Impact of Health Shocks on Time Spent on Home Production

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Abstract

This paper examines the causal impact of health shocks on time spent in home production for retirees. Using Health and Retirement Study (HRS) data combined with Consumption and Activities Mail Survey (CAMS) data, I assess the impact of doctor-diagnosed conditions and subjective health measures on time spent on household chores. On the one hand, tightened budget constraints due to the monetary costs of health shocks might induce the substitution of market expenditure with home production. On the other hand, the disutility cost of health production might restrict the time spent on home production. While the impact of health shock on home production time may be theoretically ambiguous, using the difference-in-differences framework by Callaway and Sant'Anna (2021), I find that diagnosis of a psychiatric condition, the onset of depression, and decline in self-reported health significantly decrease time devoted to home production. The impact can be as high as 19% of the median time spent in home production per week.

1 Introduction

How do individuals allocate their time when they fall sick? Majority papers have studied the impact of falling sick on time spent in market activity[1][2]. While the time spent in the market is an important economic variable, especially for consumption spending, consumption is a product of both market expenditure and home-produced goods, as has been theorized in the seminal work of Becker (1965). This makes time spent in home production an important variable to study.[3] Moreover, the US population is aging. As people become older, the fraction of total time spent in home production activities increases and health shocks become an important source of distress. At the same time, we observe an increased preference for aging in place. To better cope with these changing preferences and rising costs to the governments of the older population's dependent support, the first step is to think carefully about how adverse health impacts home production. In this paper, I study the causal impact of health shocks on time spent in home production.

To provide us with a loose structure, I construct a very simple model of health, consumption, and time spent in home production. An adverse health shock levies two kinds of cost: monetary costs in terms of higher medical expenditures and non-monetary costs by reducing the ability to do physical tasks. These costs can have at least two opposing effects on time spent in home production. On the one hand, home production can help mitigate monetary costs if people substitute consumption of market goods with more home-produced goods and increase the time spent producing them. For example, individuals may cook more at home instead of dining out. On the other hand, the non-pecuniary cost of an adverse health shock might discourage the time devoted to home production. The implications for the help provided to unhealthy individuals in these two scenarios are different. For example, suppose the home production decreases following a health shock. In that case, it is desirable to provide people with medical treatment and facilities such as home and community-based care that assist with home production tasks. However, if the home production increases following a health shock, providing home care services is not an effective policy.

To test these two opposing channels, I categorize health shocks into two separate groups. One group includes the shocks with higher monetary costs (indicated by out-of-pocket medical costs) but low non-pecuniary costs (proxied by limitations to daily activities). The other group includes health shocks with low medical costs but high non-pecuniary costs.

In this paper, I focus on the time use responses of retired individuals (aged 65-85) in the United States to health shocks, where adjustments in labor supply are not salient. My analysis requires observing health, medical expenditure, time use, and consumption spending for the same households, and such data has been notably difficult to find. To overcome this problem, I combine Health and Retirement Study (HRS) data with Consumption and Activities Mail Survey (CAMS) data, which is collected for a subset of HRS households. Both these datasets

[1]Market activity refers to time spent in the labor market as a part of work for pay.

[2]Dobkin, Finkelstein, Kluender, and Notowidigdo (2018), Jeon and Pohl (2017)

[3]Economic theories of well-being link well-being directly to consumption activities, for example, Ferranna, Sevilla, Zucker, and Bloom, 2022.

are longitudinal panel surveys representative of the US population over the age of 50 and their spouses.

I focus on both objective as well as subjective measures of health shocks. Objective measures include doctor-diagnosed conditions such as psychiatric problems, heart attack, cancer, high blood pressure, and lung conditions. Subjective measures include self-reported health and CESD depression score. The strategy I adopt to investigate the effects is as follows. First, I document significant differences in the home production time of individuals with different health statuses in the cross-section. I then exploit within-person variation in health and implement the modified difference-in-differences estimators–Callaway and Sant'Anna (2021) to identify the causal response of home production time to health shocks.

My analysis yields several findings. First, I document significant cross-sectional heterogeneity in home production time by type of health status. For example, there is no significant difference between the home production time of those with cancer and those without cancer. However, people who report suffering from a stroke spend 4 hours less than those who do not. This amounts to a variation from 0 to 24% of the average time spent in home production in a week.

Second, using a more causal approach, I find that home production does not significantly increase for costly but not debilitating shocks. Upon studying the shocks that are highly debilitating but not so costly, I find that home production significantly decreases. In the short run, the impact can be as high as 19% of the median time spent on home production tasks. In the first period after the shock, home production decreases by around 1 hour per week for CESD depression and self-reported health shock and by 3.2 hours for a psychiatric shock. The effects are concentrated on time spent in meal preparation and housekeeping tasks, including house cleaning, laundry, and yard work. For CESD depression and self-reported health, these effects persist in the longer run. The effects of psychiatric shock worsen in the subsequent periods but then dissipate in the long run.

Third, to further understand the implications of home production response, I then estimate the contribution of formal help, informal help, and change in consumption spending. I find that the shocks that decrease home production also increase the likelihood of seeking formal and informal help. The likelihood of help related to specific home production tasks such as housekeeping and meal preparation also increases. However, it is still unclear if the help provided compensates for the loss of home production time. This is reflected in the weak behavior of home production time in response to the spouse's health shock. I find that while husbands increase their time spent in home production when their wives face a shock to self-reported health, this does not hold for other shocks or wives' home production when their husbands face any health shocks. By making several contributions, my paper relates to several strands of previous literature, as discussed next.

Contributions in the context of the previous literature

The motivation of my paper builds on the literature that studies the link between health and economic outcomes. Several studies have analyzed the impact of health shocks such as the diagnosis of a chronic condition (Meyer and Mok (2014), Blundell, Borella, Commault, and De Nardi (2020), Jeon and Pohl (2017)) , hospital admission (Dobkin, Finkelstein, Kluender, and Notowidigdo (2018)), disability (Dalton and LaFave (2017)). These studies broadly argue that bad health shocks have significant adverse effects on economic outcomes such as earnings, medical expenditure, the probability of bankruptcy, labor supply, and consumption. Compared to these papers, my work finds evidence of the impact of bad health shocks on another important yet understudied variable – the time spent in non-market activities.

Few papers have studied the correlation between health and home production and the overall findings are ambiguous at best. Podor and Halliday (2012), for instance, use self-reported health information and American Time-Use Survey (ATUS) to find that better health is associated with more housework time. However, others such as Gimenez-Nadal and Ortega-Lapiedra (2013), Gimenez-Nadal and Molina (2015), and Leopold and Schulz (2020) use data from European countries to find that better health is correlated with less housework time. Studies such as Ozturk and Kose (2019) find mixed evidence. My work contributes to this literature in two ways. First, while all the studies mentioned above are descriptive in nature, I use panel data and exploit within-person variation in health to understand the causal impact on home production. Secondly, these studies use time-use surveys that offer limited health information. I sharpen the results of previous studies by using detailed health information in HRS to construct potentially exogenous measures of health shocks.

Finally, my paper gets into a conversation with the literature on the smoothing function of home production in response to income changes. Aguiar and Hurst (2005) show that a drop in consumption expenditure may be partially explained by increased time spent on home production to smooth consumption. It is also found that reduced market work during unemployment is offset by an increase in home production (Burda and Hamermesh (2010), Krueger and Mueller (2012)). Guler and Taskin (2013) find that home production protects against the consequences of income loss due to unemployment in a similar way to unemployment insurance. Alternatively, Been, Rohwedder, and Hurst (2020) find that consumption spending is only partially substitutable by time spent in home production when individuals face a wealth shock. My paper contributes to this literature by testing the role of home production in mitigating the costs of a health shock.

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

2 Economic Framework

To fix ideas, I develop a simple economic framework in which a health shock may generate increases or decreases in home production. I then analyze these impacts using health and time-use data from HRS and CAMS.

There are two types of consumption goods – market goods and home-produced goods. Consumption of market goods requires money but no or less time, for example, processed food. Consumption of home-produced goods requires less money but more time, for example, food prepared at home. These two types of consumption goods can be partially substituted (Becker, 1965). Therefore, home production can save resources. However, there are utility costs associated with time spent in home production. For example, home production can be physically tiring and create a mental resistance toward it.

I can now write a static model to interpret the impact of health shocks on home production. Individuals derives utility from the two consumption goods: market good (c_m) and home produced good (c_h). They derive disutility from hours spent in home production (h). Since I focus on retiress. I assume a corner solution where labor supply is 0 and retirement is an absorbing state. Consider the following utility maximization condition of an individual:

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

where

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

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

such that,

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

ϕ is the disutility from home production time, d is the market input required for home produced good, X is the out-of-pocket medical expenditure, and I is the total non-labor income (eg., retirement income). Taking derivative with respect to h yields the following first order condition:

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

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

$$\underbrace{u'_C \frac{\partial f}{\partial c_m}}_{\text{marginal utility of market-good consumption}} = \underbrace{\lambda}_{\text{marginal utility of economic resources}} \tag{6}$$

There are two possible channels through which health impacts time spent in home production. First, equation (5) shows that an increase in disutility (ϕ) can decrease time spent in home production, h. [4] Second, increase in medical cost following a health shock decreases the available resources in Equtaion (4) and therefore increases λ in equation (6), which can decrease c_m[5] Aassuming that there exists a partial substitutability between c_m and c_h, higher

[4]Since h in the utility function in equation (1) is a "bad" good, therefore, $v(h)$ is increasing and convex. Therefore, when ϕ increases due to bad health, to keep the marginal utility the same, h should decrease.

