the causal impact of health shocks on home production, we require exogeneity of health shocks. In other words, prior periods' health cannot affect contemporaneous home production time. To address this concern, as a first step, I use health variable that is not influenced by home production: the onset of new health events. These health conditions are diagnosed by a doctor or a medical professional. Although individuals may anticipate these health events (e.g., due to family past history), the timing of shock is unanticipated. I limit my sample to people with a new diagnosis of a given health shock. As mentioned previously, I exclude people with preexisting conditions. Furthermore, in the robustness checks below, I test if the impact on home production of a given health shock is a marginal impact of an additional shock. Additionally, I 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. 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 (for a detailed discussion, see the results section).

4.1 Categorization of Health Shocks

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

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.[16]

Columns 3–6 show that among the costly shocks, hypertension is the least impairing in terms of ADL and IADL. Cancer, heart condition, and lung condition also stand among the bottom three shocks in terms of difficulty in daily living. Because stroke induces the highest increase in daily living limitations despite being highly costly, I exclude it from the group of costly shocks and include it in the category of costly shocks.

periods. One period is equivalent to two years, given the structure of the HRS and CAMS.

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

[16] Papers studying the out-of-pocket medical costs 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.

The second group (i.e., impairing shocks) consists of shocks with a lower increase in out-of-pocket medical expenditure but a higher increase in difficulties in daily living. Table 2 shows that psychiatric condition, CES-D depression, and self-reported health shock induce high increases in activities of daily living limitations and are the least costly shocks among those considered in this paper. Psychiatric shocks are associated with a significant increase of 0.27 ADL and 0.3 IADL in the first period observed after the shock. CES-D depression and self-reported health shock 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 ADL and IADL among the impairing shocks (self-reported health shock 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 magnitude of the highest increase among impairing shocks (self-reported health shock).[17] I exclude stroke, diabetes, and arthritis from these groups, because they do not fit the 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 their effects on home production in the following section.

5 Results

I now use the three groups (costly shocks, impairing shocks, and mixed shocks) 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 with the health variables in the preceding HRS wave. Therefore, these coefficients indicate the impact of a health shock on home production at least one year after the shock. I begin by illustrating the impact of costly shocks on home production time.

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. However, this 2% increase is small and statistically insignificant relative to the

[17] 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 OoP medical expenditures, and the second is the ratio of OoP medical expenditure to the 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 OoP 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 a very similar distribution for the treated and never treated.

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

	OoP Medical Cost (Dollar)		ADL		IADL	
	(Change) (1)	(Rank) (2)	(Change) (3)	(Rank) (4)	(Change) (5)	(Rank) (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 of health shocks on home production in the first period after the shock. Top 1 percentile of real out-of-pocket medical costs is excluded. Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

average home production time. The impact of a heart condition on home production is trivial. Although costly shocks are more likely to have an effect on home production through the income effect (by triggering a shift toward consumption of more home-produced goods), I find the opposite effect for high blood pressure and lung condition.

Columns 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 the income effect of health shocks. 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 significant increase in hours allotted to these tasks.

To further understand the impact of health shocks on home production in the longer run, in Figure 2 I show the event study plots. The decrease in home production after a lung condition or high blood pressure diagnosis, discussed previously, is only short-lived, as seen in the event study plots. Overall, I do not find evidence of an increase in home production in either the short run or the long run for the costly shocks analyzed.[18]

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, I exclude individuals who ever report any ADL or IADL in the entire sample. Results are presented in

[18]The time gap between two periods in the event study plots is two years, because HRS surveys are biennial.

Table A5 in AppendixB.1. The impact of cancer and heart condition on home production is positive. However, despite showing an increase in magnitude compared to the baseline results, the effects are not statistically significant. The impact of high blood pressure and that of lung condition are in line with baseline results.

5.2 Effects of Impairing Shocks

I next consider the effects of impairing shocks on home production. In this section, I present results whether individuals decrease the time spent in home production due to impairing effects of health shocks. Column 1, 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 for psychiatric shocks. Diagnosis of a psychiatric condition significantly decreases home production time by 3.2 hours in a week (standard error = 1.61), 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 by 1.12 hours in the first period (standard error = 0.56). Self-reported health shocks also decrease the average time spent in home production by 1 hour (standard error = 0.53).

The decline in total home production is driven mostly by the biggest components of home production: time spent on meal preparation and housekeeping. A psychiatric shock decreases the time spent on 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% and 22% in the time spent on meal preparation and housekeeping, respectively. Similarly, CES-D depression and self-reported health shock decrease meal preparation time significantly by about 0.5 hours each, followed by time spent on housekeeping and gardening tasks.

Given the significant decline in home production and its various activities in the first period after a health shock, it is important to further look at the extent of these effects in the longer run. The event study graphs in Figure 2 show that the effects of a health shock on home production 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. The impact of CES-D depression and that of a self-reported health shock persist for many more periods in the longer run. Similarly, the event study graphs for meal preparation and housekeeping tasks in Figure 3 show that the impact of a health shock on home production is not restricted to the immediate period after the shock. In Appendix E I explore the heterogeneity in the effects by gender and marital status (results 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, and arthritis. Column 1 shows that total home production decreases for

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 (in hours per week) in the first period after the shock. Top 1 percentile of all time use is excluded. Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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 effect of 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 diagnosis 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), representing 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 diagnosis; however, the impacts are not statistically significant. Additionally, although home production shows a downward trend prior to the onset of diabetes, it has no significant impact on home production after the shock. Among other unexplored reasons, the absence of any impact on home production for mixed shocks could be a result of the income effect and impairing effect canceling each other.

5.3.1 Identifying Assumptions and Robustness

Interpreting the coefficients from the event study as the causal effect of a given impairing shock would require the identifying assumption that in the absence of a health shock, the average home production would have evolved parallelly for the treated and never treated groups. An implication is that there should be no downward trends in home production time in the periods leading up to the shock. Although Figure 2 may visually indicate this is the case for all the impairing shocks, I further test the sensitivity of my estimates to potential violations of the parallel trends assumption. Following the procedures described by Rambachan and Roth (2022), I compare 95% confidence intervals obtained from my primary model against those obtained after allowing for deviations from a linear trend of up to an arbitrary amount, M. 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 Use

To test whether the impact of a health shock on home production is driven predominantly by people with a severe impairment, I design two specifications that exclude the people who (1) reside in a nursing home at the time of the interview and (2) report an overnight nursing home stay since the previous wave if in the previous wave they did not report any overnight nursing home stay. Column 1 in Table A6, Appendix B.2, shows that average home production declines in the first period after the shock, despite the fact that I exclude the people living in a nursing home at the time of the interview. The magnitude of the decline is comparable to the baseline results for all the impairing shocks considered in this study. People who are in a nursing home at the time of the interview mechanically carry out less home production than those living at home.[19] Therefore, the decrease in home production, despite the fact that I exclude nursing home use, additionally informs that the decline in the baseline specification is not a trivial observation. Upon excluding the people whose timing of nursing home stay is concurrent with the health shock, I find that the baseline results not only hold but also increase in magnitude (column 2 in Table A6). This result shows that the baseline results are not driven by only the people with a severe impairment.

Decline in Cognition

In this section, I test whether the drop in home production is a mechanical function of deteriorating memory coinciding with a health shock. It is documented that two out of the three impairing shocks considered in this study, namely, diagnosis of a psychiatric condition and CES-D depression, are commonly associated with cognitive impairment (Lee et al., 2012; CDC, 2020). Such impairment may lead to short-term forgetfulness and affect the recall of time-use responses in the survey. Based on the summary statistics, people diagnosed with a psychiatric condition and CES-D depression are more likely to have poor self-reported memory (by 15 and 22 percentage points, respectively). Given the possibility of a decline in cognition of the respondents, I estimate the DiD model after a series of exclusions. I do so by excluding the people whose memory state worsens between the period before and after the shock. I employ two measures to capture the decline in cognition – Langa-Weir classification and self-reported memory.

The Langa-Weir classification of cognition function (Langa et al., 2022) is a researcher-contributed data set that provides a summary score for cognition using measures[20] from the core HRS interview.[21] This score is used to classify respondents into three Langa-Weir categories: Normal, Cognitively Impaired but not Demented (CIND), and Demented.

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

Results in Table A7, Appendix B.2, suggest that the baseline impact of impairing health shocks is not predominantly driven by poor recall or forgetfulness of the respondents who suffered a health shock. Column 1, which displays the results with Langa-Weir restrictions, shows the impacts of psychiatric condition and CES-D depression on home production are moderately weaker in magnitude and lower in statistical significance compared to the baseline results, but

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

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

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

the impact of self-reported health shocks does not change much. Column 2 shows the impact of a health shock on home production of the people with self-reported memory restriction is roughly similar to the baseline results, with a significant decline in home production of more than 3 hours and 1 hour (significant at the 10% level) after a psychiatric shock and CES-D depression, respectively. The impact of self-reported health shocks decreases relative to the baseline results.

Marginal Effect of an Additional Shock

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

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

Figure A11 charts the evolution of ADL and the number of other medically diagnosed conditions before and after the shock. A discernible jump in ADL can be observed before and after an impairing shock. Moreover, no noticeable pre-trends seem to exist in the number of medically diagnosed diseases 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.[22] The impact of a psychiatric shock on time spent in home production is very robust to all these specifications. For all of them, the impact is around 3 hours weekly and is statistically significant at the 5% level. Similarly, the impact of CES-D depression and that of self-reported health shock on time spent in home production are robust for most of the aforementioned specifications, and the magnitudes are similar to those in the main specification.