[5]If the marginal utility of c_m increases on the left-hand side of equation (6), c_m could decrease.

medical expenditure drives dubstitution from c_m to c_h. [6] This can increase time spent in home production, h. Given this theoretical ambiguity, the impact of health on home production is, eventually, an empirical question.

2.1 Mechanisms

An adverse health shock can have two types of costs. First is a monetary cost, such as higher medical bills. Several studies have analyzed the monetary cost of health shocks such as diagnosis of chronic health disease or a hospital admission on medical expenses (Dobkin, Finkelstein, Kluender, and Notowidigdo (2018); Poterba, Venti, and Wise (2017); Cheng, Li, and Vaithianathan (2018). They find that bad health shocks significantly and negatively impact medical expenses, increased unpaid medical bills, and chances of bankruptcy. The second is non-monetary cost, such as reduced ability to carry out physical tasks or higher mental resistance to home production. For example, the medical literature has documented that depression is associated with fatigue, lack of motivation and concentration, and feeling overwhelmed (Marsh, Dobson, and Maddison, 2020)

These two consequences of adverse health shock propel us to ask two critical questions. First, whether home production smoothen the monetary cost of an adverse health shock. This question can be answered in affirmation if we see substitution away from consumption spending and towards more home production time after the health shock. Although empirical evidence supports that home production mitigates the consequences of income loss due to unemployment (Hicks (2015); Aguiar, Hurst, and Karabarbounis (2013)), how it responds to increased monetary cost of health shock is not clear.

Second, whether home production worsen the non-pecuniary cost of health shock because health shock debilitates people to the extent that it restricts home production. This question can be answered if we see a reduction in home production after the health shock.

To convincingly answer these two questions, I separate health shock into two groups: Group 1 consists of the shocks with higher increase in medical cost after the shock but lower non-pecuniary cost. Shocks in this group are likely to see the first mechanism, i.e increase in home production. Group 2 consist of the shocks with lower increase in medical expenditure but higher non-pecuniary cost. Group 2 shocks are more likely to see the second mechanism, i.e, a decrease in home production.

3 Data

The data for this paper comes from the Health and Retirement Study (HRS), a nationally representative longitudinal survey of the US population over the age of 50 and their spouses. It conducts interviews with about 20,000 individuals every two years. In addition, the HRS

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

conducts supplementary studies to collect information on several other specific topics. The time use and expenditure data I use in this paper are collected as a part of a supplementary study, the Consumption and Activities Mail Survey (CAMS). I combine information from the HRS core interviews and the CAMS, which is administered to a subset of HRS respondents.

A. Health and Retirement Study – The HRS collects information on labor force participation, income, household wealth, and social well-being, along with elaborate information on health, and health spending, including out-of-pocket (OoP) medical expenditure.[7] HRS collates spending information for the following medical cost categories: hospitalization, nursing home, clinic visits, dental care, outpatient surgery, prescription drugs, home health care, and community care. The recall period for OoP medical expenditure is last two years. Detailed information on functional limitations such as difficulty in activities of daily living (ADLs) and instrumental ADLs is also gathered.[8] I use these functional limitations to measure disutility. HRS also collects comprehensive information on cognition and formal and informal help utilization.

B. Consumption and Activities Mail Survey: The CAMS collects detailed measures of time use on more than 31 categories and household spending on around 38 items. Both HRS and CAMS are biennial. The CAMS is conducted in the HRS off-years, but the information mostly overlaps because health questions refer to the last two years, whereas time use refers to the last week or month, and consumption spending refers to the last month or past year. The variables in CAMS are merged to the preceding HRS wave, for example, CAMS 2001 to HRS 2000. Around 4666 individuals completed CAMS in 2019. Item response rates related to more than 30 time-use categories questions in CAMS are very high. Collectively among all waves, figure A5 shows that 71% have 0 missing item response, 17% have only 1 item missing, and only 6% have two items missing.[9] To further assess the data quality, in Appendix A.2 , I compare the summary statistics and distribution of various categories of time-use in CAMS with the American-Time Use Study (ATUS). ATUS is collected by the Bureau of Labor Statistics (BLS) and is the only survey that collects comprehensive data on time-use and is representative of the US population. Overall the summary statistics and distribution of hours turn out to be very close in CAMS and ATUS.

My merged sample covers the years 2000 to 2019 and individuals who answered both CAMS and HRS. My analysis focuses on retired elderly aged 65 to 85 to eliminate impacts on time use that operate via changes in labor supply and earnings. To obtain a cleaner sample of retirees, I exclude individual-year observations of the elderly who earn more than $3000 per annum in labor earnings.[10] I further restrict my sample to the individuals observed for at least two consecutive waves. This trims the sample down to 19,797 individual-year observations. All financial variables are converted into real variables using 2015 as the base year.

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

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

[9] Author's calculations.

[10] I include their individual-year observations once their labor earnings turn to 0 or less than $3000 per annum for the remaining sample period observed.

3.1 Time Use

Respondents were asked about 31 time-use categories in wave 1 (the year 2001). More categories were added in the subsequent waves. I use time-use activities that are available in all the waves. For most categories, respondents are asked how many hours they spent on this task "last week". For less frequent categories, respondents are asked about hours spent "last month". I convert the variables with monthly frequency into weekly by dividing the response by 4.3 (number of weeks in a month). CAMS asks about time spent on various home production tasks. Following the definition of home production used by Been, Rohwedder, and Hurd (2020)[11] [12], time spent in home production is the sum of the following time use activities:

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

Other tasks may also be considered home production, such as taking care of grandchildren. However, this information is not collected in the first six waves. Therefore, I do not include them in my definition of home production.

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

3.2 Health Status

The HRS gathers information on a set of doctor-diagnosed chronic health problems, including cancer, heart disease, stroke, diabetes, lung disease, hypertension, arthritis, and major psychiatric problems. Respondents are asked whether they have been diagnosed with a given condition by a medical specialist since the last interview. [13] In addition to these chronic conditions, data on self-reported health and self-reported mental health are also collected. HRS

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

[12]Other papers such as Aguiar, Hurst, and Karabarbounis (2012) also use these tasks under home production.

[13]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. Psychiatric condition includes emotional or nervous problems (more on this in Appendix D).

collates information on several indicators to derive a mental health index using a score on the Center for Epidemiologic Studies Depression (CESD) scale, which ranges between 0 and 8. 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, a CESD score above the cutoff of 3 indicates a positive depression screen.

Before analyzing the causal impact of health shocks, I explore the links between current health status and time spent in home production in cross-section. I regress the weekly time spent in home production on a health indicator such as a given doctor-diagnosed disease or indicator for depression as obtained from the CESD-8 score or an indicator of self-reported health.[14] Each regression includes age, a polynomial of age, gender, marital status, number of members in the household, race, education, and year dummies.

Figure 1 displays the results and highlights that, on average, people suffering from a given health condition or those with worse subjective health indicators spend less time in home production. This is especially true for people suffering from heart disease, diabetes, psychiatric condition, lung disorder, stroke, and those who report bad self-reported health. The significant difference can be as high as 4 hours a week, which amounts to 24% of the average time spent in home production in a week.

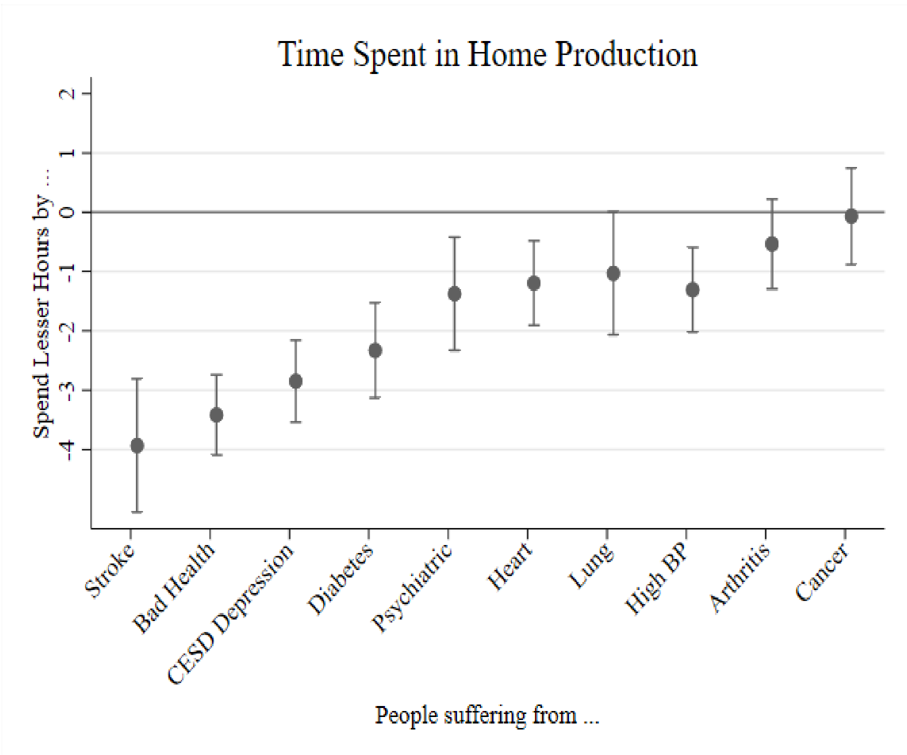

Figure 1: Home production by current health status

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

[14]Self-reported "excellent", "very good", and "good" responses are combined into good health; "fair" and "poor" are denoted by bad health.

3.3 Health Shocks

To carry out causal analysis for each type of health shock, I restrict the sample to individuals with a new diagnosis by excluding those who enter the sample with a pre-existing condition. For example, to understand the impact of cancer, I exclude people who enter the sample with a pre-existing cancer diagnosis. A person is considered to have undergone a particular doctor-diagnosed health shock if they report not being diagnosed with a given condition and then get diagnosed in the subsequent wave. Subjective health shocks are also defined likewise. A person faces a depression shock if their CESD score is ≥ 3 in the current wave but less than 3 in the previous wave. The same holds for defining self-reported bad health shock.

3.4 Descriptive Statistics

Table 1 shows differences in the characteristics of the treated and never-treated groups for the two subjective and five objective health shocks – cancer, heart, hypertension, lungs, and psychiatric condition. After imposing all the sample restrictions mentioned in the previous section, the individual-year observations in treatment groups range between 1367 and 5153, depending on the type of shock. The never-treated sample ranges between 4800 and 16,292 individual-year observations. There is no noticeable age difference between the treated and never treated samples. Individuals in treated groups are more likely to be women, except for cancer, heart, and self-reported health conditions. Treated individuals are less likely to be married, except for cancer and heart conditions.

Individuals in the treated samples have more ADLs and IADLs and are more likely to have relatively poor cognition except for cancer. Not surprisingly, treated samples are more likely to be hospitalized, stay overnight in a nursing home, and have higher out-of-pocket medical expenditures. They have less wealth than never-treated samples, except for cancer and heart. The most noticeable difference is in the utilization of help. On the one hand, the treated and never-treated samples for cancer, heart, hypertension, and lung do not differ much in the utilization of formal help, informal help, and hours of help received. On the other hand, the utilization of help is strikingly higher for the treated samples under psychiatric shock, CESD depression, and self-reported health.

Table 1: 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
Home Health Care (%)	0.10	0.08	0.11	0.07	0.08	0.07	0.14	0.08	0.14	0.08	0.11	0.06	0.10	0.05
Wealth														
Total Net Wealth	524075	461838	495408	489861	506789	629836	374382	507504	441427	515839	460428	561288	446218	602281
Net Non Housing Wealth	339740	307637	330021	324896	339303	432667	235036	340455	313512	343428	305584	380016	296396	409050
Housing Wealth	196118	169306	175759	182091	179559	211495	149324	182840	152275	186586	163195	200429	164455	210438
N	2110	14722	3461	11414	3358	4800	1544	16292	1367	15533	4908	10793	5153	9872

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

4 Empirical Methodology

The canonical Difference-in-Differences (DiD) case involves two groups – treated and control – and two time periods – pre and post. The treated group faces the treatment in the second period but control group does not. The effect of the treatement on the treated group can be estimates empirically by comparing the change in the average outcome of the treated group to the change in the average outcome of the control group:

$$\text{DD} = \bar{Y}_{post}^{treated} - \bar{Y}_{pre}^{treated} - (\bar{Y}_{post}^{control} - \bar{Y}_{pre}^{control})$$

Under parallel trends assumption [15] and no anticipation assumption [16], average treatment effect on the treated (ATT) can be estimated by OLS using the two-way fixed effects (TWFE) regression specification (individualfixed effects and time fixed effects). TWFE estimation can be extended to cases with variations in treatment timing. However, recent econometric literature casts doubt on the validity of the causal interpreation of TWFE DiD estimator when it is applied to settings with staggered treatment. This is due to the presence of heterogeneity in treatment effects Borusyak and Jaravel (2018), de Chaisemartin and D'Haultfoeuille (2020b), and Goodman-Bacon (2021)

Treatment effects can be heterogenous across either time since treatment or across units, for example, the impact keeps accumulating after the treatment. Presence of dynamic treatment effects may lead to biased TWFE DiD estimates. This can be understood through figure 2. Let's say there are three groups – Early Treated (ET), Late Treated (LT) and Never Treated (NT) – and three time periods – Pre, Mid, and Post. Early Treated receives treatment at t_1 and Later Treated receives treatment at time t_2. In this case, the TWFE estimated ATT between *post* and *mid* is a weighted average of all possible DD paired differences – 1. ET as treated group, NT as control; 2. ET as treated, LT as control; 3. LT as treated group, NT as control; 4. LT as treated group, ET as control.

One of these paired differences – LT as treated group and ET as control – is called "forbidden comparison". It yields a biased DiD to the extent that the sign of the impact is inverted. It yields a negative DiD because the large changes in the outcome for ET (the control in this case), are *subtracted* from the relatively smaller changes in the outcome for LT (treated group). In other words, heterogenous treatment effects for ET bias the ATT between *post* and *mid* periods when ET is used as a control group for LT.

The effect of health shocks on home production is potentially heterogenous across individuals in different waves. Individuals faced with a shock in later waves are mechanically older and more frail at the time of the shock than individuals falling ill in earlier waves. In order to estimate unbiased causal estimates, I use the DiD estimator proposed by Callaway and Sant'anna (2021). In simpler words, this approach avoids making "forbidden comparisons".

Consider that G is the time period when a unit first gets the treatment. For all the units

[15] Average outcome for the treated and control would have evolved parallelly if the treatment had not occured

[16] Treatment has no causal effect prior to its implementation.

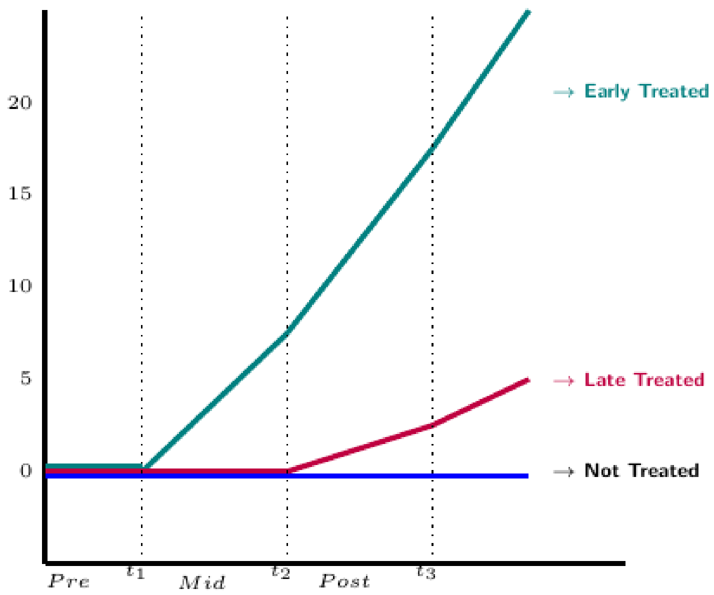

Figure 2

that are eventually treated, G defines the "group" they belong to. We can define G_g to be a binary variable that is equal to 1 if a given unit is first treated in period g. Callaway and Sant'anna (2021) use the ATT for units that are members of a particular group g at a particular period t, as denoted by:

$$ATT(g,t) = E[Y_{it}(g)\text{-}Y_{it}(\infty)|G_g = 1] \tag{7}$$

They call this causal parameter the *group-time average treatment effect*. Under the assumptions of 1. limited treatment anticipation[17]; 2. conditional parallel trends[18]; and 3. overlap[19], ATT(g, t) can be identified by comparing the the expected change in outcome for group g between periods $g-1$ and t to that for a control group at period t. Formally:

$$ATT(g,t) = E[Y_{it} - Y_{i,g-1}|G_g = 1] - E[Y_{it} - Y_{i,g-1}|C = 1] \tag{8}$$

where C=1 for a control group.

Callaway and Sant'anna (2021) consider two options for control groups. The first uses only never-treated units and the second uses all not-yet treated units (which includes never treated in the sample). A weighted average of the ATT(g, t)s can be obtained for the intended parameter of interest. I use event-study aggregation to obtain weighted average of the treatment effect l periods after the treatment across different groups. In my main results, I consider not yet treated (which also includes never treated in my sample) as the control units. I also show results in appendix with two more specifications – strictly not-yet (but eventually treated) and never treated units as controls.

[17]This assumption alows for for anticipation behaviour, within sime anticipation window δ, where $\delta \geq 0$. When δ=0, it imposes a standard no-anticipation assumption.

[18]It states that a standard parallel trend assumption holds event after conditionaing on covariates.

[19]It states that treatment and comparison groups have units that have the same probability of being treated conditional on covariates.

5 Results

To test the two mechanisms, I split the health shocks into two groups based on out-of-pocket medical expenses and limitations in daily living. To measure limitations in daily living, I use ADLs and IADLs. Table 2 shows the increase in medical cost and daily limitations in the first period following a given health shock and their relative rankings in terms of severity.

Group 1 consists of shocks with a higher increase in out-of-pocket medical cost but a lower increase in daily limitations. Cancer, heart condition, hypertension, and lung condition fall into group 1.[20] 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 after these shocks.[21] Column (3)-(6) shows that among the costly shocks, hypertension is the least debilitating in terms of ADLs and IADLs. Cancer, heart, and lung condition also stand among the bottom three shocks in terms of difficulty in daily living based on ADLs or IADLs. Since stroke is highly debilitating despite being highly costly, I exclude it from group 1 shocks.