6 Possible Adjustments to Decrease in Home Production

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

6.0.1 Use of Help

In this section I first examine whether people who face shocks rely more on formal and informal help with home production-related tasks? HRS collects data on the use of help received by the respondents and the helpers who assisted them with ADL and IADL, 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 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 psychiatric condition, CES-D depression, and self-reported health shock, respectively. Although larger in magnitude than the likelihood of using formal help, the likelihood of using informal help (in column 2) exhibits a similar trend. Informal help received increases by 10, 6, and 7 percentage points for

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

psychiatric condition, CES-D depression, and self-reported health shock, respectively. Among the specific home production-related tasks, the most significant increase is observed for reliance on help related to work around the house and yard for all the impairing shocks (columns 3–7). The increase in the likelihood of using help continues in the longer run. The increase persists for more periods for CES-D depression and self-reported health shock than it does for 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 using help. The magnitude of impact of costly shocks on formal and informal help received is much smaller than the impact of impairing shocks, with the impact being not significant for most costly shocks, as shown in Table A9. Likewise, in the long run, the impact of costly shocks 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 following CES-depression and self-reported health shocks. Hours of help increased by 1.7 hours (half the amount of decrease in home production) following a psychiatric shock. This result might suggest that the loss in home production is partially recovered by the increase in the amount of help. However, in the survey, only the respondents who report functional limitations are asked about the hours of help they received. Therefore, hours of help may not strictly include assistance with home production tasks.[23]

The results 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 that person's own time spent in home production. Table A14 shows husbands significantly increase their time spent in total home production by 2.3 hours (standard error = 0.9) when their wives face a self-reported health shock. Most of the increase comes from meal preparation and housekeeping time (around 1 hour each). The event study graph for husbands' total home production upon their wives' self-reported health shock shows a significant positive shift in coefficients after the shock. However, no significant change in husbands' time spent in home production is observed when their wives' face a psychiatric or CES-D depression shock. 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 that husbands 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

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

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 combine 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 spending has been converted into log of monthly figures.[24]

Table A10 shows the impact of the impairing shocks on consumption spending for the first two periods after the shock.[25] Spending on purchasing house and yard services seems to be the most responsive spending category to health shocks. Expenditure on other services does not increase. Similarly, total non-medical spending does not change. Additionally, although following a psychiatric shock, the purchase of housekeeping and yard services decreases by around 30 percent, it significantly increases by around 20 percent following CES-D depression and self-reported health shocks. However, the event study graphs show an increasing trend prior to CES-D depression and self-reported health shocks. 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 shocks and evidence towards a reverse substitution – away from home

[24]Even though the 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 not only increase as a part of substitution away from home production but also 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 estimate of substitution of consumption spending is a lower bound.

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

production and toward 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.[26] A decline in utility derived from consumption might reduce the need to compensate the decrease in home production with increased market spending.

7 Summary and Concluding Remarks

People can substitute consumption spending with home production to protect overall consumption against falling 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.

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. Moreover, the decrease in home production is not short-lived. Though the effect dissipates for psychiatric shocks after a few periods, it persists in the long run for depression measured through the CES-D score and self-reported health shocks. I employ several robustness checks to test the sensitivity of the results and understand the nature of the shocks. In addition to considering various alternate econometric specifications, I explore the role of a 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 ser-

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

vices 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 data that may hinder my ability to detect the impact of health shocks on home production. One limitation is the time lag between health and time-use data. As mentioned earlier, the time-use data in the CAMS are merged with the health data in the preceding wave of the HRS. Therefore, there could be a maximum time lag of around three years between the two. This time lag limits my ability to capture short-term change in home production in response to a health shock, especially for costly shocks that do not lead to high ADL. 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 of health shocks on home production.

Another limitation is that even though the number of time-use activities reported in the CAMS may be high enough to provide a picture of overall time use in a typical week, data on certain categories where people with good or poor health may be spending time differently are not collected (for example, time spent resting, which may be different from sleeping). Finally, I use ADL and IADL to capture the disutility induced by health shocks. However, these measures may not fully capture the disutility cost of health shocks. For example, even though a lung condition does not induce a significant increase in ADL and IADL, the fact that cleaning house involves the use of aerosols to clean dust, this could inhibit people suffering from lung conditions from undertaking some 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 people's time spent in home production differentially and whether reliance on help with home production-related tasks changes in response to these shocks.

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

Future work should explore other channels through which health shocks can impact home production. One such mechanism is a change in the marginal utility of consumption upon a health shock. Another channel can be adjustments in life expectancy. Suppose people expect to live a shorter life after a health shock, for example, cancer diagnosis. A shortened life span can increase the monetary resources available in each period, which can have an impact on house production opposite to that of the 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 the people who suffered the shock and their spouses, especially retired people.

Main Figures and Tables

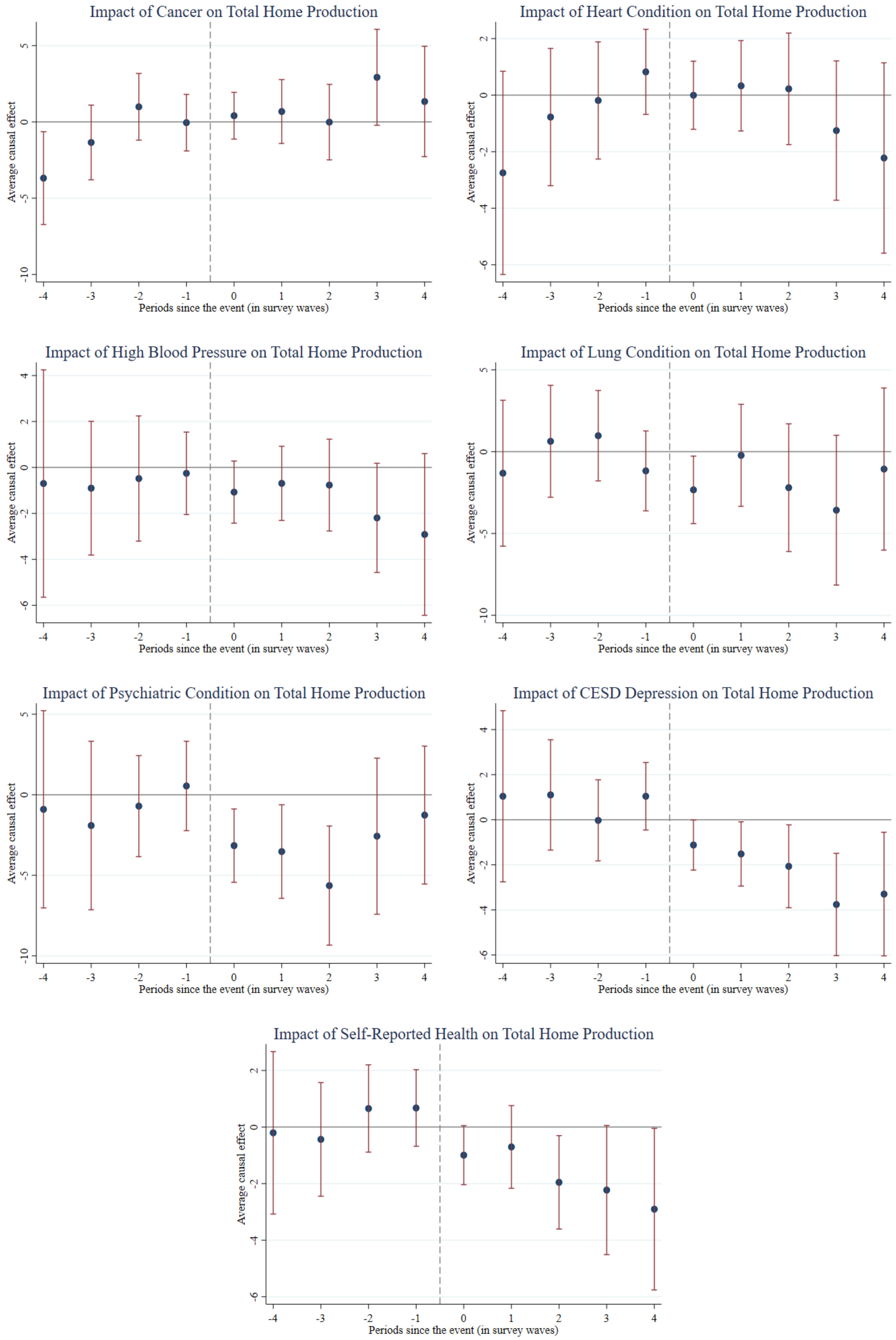

Figure 2: Impact of Health Shocks on Time Spent in Home Production

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 the 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 people who eventually stop responding to the surveys, because of death or other reasons. Other diagnosed conditions refer to the total number of medically diagnosed conditions other than the condition listed in the column head. The three categories to measure cognition are taken from the 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 people who eventually stop responding to the surveys, because of death or other reasons. Other diagnosed conditions refer to the total number of medically diagnosed conditions other than the condition listed in the column head. The three categories to measure cognition are taken from the Langa-Weir cognition classification (Langa et al., 2022).