Group 2 consists of shocks with a lower increase in out-of-pocket medical expenditure but a higher increase in difficulties of daily living. Table 2 shows that psychiatric conditions, CESD depression, and self-reported health are the most debilitating and least costly shocks. Psychiatric shocks are associated with a significant increase of 0.27 ADLs and 0.3 IADLs in the first period observed after the shock. CESD depression and self-reported health also affect daily limitations within a similar range. I now use these two groups of health shocks to test the two channels of the impact on home production.[22]

5.1 Does Home Production Smooth Monetary Cost?

I use health shocks in group 1 to test if a costly bad health shock increases time spent in home production due to substitution away from market goods towards home-produced goods. In other words, does home production smooth the monetary cost of a bad health shock? Panel A in Table 3 shows the impact of group 1 health shocks on total home production and different tasks of home production. For each shock, the coefficients represent the impact in the first period after the shock. To understand the impact in the longer run, I also show event study plots in the figure 3.

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

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

[22] I exclude stroke, diabetes, and arthritis from these groups as 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 debilitating.

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

	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)	
CESD 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)	

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

There is no statistical or substantive evidence of an increase in time spent in home production after the diagnosis of any condition in group 1. In fact, instead of increasing, home production declines in the first period after the diagnosis of high blood pressure (not statistically significant) and lung condition by 1 hour and 2.3 hours, respectively . Although the impact for lung and high blood pressure is only short-lived, as seen in the event study plots.[23] In the first period after the shock, cancer is associated with an increase in home production and yard work by around half an hour per week, albeit the impact on total home production is statistically insignificant. Diagnosis of a heart condition does not impact home production or any of the individual tasks with trivial changes in magnitudes both in the short and long run.

Robustness Checks

I further report two specifications to investigate the sensitivity of these results. To restrict the severity of these health shocks, in table A5 (Appendix B.1), I exclude individuals who ever report any ADLs or IADLs in the entire sample. Even for those for whom the health shocks are not seriously debilitating, home production does not increase. The increase is higher in magnitude for cancer in column (2) and for heart in column (1) than the baseline results, but it is not statistically significant. In accordance with baseline results, home production decreases

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

upon diagnoses of high blood pressure and lung condition.

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
Group 1				**Panel A**			
Cancer	0.405	0.136	0.0263	0.412**	0.190	-0.0585	0.0647
	(0.782)	(0.293)	(0.334)	(0.153)	(0.184)	(0.0646)	(0.0705)
Pre-treatment mean	20.93	6.42	6.72	2.14	3.70	0.78	0.54
Heart	-0.00320	0.0435	0.0547	-0.0942	-0.113	-0.0416	-0.0573
	(0.614)	(0.225)	(0.270)	(0.141)	(0.156)	(0.0492)	(0.0570)
Pre-treatment mean	21.46	6.63	6.94	2.18	3.78	0.79	0.55
High BP	-1.073	-0.0841	-0.234	-0.0827	-0.231	-0.0360	-0.0732
	(0.690)	(0.263)	(0.282)	(0.161)	(0.168)	(0.0506)	(0.0596)
Pre-treatment mean	21.89	6.54	6.74	2.44	3.87	0.82	0.65
Lung	-2.332*	-0.247	-0.529	-0.252	-0.143	-0.00575	0.0737
	(1.052)	(0.411)	(0.435)	(0.184)	(0.223)	(0.0623)	(0.0780)
Pre-treatment mean	20.81	6.37	6.57	2.17	3.73	0.79	0.55
Group 2				**Panel B**			
Psychiatric Condition	-3.156**	-0.744+	-1.409**	-0.358	-0.317	-0.0693	0.0556
	(1.161)	(0.416)	(0.448)	(0.225)	(0.232)	(0.0768)	(0.0519)
Pre-treatment mean	20.76	6.37	6.47	2.19	3.72	0.80	0.55
CESD Depression	-1.123*	-0.497*	-0.119	-0.0212	-0.0762	-0.0205	0.0234
	(0.568)	(0.214)	(0.238)	(0.114)	(0.131)	(0.0404)	(0.0461)
Pre-treatment mean	21.27	6.48	6.54	2.32	3.86	0.82	0.60
Self Reported Health	-0.994+	-0.552**	-0.339	-0.245*	0.0155	0.00580	0.0180
	(0.532)	(0.198)	(0.217)	(0.110)	(0.125)	(0.0399)	(0.0502)
Pre-treatment mean	21.94	6.68	6.81	2.38	3.97	0.82	0.61

Coefficients represent the impact (hours per week) in the first period after the shock.
Standard errors in parentheses
Top 1 pctile of all time-use is excluded.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2 Does Home Production Accentuate Non-Monetary Cost?

I use health shocks in group 2 to test if home production decreases upon a bad health shock. Group 2 shocks yield a relatively lower increase in out-of-pocket medical costs but are highly debilitating. Panel B in table 3 shows the impact of group 2 health shocks on total home production and different tasks of home production. Highly debilitating shocks significantly decrease the time spent in home production. In the first period after the shock, the impact can be as high as 19% of the median time spent in home production (after psychiatric condition).

The impact of the diagnosis of a psychiatric condition on time spent in home production is visually apparent immediately (i.e., period 0, the first wave observed after the health shock).

The impact persists for a few subsequent years before waning, as seen in the figure 3. On average, home production declines immediately by 3.2 hours (per week) after a psychiatric shock. Most of the impact arises from the decline in time spent on tasks such as housekeeping (1.4 hours) and meal preparation (0.7 hours). The event study graphs in Appendix B.2 also suggest that the decline in housekeeping persists for a few periods after the shock.

Onset of depression as measured by CESD score decreases average home production time by 1.12 hours in the first period. The decrease continues in the long run, and the magnitude augments in the subsequent years, as seen in the event study graphs. Much of this impact comes from meal preparation time, which, on average, decreases by half an hour in the first period. The decrease persists in the long run as well. An adverse health shock defined by self-reported health also decreases the average time spent in home production by an hour in the first period. Like other health shocks in group 2, a considerable decline in total home production is due to a decrease in average meal preparation time (by half an hour). The decline also continues in the long run (although the confidence intervals get bigger in the subsequent periods). In the short run, the average time spent on yard work and gardening decreases.

One concern that might cloud the interpretation of non-zero estimates as causal is the exogeneity of health shocks., especially the subjective health shocks – CESD depression and self-reported health shock.

Robustness Checks

I further inspect the sensitivity of the results to ensure that the impact on home production is not driven predominantly by severely debilitated individuals. To do so, I design two specifications that exclude individuals who a. reside in a nursing home at the time of the interview, b. report an overnight nursing home stay in the same wave as the shock but did not report any stay in the previous wave. Column (1) in table A6 shows that despite excluding those in nursing home institutions during the interview, average home production declines in the first period after the shock. The magnitude of the decline is comparable to the baseline results for all the shocks in group 2. People who go to nursing homes mechanically carry out less home production than those staying at home. Therefore, the decrease in home production despite excluding nursing home utilization additionally informs us that the decline in the baseline specification is not a trivial observation. Upon excluding those whose timing of nursing home stay is concurrent with the shock, baseline results not only hold but also strengthen in magnitude (see Column (2) in table A6). This sheds light on an important point – the baseline results are not driven by the individuals so severely debilitated that they require nursing home assistance after the shock.

Decline in cognition? It is documented that two out of the three shocks in group 2 – diagnosis of psychiatric condition and CESD depression – are commonly associated with cognitive impairment (Lee et al., 2012; CDC, 2020). This may lead to short-term forgetfulness and impact the recall of time-use responses in the survey. From the summary statistics, people diagnosed with a psychiatric condition and CESD 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, it is important to scrutinize the baseline results and examine whether the drop in home production is a mechanical function of a deteriorating memory. I do so by excluding all those whose memory state worsens between the period before and after the shock. I employ two measures to capture the decline in cognition.

First, I use the Langa-Weir classification of cognition function (Langa et al., 2022). It is a researcher-contributed dataset that provides a summary score for cognition using measures[24] from the core HRS interview.[25] This score is used to categorize respondents into three Langa-Weir classifications: Normal, Cognitively Impaired but not Demented (CIND), and Demented. Second, I use self-reported memory. Respondents are asked to rate their memory at present. I categorize "excellent", "very good", and "good" responses as a good memory. "Fair" and "poor" are categorized as bad/impaired memory. In table A7, I exclude all those whose memory state worsens after the shock. For example, people who move from Langa-Weir category Normal to CIND or from CIND to Demented, etc., are excluded in column (1).

Results in table A7 are generally reassuring that the baseline impact of group 2 health shocks is not predominantly driven by poor recall or forgetfulness of respondents suffering from health shocks. In column (1), which displays results with Langa-Weir restriction, the impact of psychiatric condition and CESD depression is moderately weaker in magnitude and statistical significance compared to the baseline results. The impact of self-reported health does not change much. The impact in column (2), with self-reported memory restriction, is roughly similar to the baseline results with a significant decline in home production of more than 3 hours and 1 hour (significant at 10%) after a psychiatric shock and CESD depression, respectively.

Marginal effect of an additional shock?: The impact of a health shock in the baseline result could reflect not the plain effect of one shock but a marginal effect of an additional shock. I address and inspect this concern in three ways. First, I condition the baseline specification on the presence of a given number of total doctor-diagnosed conditions. For example, from the summary statistics, it is known that people with and without psychiatric conditions have, on average, 2 other doctor-diagnosed conditions. Therefore, in one specification, I exclude people who reported being diagnosed with more than 2 doctor-diagnosed conditions (other than the shock itself) in the observed sample period. Second, since Callaway and Sant'anna's (2021) specification allows for parallel trends assumption to hold after controlling for covariates, I control for the total number of doctor-diagnosed conditions (other than the shock itself). Third, I examine the evolution of the number of ADLs and the number of other (than the shock itself) doctor-diagnosed conditions pre and post-shock. Significant pre-trends in any of these variables would indicate a gradual health degradation even prior to the shock in question. However, an absence of significant pre-trends would reassure us that the shock in question is indeed a shock

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

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

and the baseline results are not picking up the marginal effect of an additional shock.

As seen in table A8, controlling for the number of other doctor-diagnosed conditions in column (1) does not change the baseline results remarkably in the short and long run. Columns (2) and (3) exclude people with more than 3 and 2 other doctor-diagnosed diseases, respectively. First-period impact of psychiatric condition and self-reported health shock is in accordance with the baseline results.

Figure A9 charts the evolution of ADLs and the number of other doctor-diagnosed conditions before and after the shock. A discernible jump in ADLs can be observed before and after diagnosing psychiatric conditions and depression. No noticeable pre-trends exist in the number of doctor-diagnosed diseases as well

To further test the sensitivity of the results, I several other econometric specifications. The results are shown in Appendix B.3. In the main specification, I include the not-yet and never treated individuals as control groups. In Appendix B.3, I consider two additional specifications with control groups as strictly not-yet treated and strictly never treated. I also control for several important covariates in the main specifications – age, age polynomial, gender, race, marital status, and the number of members in the household. 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. In the main specification, the treatment cohorts are based on the first 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 test the robustness of the results using age-based treatment cohort groups as well.[26] The impact of the psychiatric shock on time spent in home production is super robust to all these specifications. In all the specifications, the impact is around 3 hours weekly and is statistically significant at the 5% level. Similarly, the impact of CESD depression and self-reported health is robust for most of the specifications, and the magnitude is similar to that in the main specification. Finally, I also show results from a standard event study specification.

5.3 Implications of Decrease in Home Production

Thus far, my findings highlight the nature of insurance that is provided by home production against health shocks. I find very weak evidence in favor of home production as a means to smoothen the monetary cost. However, I do find strong evidence to support the claim that home production declines, thereby adding to the non-monetary costs of health shocks. Since home production is necessary for consumption, a decrease in home production due to a health shock can't be without any implications. Individuals who face a decline in home production may either choose to do nothing, in which case their overall consumption and welfare might decrease. They might seek help or increase the consumption of good purchased from the market. In this section, I address the latter two implications: increase in utlization of formal and informal help, increase in consumption spending.

Thus far, my findings highlight the nature of insurance that is provided by home production

[26] More details on how the age-based treatment cohorts are created can be found in Appendix B.3.

against health shocks. I find weak evidence in favor of home production as a means to smoothen the monetary cost. However, I do find substantial evidence to support the claim that home production declines, thereby adding to the non-monetary costs of health shocks. Since home production is necessary for consumption, a decrease in home production due to a health shock cannot be without any implications. Individuals who face a decline in home production may either choose to do nothing, in which case their overall consumption and welfare might decrease. Alternatively, they might seek help or increase the consumption of goods purchased from the market. In this section, I address the latter two implications: an increase in the utilization of formal and informal help and an increase in consumption spending.

Utilization of Help

Two questions arise: whether people who face shocks rely more on formal and informal help with home production-related tasks. Whether the help provided compensates for the home production time lost. HRS collects information on the use of help received by the respondents and the helpers. I use the following measures to understand the implications on the utilization of help. HRS asks the respondents who helped them with ADLs, their relationship with the helpers, total hours of help received, and the type of ADL for which help was availed. I use this information to categorize the nature of help into formal and informal. I categorize formal help as any help provided by an organization, employee of an institution, paid helper, or professional in the last month. Informal help is provided by a spouse, children, grandchildren, or other relatives in the last month.[27]

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 3 percentage points for a psychiatric condition, CESD depression, and self-reported health, respectively. [28] While the increase persists in the long run for CESD depression and self-reported health, it dwindles after a few periods for psychiatric conditions, as shown in figure A13. Although larger in magnitude than formal help, the likelihood of using informal help in Column (2) exhibits a similar result. Informal help received increases by 9, 7, and 7 percentage points for a psychiatric condition, CESD depression, and self-reported health, respectively. The increase in the utilization of informal help persists for all three shocks in the longer run (although the estimates in the later periods are not precisely estimates and have large confidence intervals). Among the specific home production-related tasks, the most significant increase is observed in the reliance on help related to work around the house and yard for all the shocks in group 2 (Column (3)-(7)). Not only the likelihood of help availed increase for these shocks, but the number of hours of help received per week also increased (Column (8)). The increase is somewhat comparable to the decline in the total hours of home production. This might suggest that the loss in home production is partially recovered by the increase in the amount of help. However, the hours

[27]My measure of formal help and informal help are not mutually exclusive. Various kinds of helpers may assist people at a given time.

[28]Since the questions related to the utilization of help are only posed to those respondents who report at least 1 ADL or IADL; there are many 0s in response to questions related to help availed. Therefore, I consider the group of not-yet-treated individuals as the control group for this analysis.

of help are asked for those who report and need help with functional limitations. Therefore, hours of help may not strictly include assistance with home production tasks. [29] These results also suggest that the appropriate supports (in terms of type and generosity) differ across the type of health shocks.

To understand the generosity of informal help, I look at the impact of a spouse's health shock on own time spent in home production. The results in table **??** complement and enrich this analysis. Husbands significantly increase their time spent in total home production by around 2 hours when the wife faces a shock in self-reported health. Most of the increase comes from meal preparation and housekeeping time. The event study graph for the husband's total home production upon the wife's self-reported health shock shows a significant positive shift in coefficients post shock. However, no significant change in the husband's time for the wife's psychiatric and CESD depression shock is observed.

For comparison, I also show the impact of group 1 shocks (cancer, heart condition, high blood pressure, and lung condition) on the utilization of help. The magnitude of impact on formal and informal help received is smaller than group 2 shocks. However, the impact is also not significant for most cases, as shown in table A9. The pattern holds in the long run as well, where the impact on both formal and informal help availed is minimal in magnitude and statistically insignificant. Similarly, the impact on hours of help received for these shocks is trivial in magnitude and statistically significant (except for cancer).

Consumption Spending

Respondents were asked about 39 spending categories in the CAMS waves. Information on consumption spending is collected at the household level. I am interested in the spending categories that can potentially be replaced by time in home production. 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 $\Longleftrightarrow$ House cleaning; washing, ironing, or mending clothes
- Gardening services $\Longleftrightarrow$ Yard work or gardening
- Home Repair Services $\Longleftrightarrow$ Doing home improvements, including painting, redecorating, or making home repairs
- Dining Out $\Longleftrightarrow$ Preparing meals and cleaning up afterward

I combined expenditure on housekeeping services and gardening services because, in the first wave (2001), respondents were asked jointly about the expenditure on these two categories. All spending has been converted into monthly figures.[30]

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

[30] Even though CAMS is designed to map time-use and spending categories, such a mapping may have missed

Table A10 shows the impact on consumption spending for the first two periods after the shock.[31] Spending on purchasing house and yard services seems to be the most responsive to health shocks. Expenditure on other services does not increase. While the purchase of housekeeping and yard services decreases by around 30 percent for psychiatric shocks, it increases by around 20 percent for CESD depression and Self-Reported health shock. However, the event study graphs show an increasing trend prior to the depression and self-reported health shock.This could potentially violate the identifying assumption of no pre-trends. Hence I am cautious in interpreting these results as a causal effect of health shock.

6 Summary and Concluding Remarks

The theory of home production propounded in the seminal work of Becker (1965) suggests that people substitute consumption spending with home production when they face a negative economic shock. This is because home production might be used to mitigate the consequences of a decrease in economic resources. Prior research has confirmed an increase in home production in the face of income changes such as retirement and unemployment. However, studying the impact of health shock on home production, I do not find a positive effect on home production. I show that home production does not increase for the health shock that brings about a more significant increase in out-of-pocket medical costs. In other words, I do not find strong evidence that home production mitigates the monetary cost of an adverse health shock.

Moreover, I find that home production declines significantly for highly debilitating health shocks. Most of this decline comes from tasks essential for welfare, such as meal preparation and housekeeping. The decrease in home production is not short-lived. Though the effect dissipates for psychiatric shock after a few periods, it persists in the long run for depression measured through CESD score and self-reported health shock. I employ several robustness checks to test the sensitivity of the results and understand the nature of the shocks. In addition to various alternate econometric specifications, I explore the role of decline in cognition in driving the results.

Taken together, my findings underscore the nature of cushioning provided by home production in the face of a health shock. When the retired elderly face a health shock, home production does not increase to mitigate the monetary cost and reduced resources; instead, it decreases, thereby adding to the non-monetary cost of a health shock. My results find weak

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

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

evidence of a decline in home production being compensated by spouses or increased market spending.

I find a significant increase in the likelihood of utilization of formal and informal help for the highly debilitating but less costly health 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. While I do find that husbands increase their time spent in home production when their wives face a shock to self-reported health, this does not hold for other shocks or wives' home production when their husbands face any health shocks. I also find weak evidence of substitution towards consumption spending. Except for an increase in the purchase of housekeeping and yard services after CESD depression and self-reported health shock, spending on other consumption categories mapped to time-use does not increase despite a decrease in home production.