Impact of Health Shocks on Tasks of Home Production

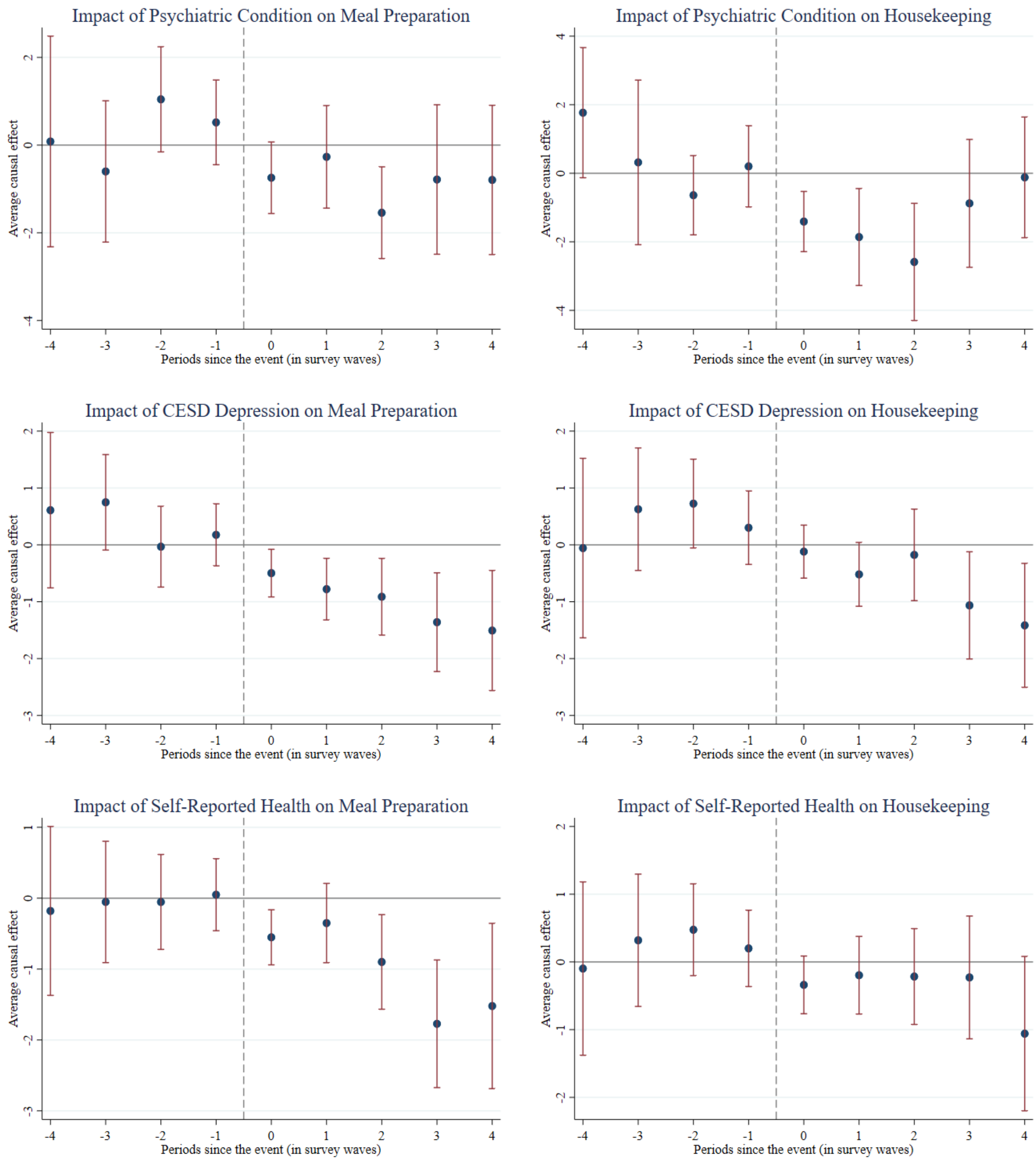

Figure 3: Impact of Health Shocks on Tasks of Home Production

Note: These event study graphs show the expanded results of columns 2 and 3 in Table 3 for cancer, heart, and high blood pressure. The points in each figure represent the estimated effects in the 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.

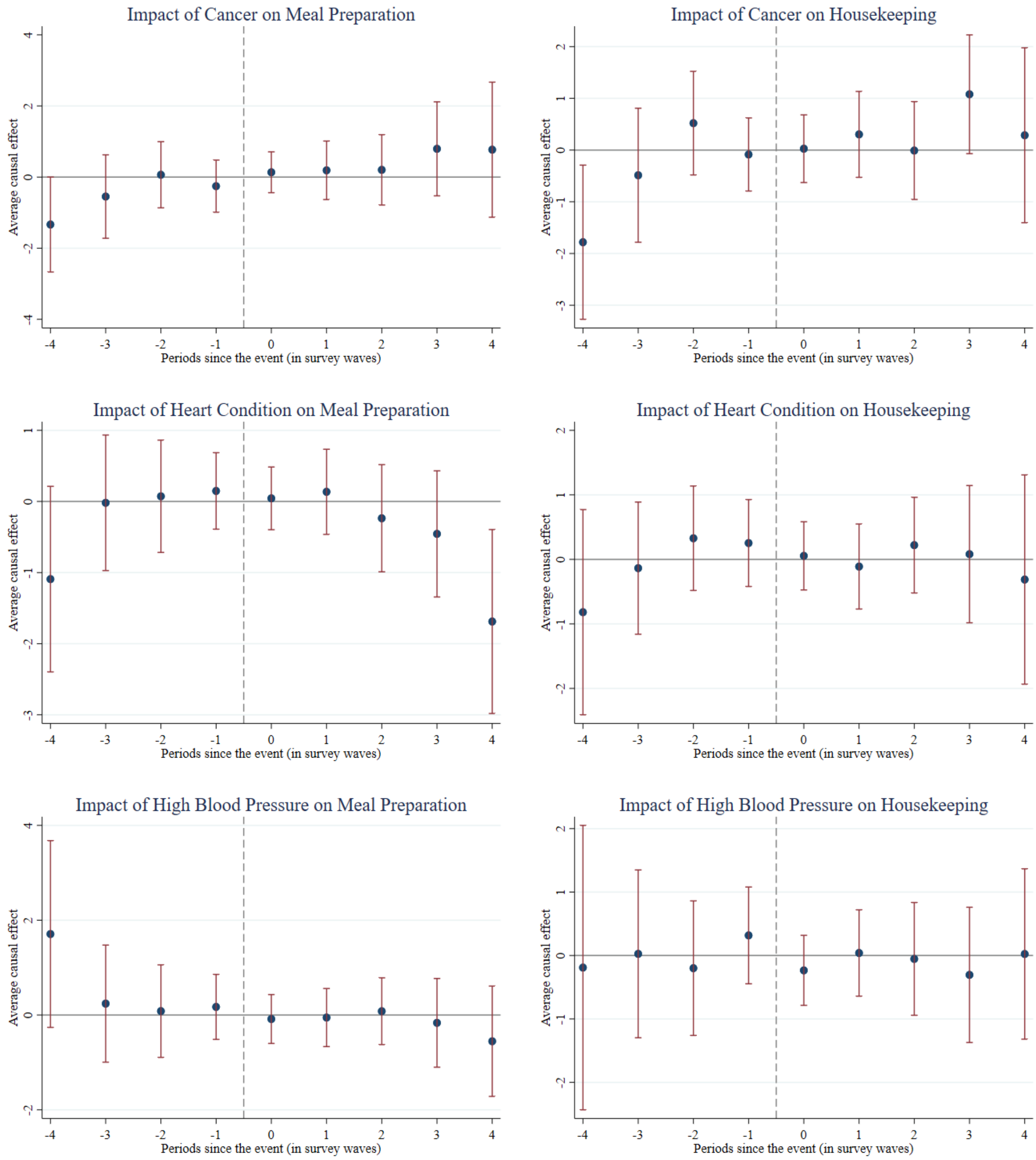

Figure 4: Impact of Health Shocks on Tasks of Home Production

Note: These event study graphs show the expanded results of columns 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 the 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.

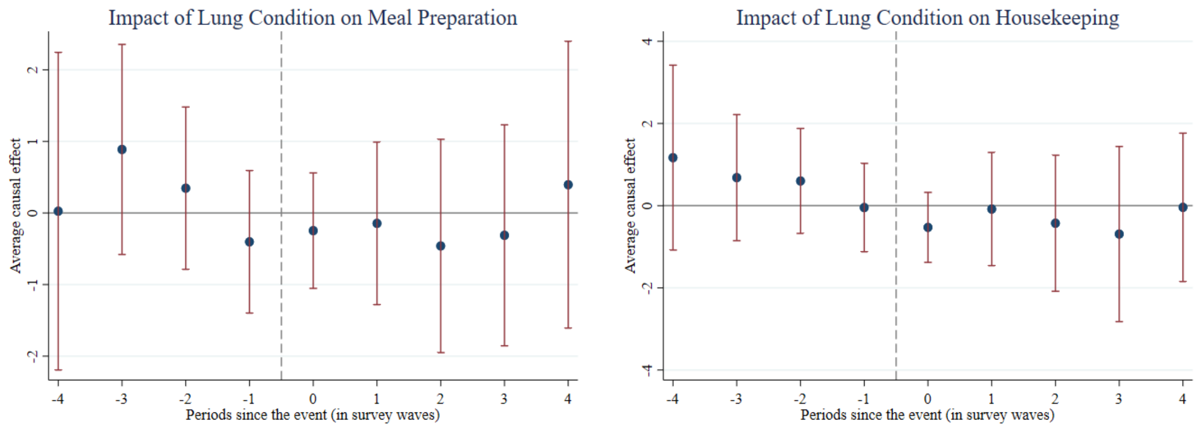

Figure 5: Impact of Health Shocks on Tasks of Home Production

Note: These event study graphs show the expanded results of columns 2 and 3 in Table 3 for self-reported health shocks. The points in each figure represent the estimated effects in the 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.[27]

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 .

[27]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.

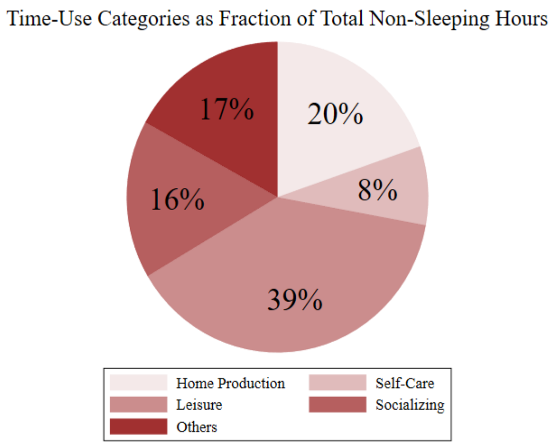


Figure A1

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.