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. However, aging in one's place requires understanding how health shocks affect the time spent producing goods at home. My results show how different types of health shocks impact an individual's time spent in home production and whether their reliance on help with home production-related tasks changes in response to these shocks. This seems to have important policy implications for how we might structure supports for home- and community-based services (HCBS) such as personal care, chore services, and meal delivery – a recent topic of discussion in President Biden's proposed Build Back Better bill.

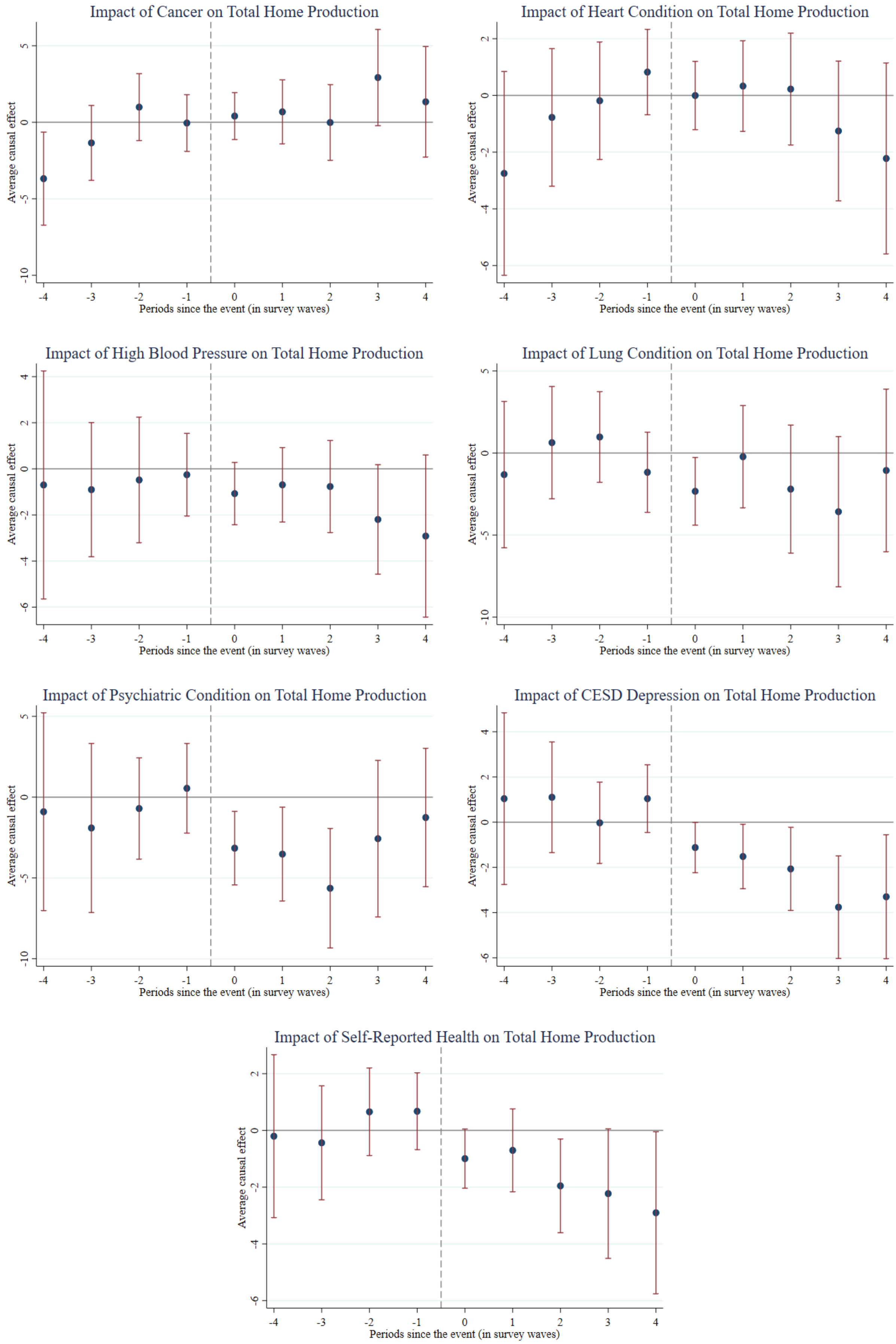

Figure 3: Impact of Health Shocks on Time Spent in Home Production

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

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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.[32]

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 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

[32]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.

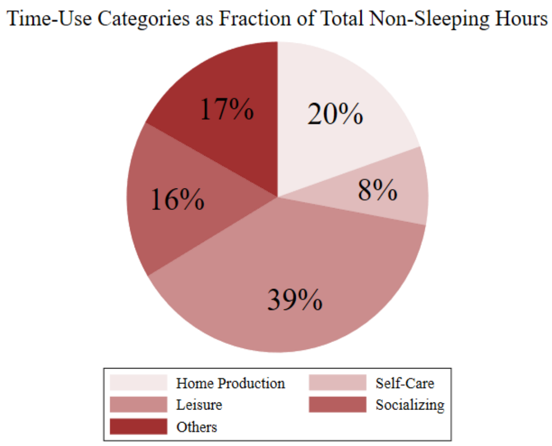


Figure A1

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.

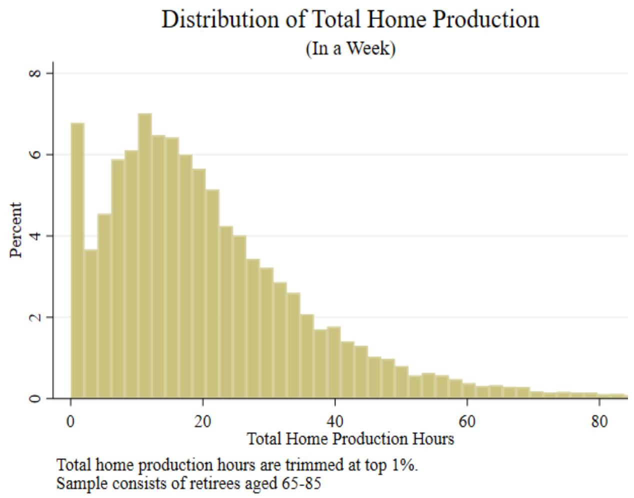


Figure A2

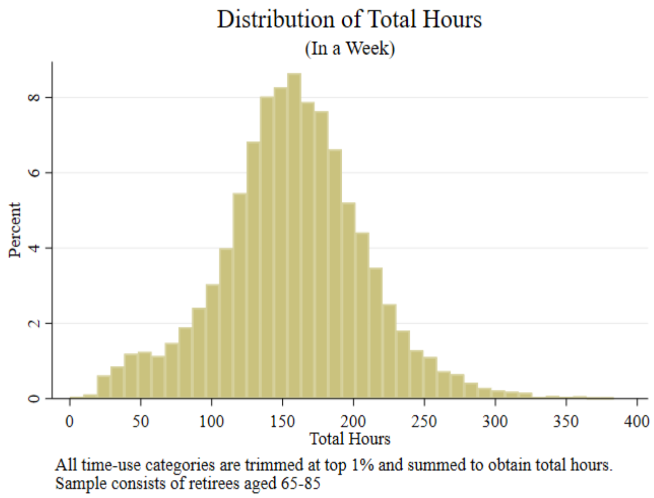


Figure A3

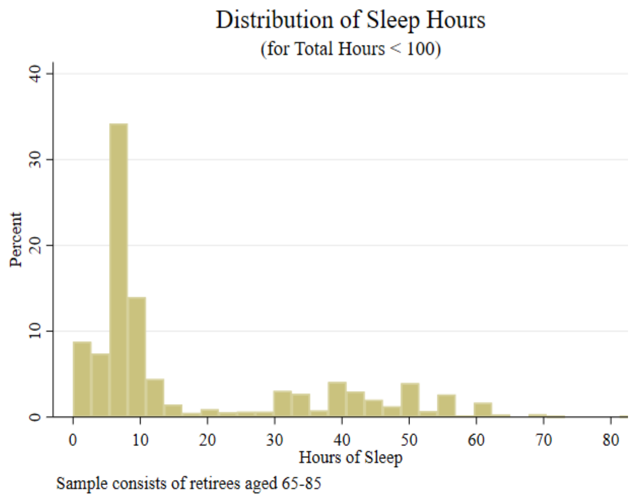


Figure A4

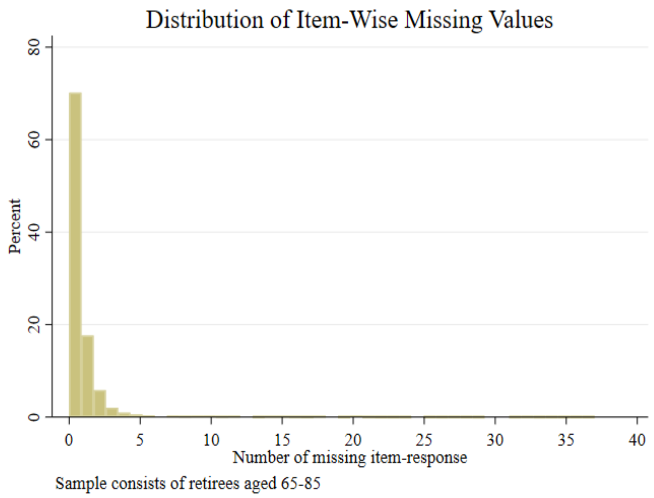


Figure A5

A.1 Correlation among health shocks

[Expand] – How is correlation calculated, takeaway

	Psychiatric Condition	Lung	High Blood Pressure	CESD Depression	Diabetes	Arthritis	Self-Reported Health	Stroke	Heart	Cancer
Psychiatric Condition	1									
Lung	0.158**	1								
High Blood Pressure	0.0684**	0.0336*	1							
CESD 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[33] 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.

[33]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

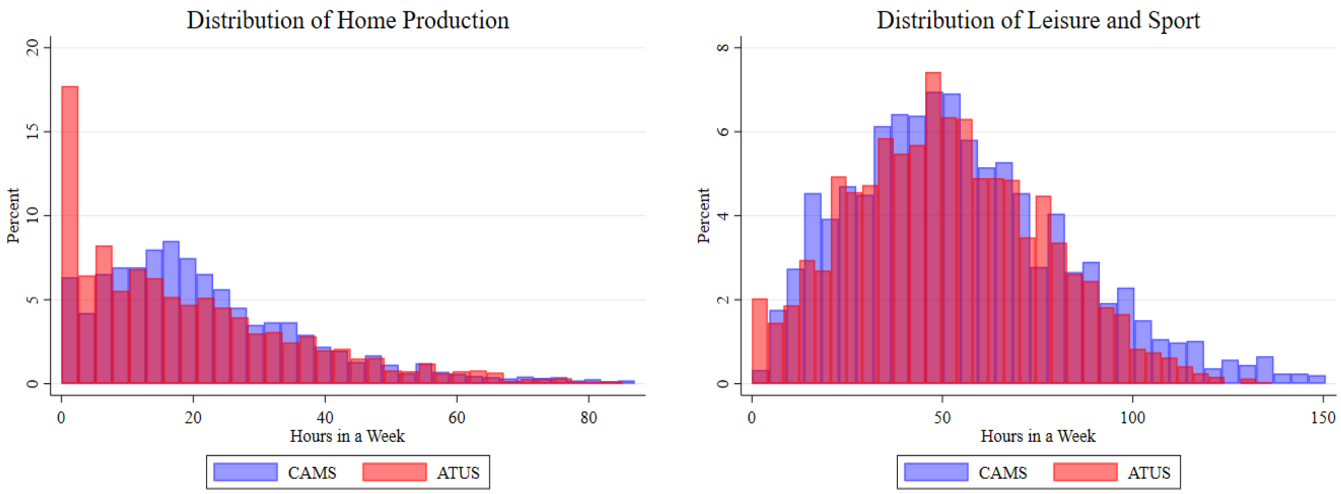


Figure A6

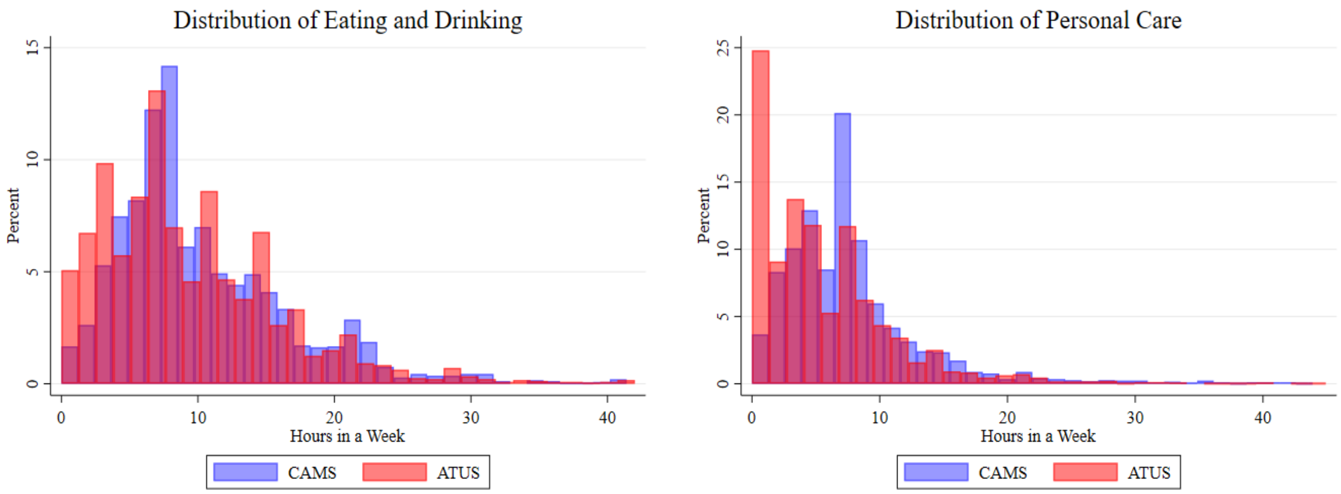


Figure A7

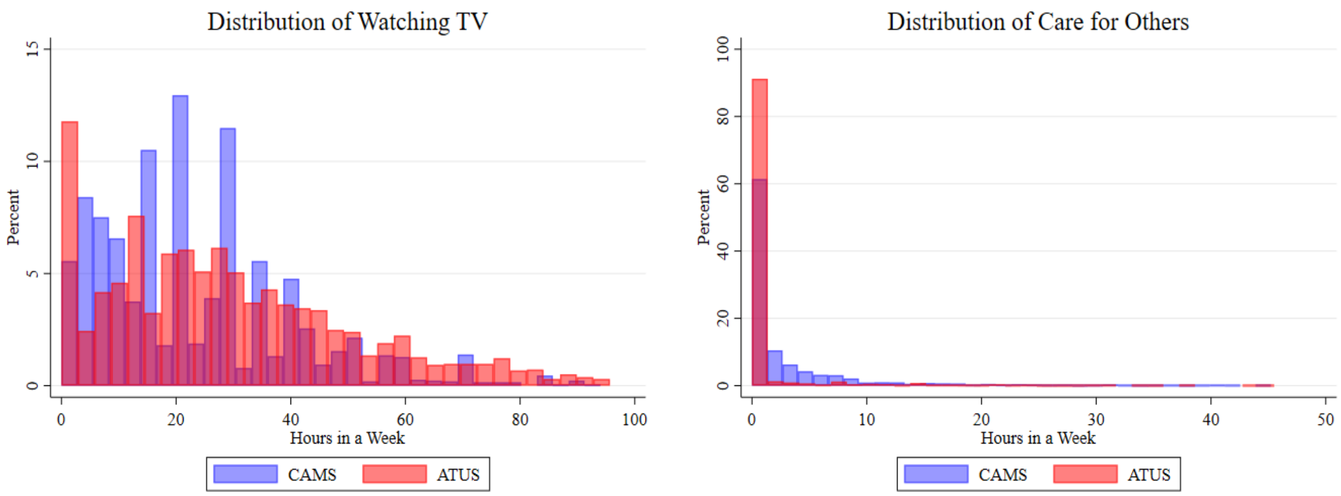


Figure A8

B Robustness Checks

B.1 Mechanism 1

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

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

B.2 Mechanism 2

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)