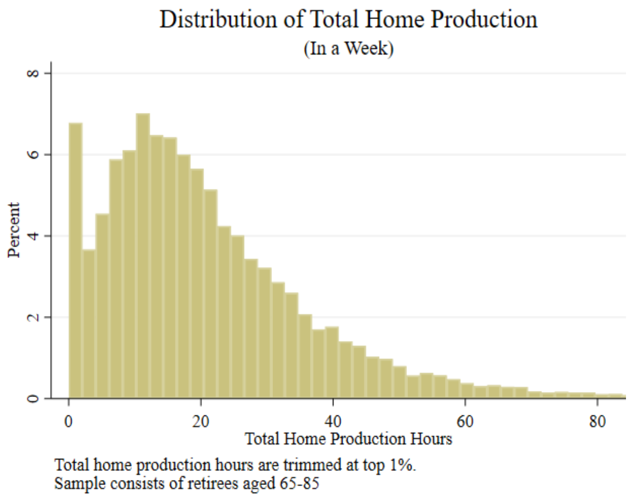


Figure A2

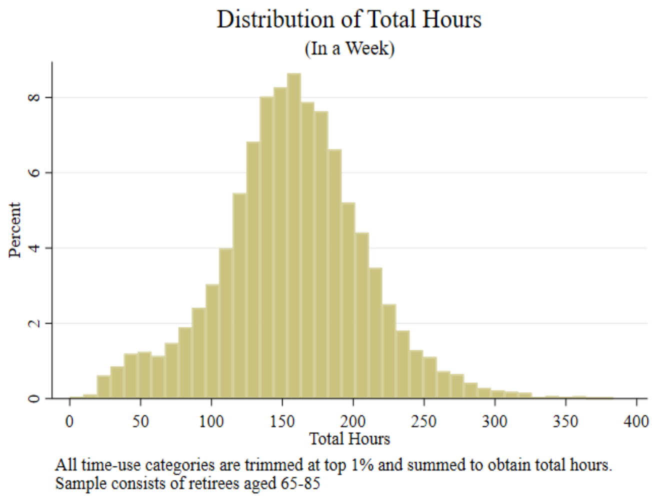


Figure A3

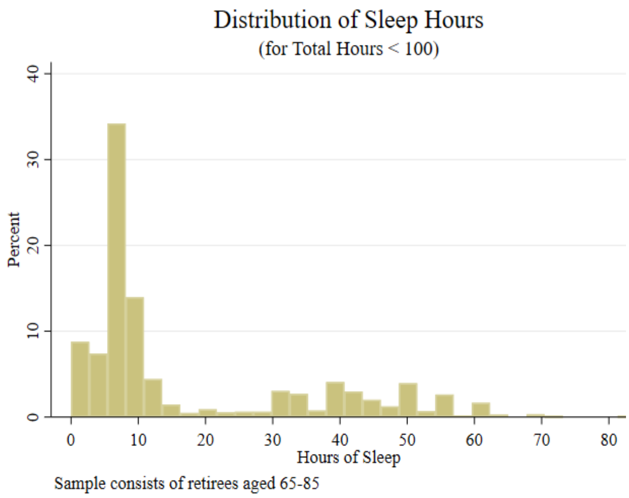


Figure A4

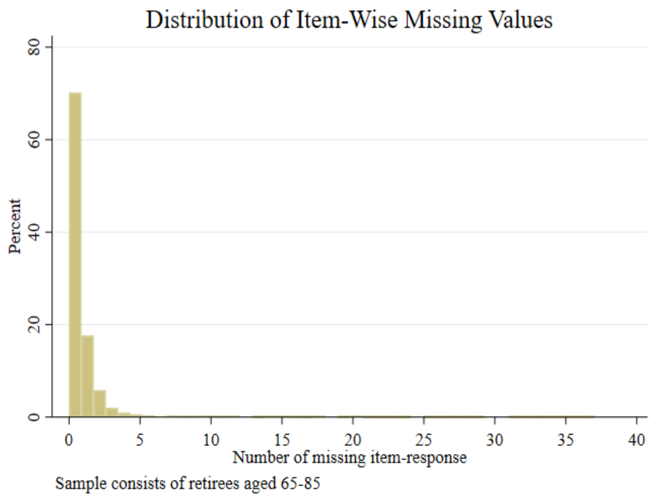


Figure A5

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[28] 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.

[28] 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

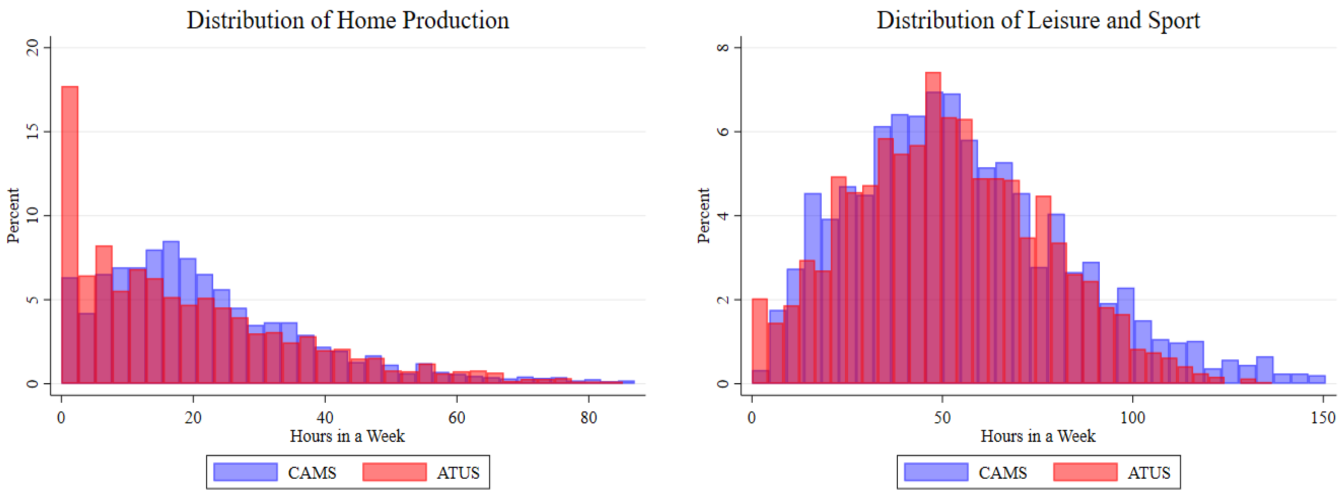


Figure A6

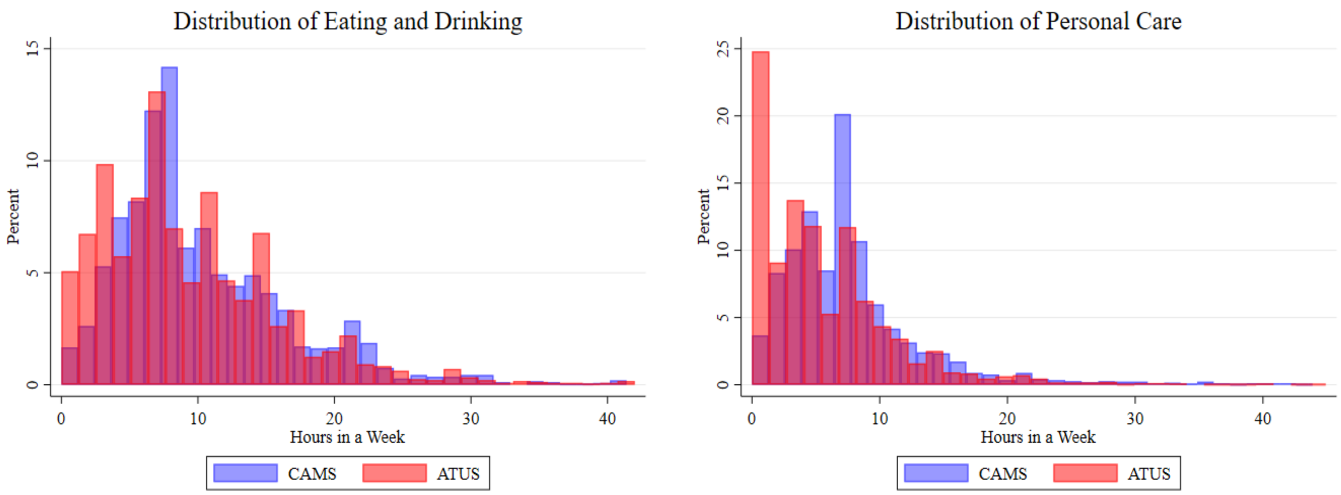


Figure A7

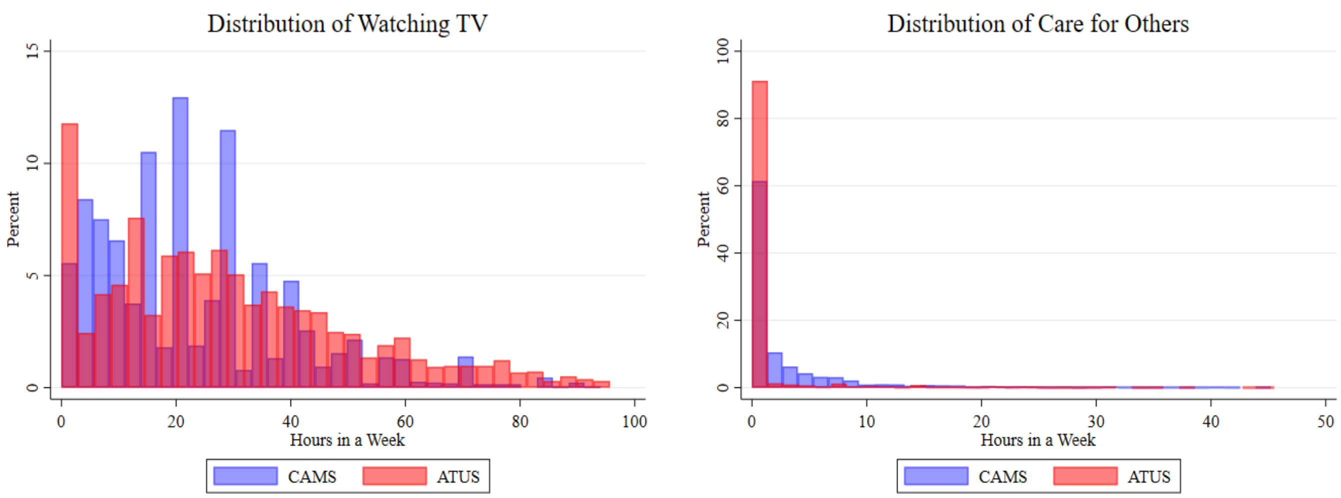


Figure A8

B Robustness Checks

B.1 Income Effect

Table A4: Impact on Medical Cost

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

Top 1 pctile of Fraction is excluded

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

Table A5: Impact on Home Production (No Limitations)

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

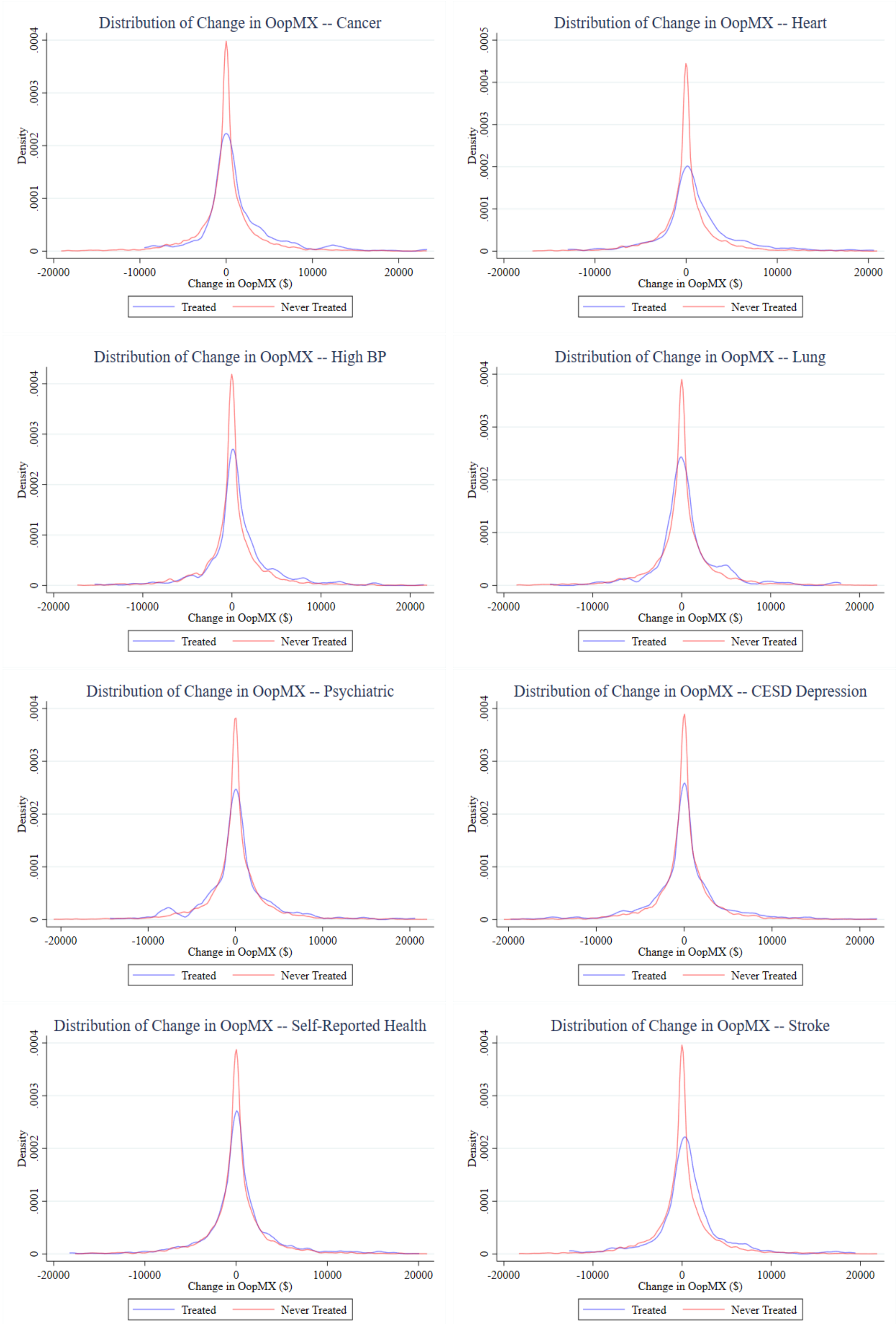
Standard errors in parentheses

Control Group: not yet+never treated.

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

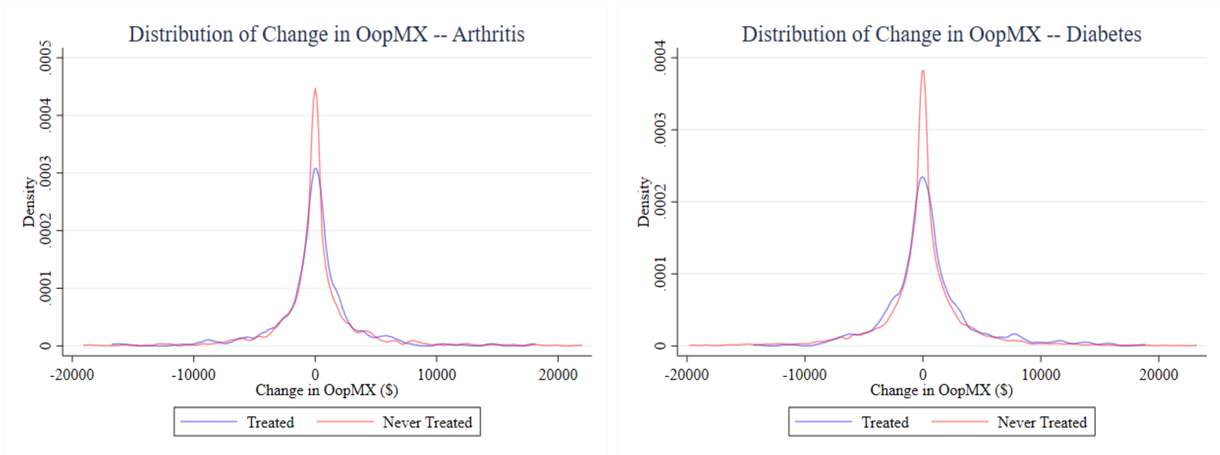
Column 2 excludes individuals who ever reported IADLs greater than 0

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



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
0
.0001
.0002
.0003
.0004
.0005
-20000
-10000
0
10000
20000
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)

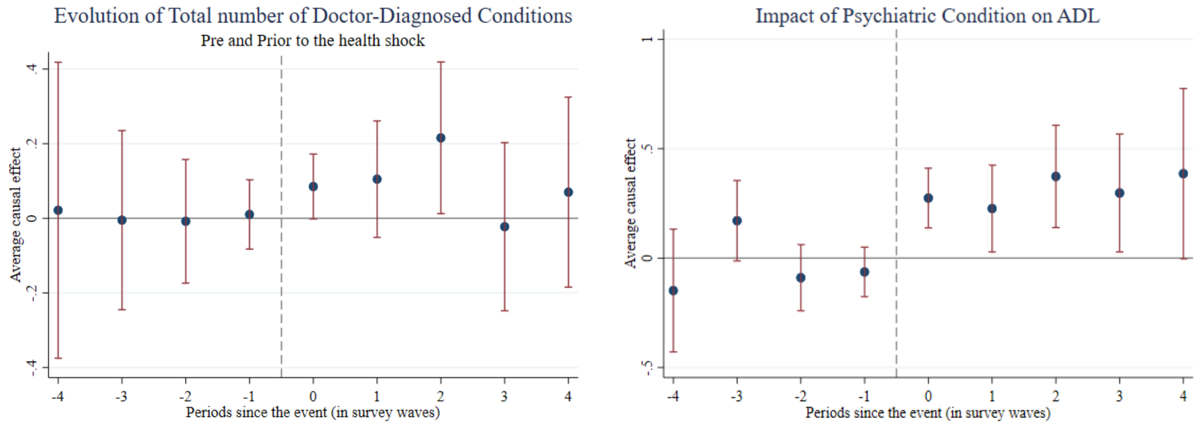


Figure A11: Psychiatric Shock

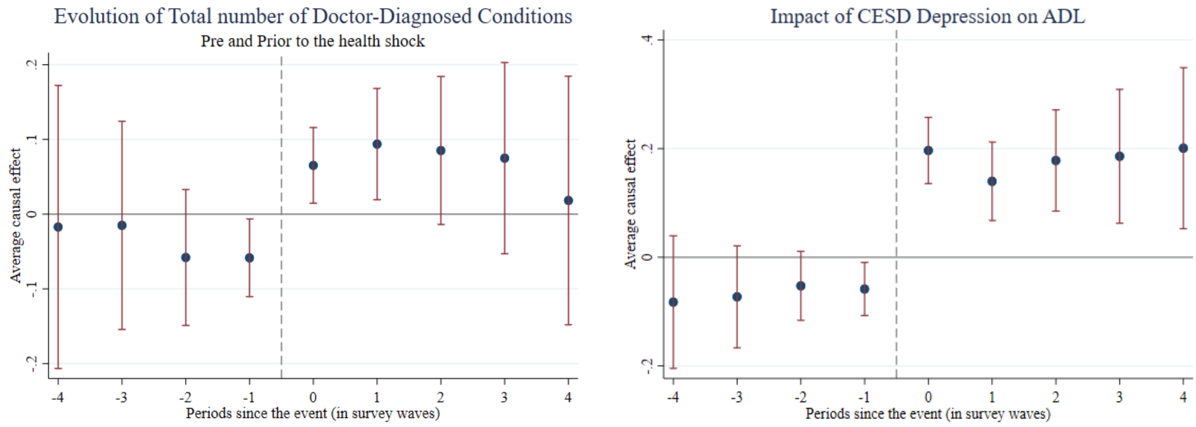


Figure A12: CES-D Depression Shock

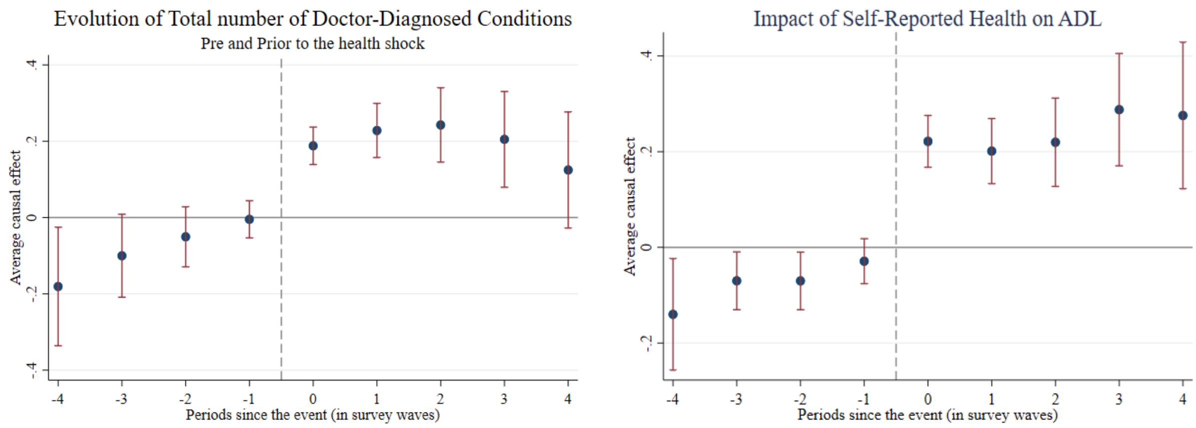
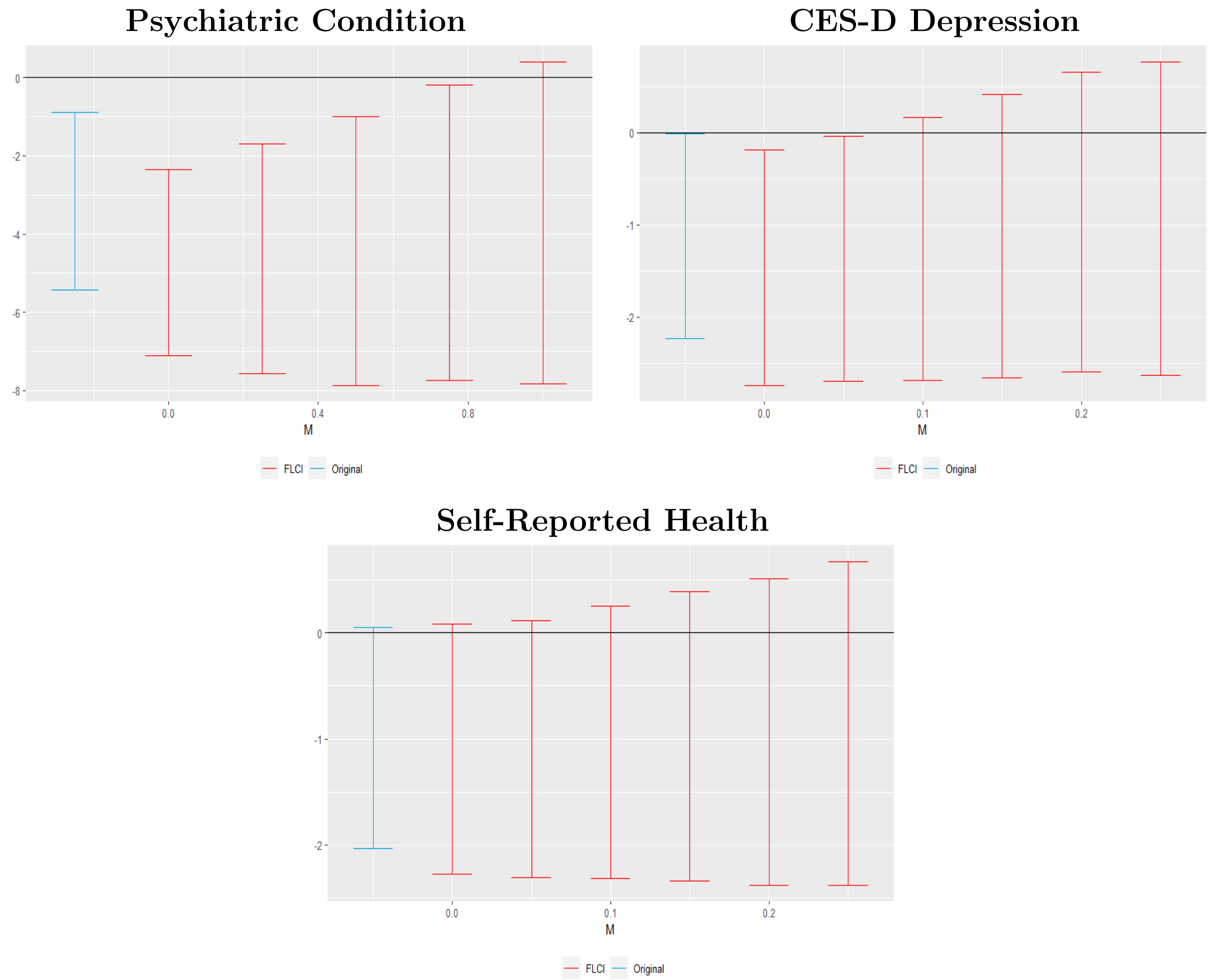


Figure A13: Self-Reported Health Shock

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.

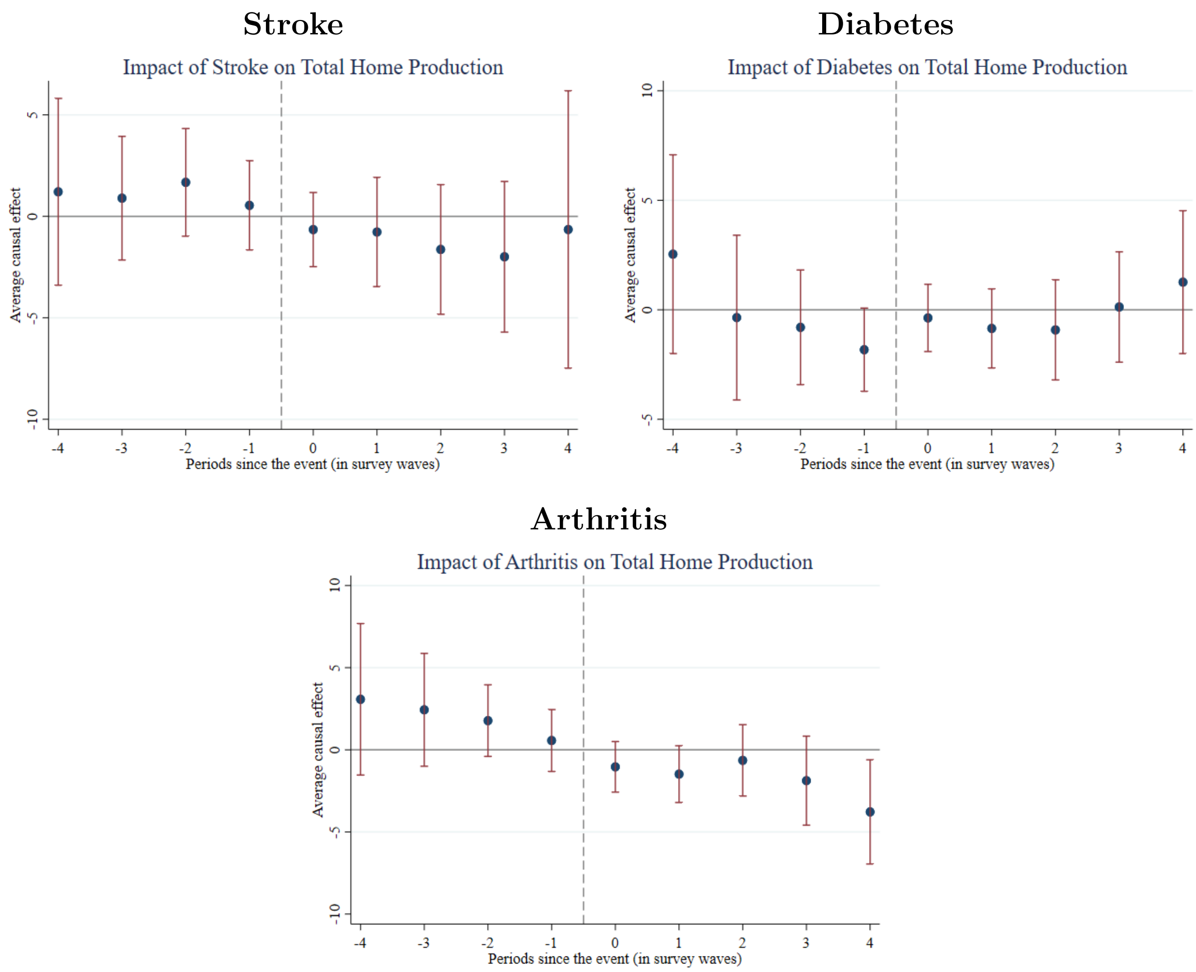
Figure A14: Effects on Home Production: Parallel Trends Test



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

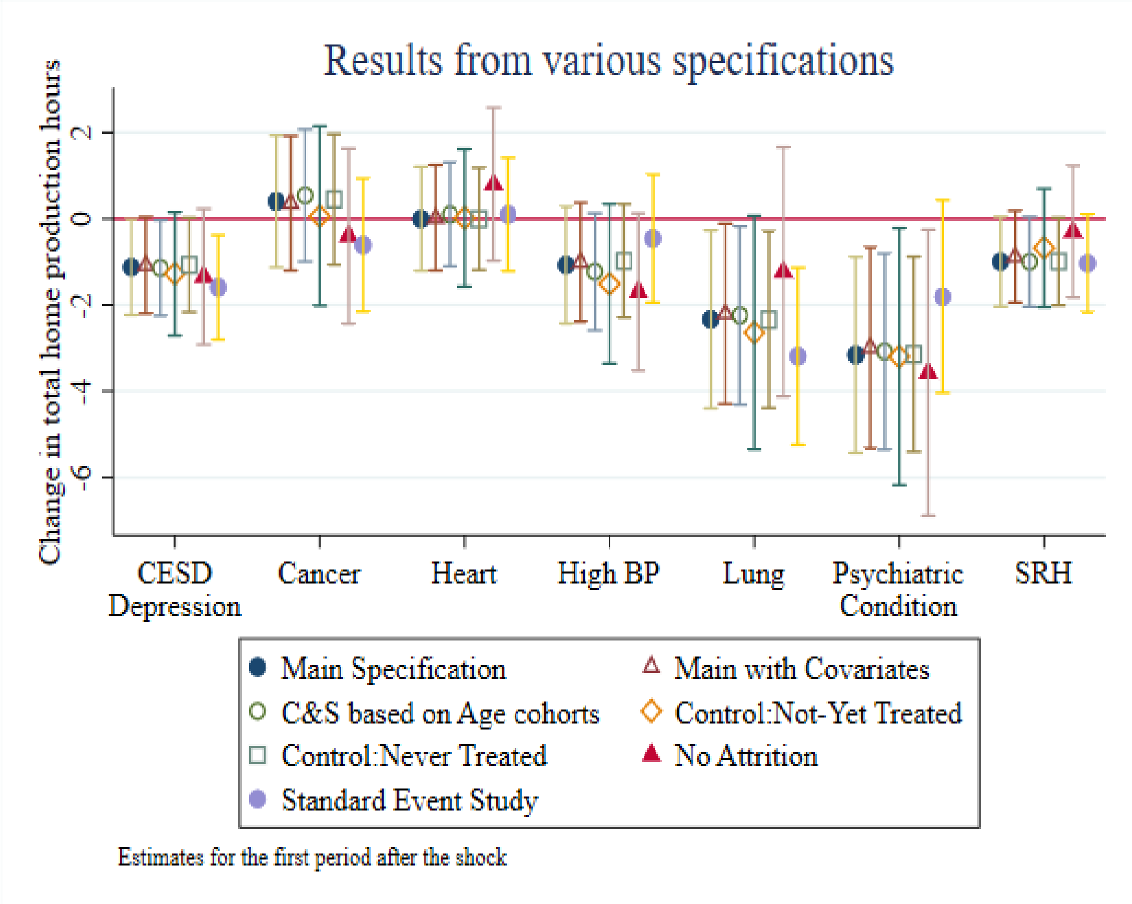


Figure A16

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

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

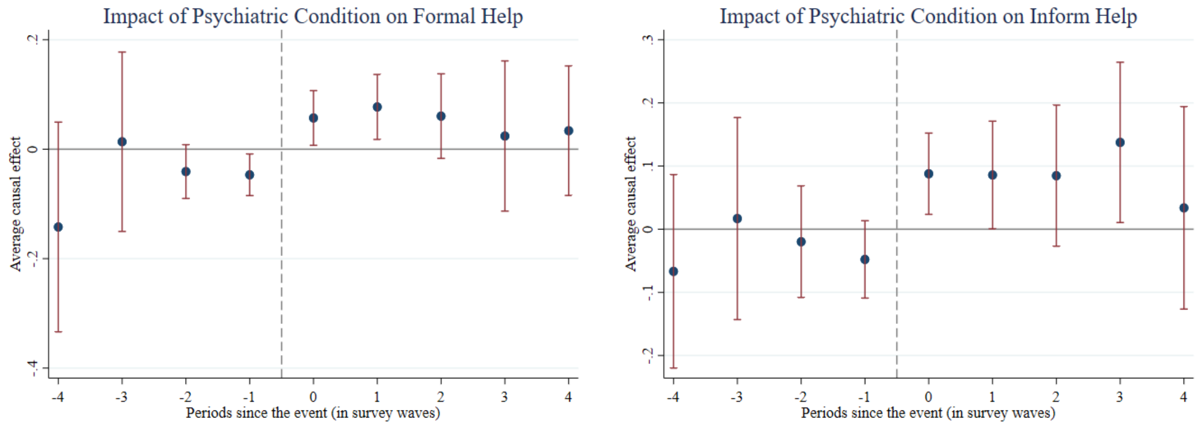


Figure A17: Psychiatric Shock

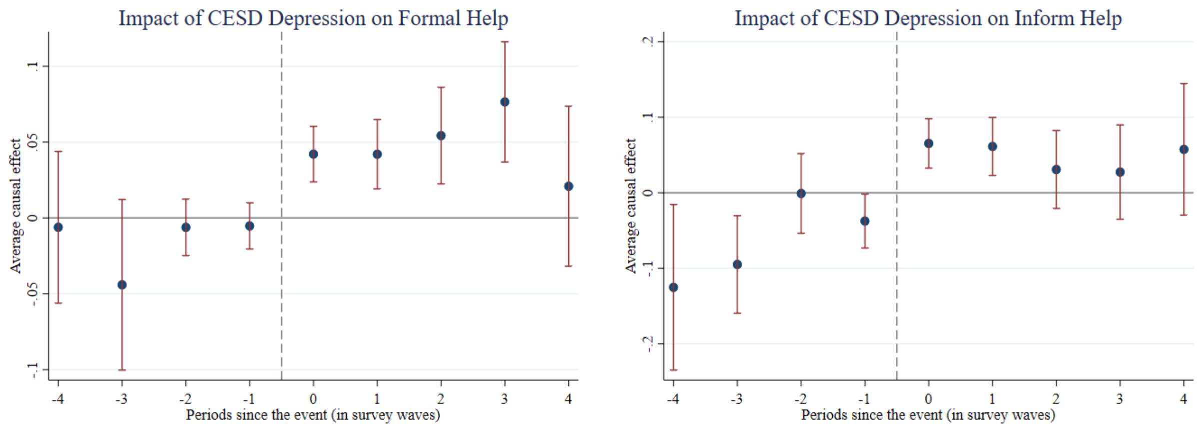


Figure A18: CES-D Depression Shock

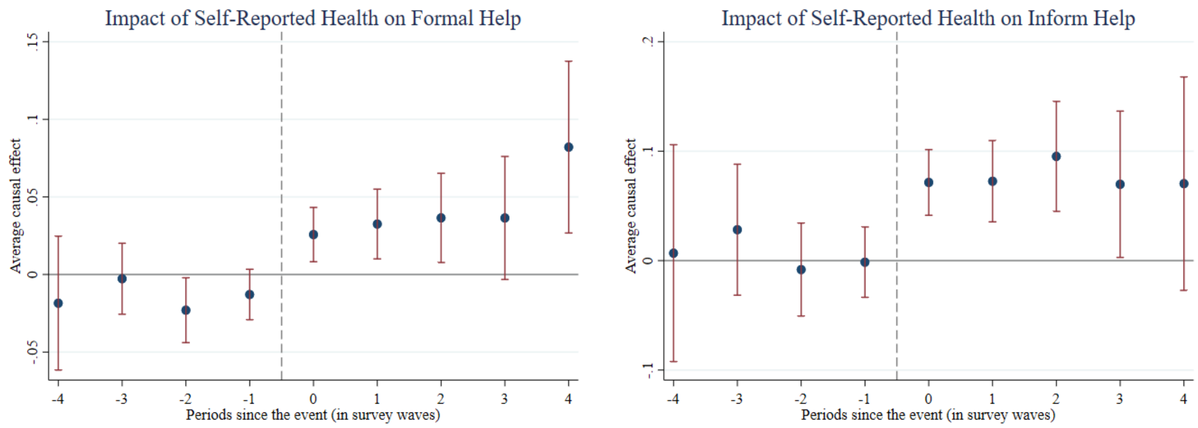


Figure A19: Self-Reported Health Shock

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.

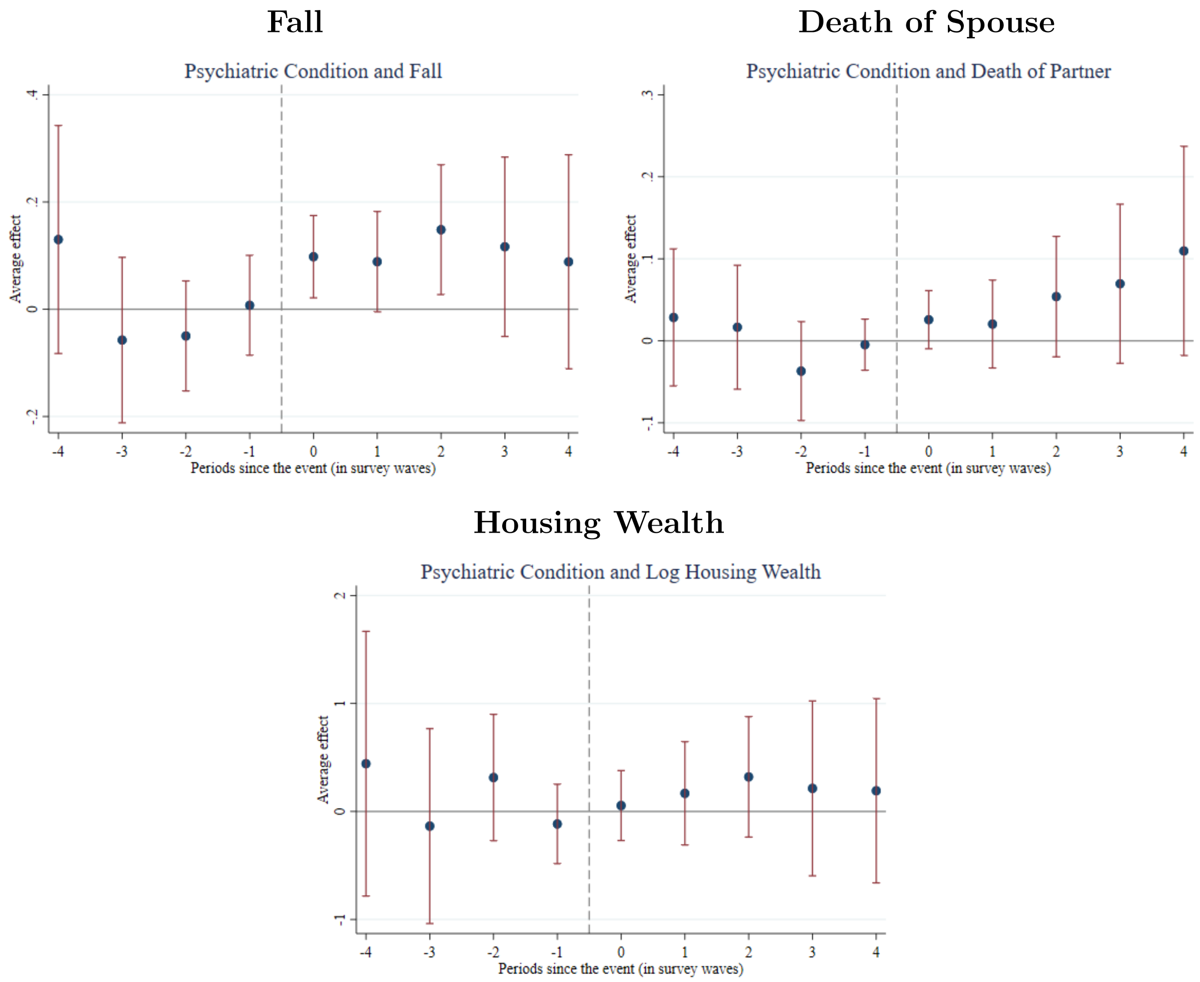


Figure A20: Events Coinciding with Psychiatric Shock

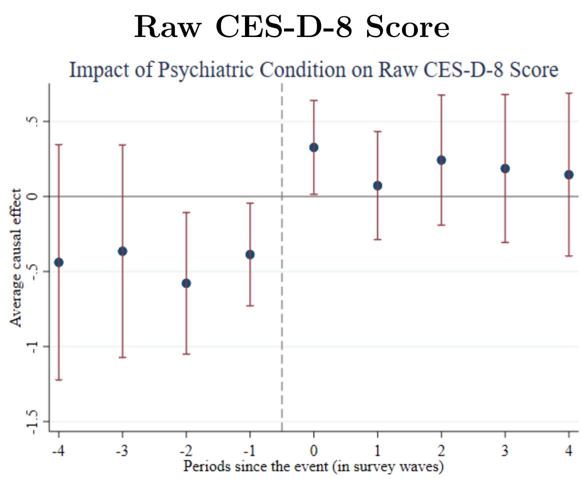


Figure A21: Psychiatric Shock and Depression

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

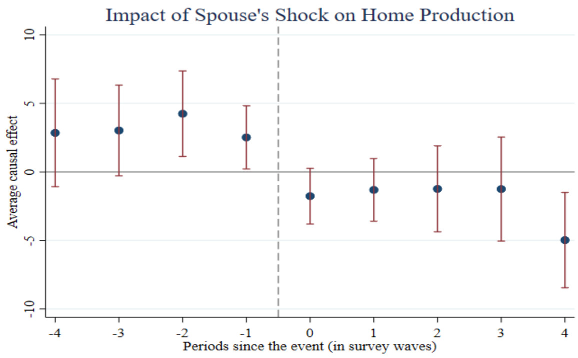
	(1) HP	(2) Meal Prep	(3) Housekeeping	(4) Shopping	(5) Home Maint.	(6) Yard work
Psychiatric	-1.766^{+}	-0.806^{+}	-1.042*	-0.312	0.00428	0.00340
	(1.038)	(0.429)	(0.473)	(0.205)	(0.0681)	(0.164)
CES-D Depression	-1.506	-0.614	-0.835	-0.156	0.0636	0.206
	(0.970)	(0.398)	(0.514)	(0.196)	(0.0634)	(0.156)
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.

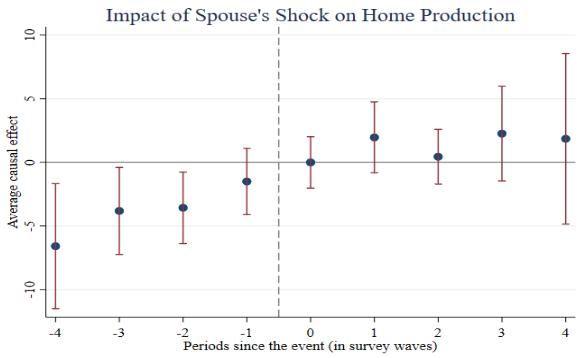
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Psychiatric Condition

Wife's HP

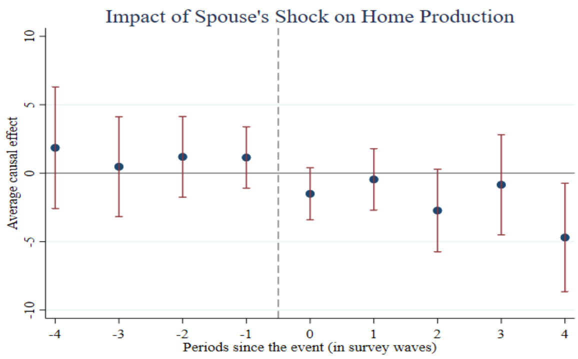


Husband's HP

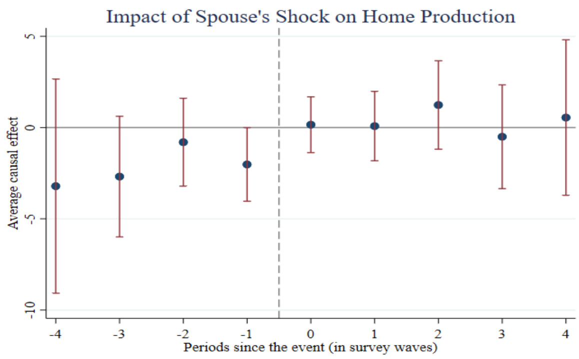


CES-D Depression

Wife's HP

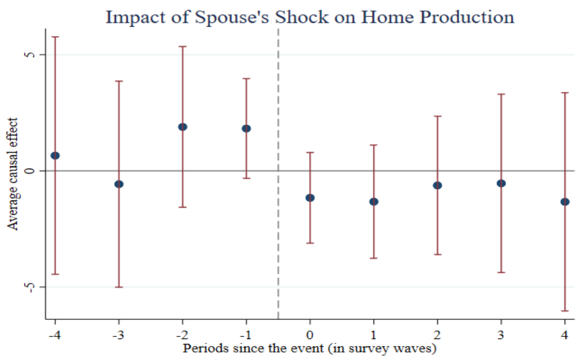


Husband's HP



Self-Reported Health

Wife's HP



Husband's HP

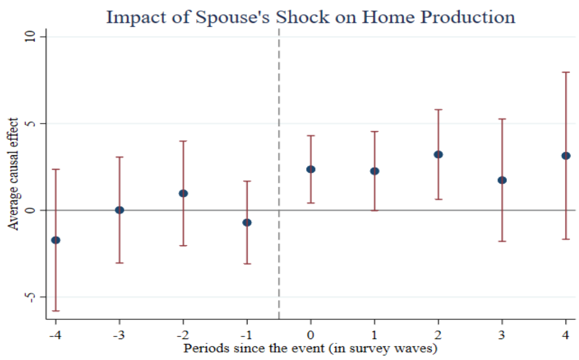


Figure A22

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

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