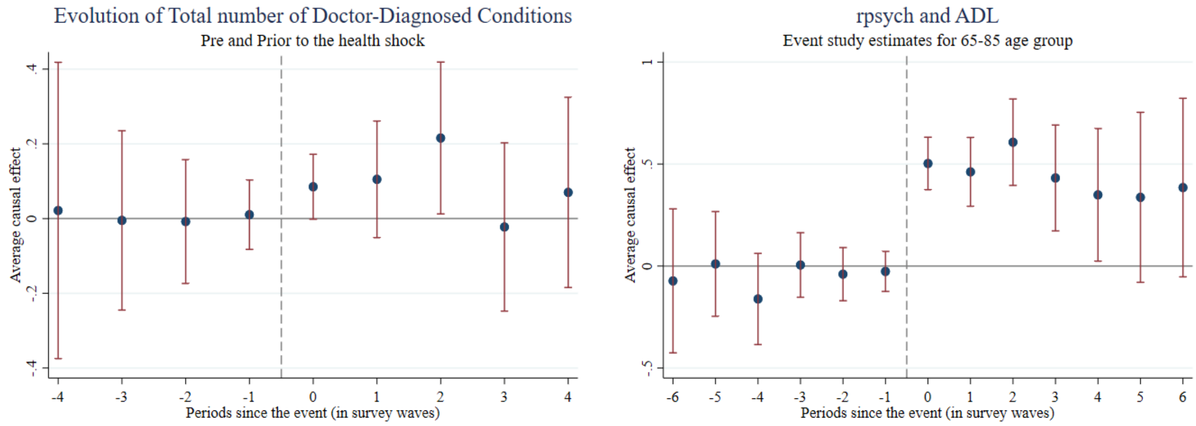


Figure A9: Psychiatric Shock

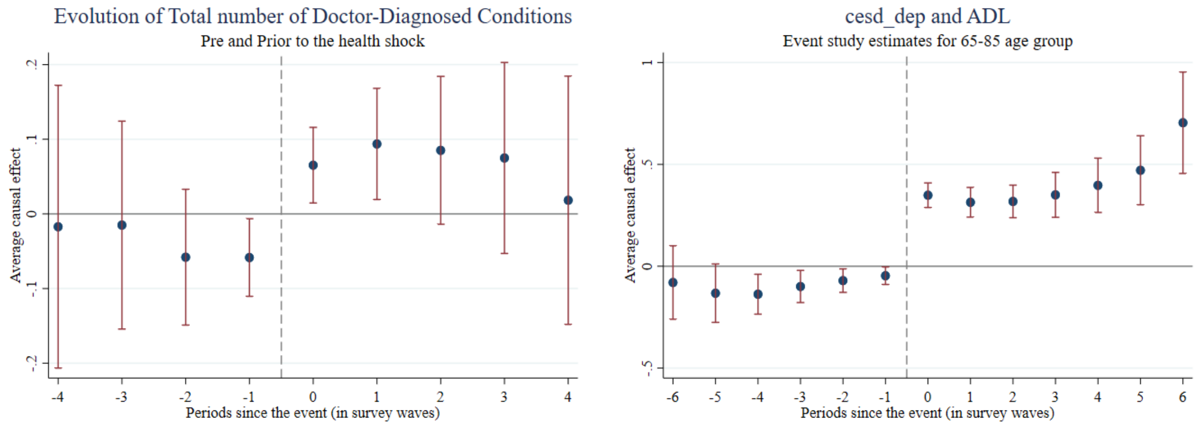


Figure A10: CESD Depression Shock

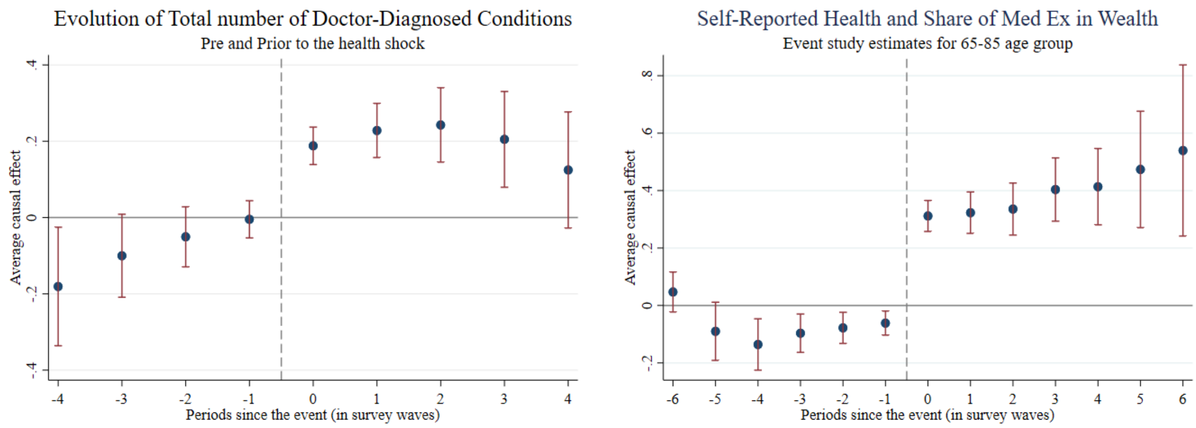


Figure A11: Self-Reported Health Shock

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.

B.3 Various Econometric Specifications

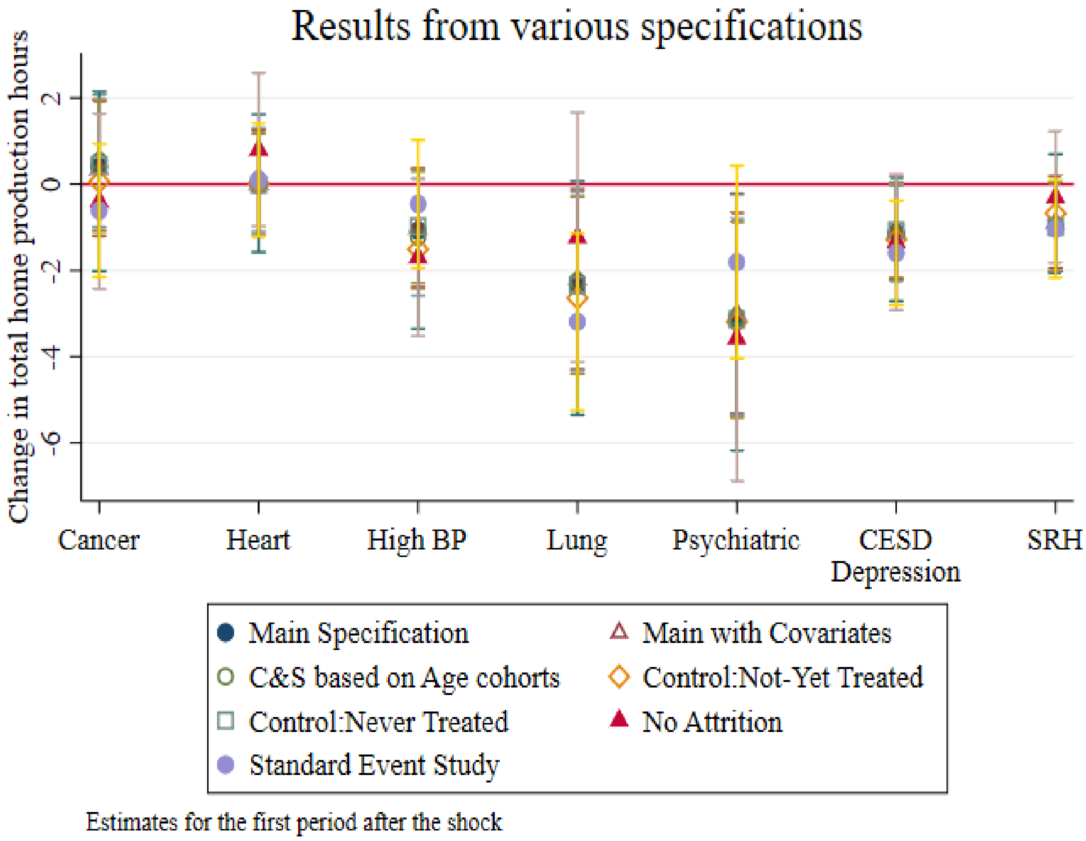


Figure A12

[Explain in detail all the alternate econometric specifications.]
[Explain in detail about the Age based cohorts specification]

C Implications of 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
Psychiatric Condition	0.052**	0.088***	0.051**	0.057**	0.052***	0.082**	0.077***	2.044
	(0.025)	(0.033)	(0.025)	(0.026)	(0.020)	(0.041)	(0.024)	(1.267)
Pre-treatment mean	0.029	0.126	0.041	0.070	0.015	0.244	0.041	2.194
CESD Depression	0.042***	0.065***	0.043***	0.047***	0.010	0.081***	0.047***	1.836***
	(0.009)	(0.017)	(0.011)	(0.013)	(0.007)	(0.023)	(0.011)	(0.403)
Pre-treatment mean	0.015	0.081	0.019	0.035	0.010	0.245	0.019	0.907
Self-Reported Health	0.026***	0.071***	0.017*	0.041***	0.009	0.111***	0.027***	1.606***
	(0.009)	(0.015)	(0.010)	(0.012)	(0.007)	(0.022)	(0.008)	(0.355)
Pre-treatment mean	0.014	0.064	0.022	0.030	0.008	0.211	0.021	0.727
Cancer	0.020	0.060***	0.032**	0.044**	0.014	-0.016	0.000	1.481***
	(0.015)	(0.020)	(0.014)	(0.017)	(0.011)	(0.031)	(0.013)	(0.425)
Pre-treatment mean	0.014	0.062	0.011	0.024	0.005	0.186	0.015	0.596
Heart Condition	0.015	0.047**	0.016	0.036***	0.008	0.060**	0.021**	0.347
	(0.011)	(0.018)	(0.011)	(0.013)	(0.007)	(0.026)	(0.009)	(0.492)
Pre-treatment mean	0.017	0.084	0.016	0.038	0.008	0.208	0.018	1.021
High Blood Pressure	0.027***	-0.002	0.017*	0.009	0.001	0.071***	0.001	0.734*
	(0.009)	(0.016)	(0.009)	(0.013)	(0.007)	(0.024)	(0.007)	(0.396)
Pre-treatment mean	0.006	0.052	0.008	0.024	0.002	0.148	0.013	0.479
Lung Condition	0.019	-0.008	0.052***	0.020	0.025	-0.012	-0.025	0.380
	(0.014)	(0.030)	(0.018)	(0.025)	(0.017)	(0.040)	(0.016)	(1.021)
Pre-treatment mean	0.015	0.107	0.013	0.042	0.003	0.351	0.020	1.229

Standard errors in parentheses

Control group includes only not yet treated individuals.

Top 1 pctile of hours of help has been trimmed.

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

Table A10: Impact on Consumtpion Spending

	(1) House and Yard Services	(2) Dining Out	(3) Home Maintenance Services
Psychiatric Condition			
Event Period 1	-0.31*	0.16	0.13
	(0.16)	(0.22)	(0.16)
Event Period 2	-0.35*	-0.11	0.22
	(0.21)	(0.26)	(0.17)
CESD Depression			
Event Period 1	0.20**	-0.23**	-0.14*
	(0.10)	(0.11)	(0.08)
Event Period 2	0.04	-0.03	-0.19**
	(0.11)	(0.13)	(0.09)
Self-Reported Health			
Event Period 1	-0.00	0.01	0.02
	(0.08)	(0.12)	(0.08)
Event Period 2	0.23**	-0.14	-0.13
	(0.10)	(0.14)	(0.09)

Standard errors in parenthesis

Control Group: not yet and never treated individuals

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

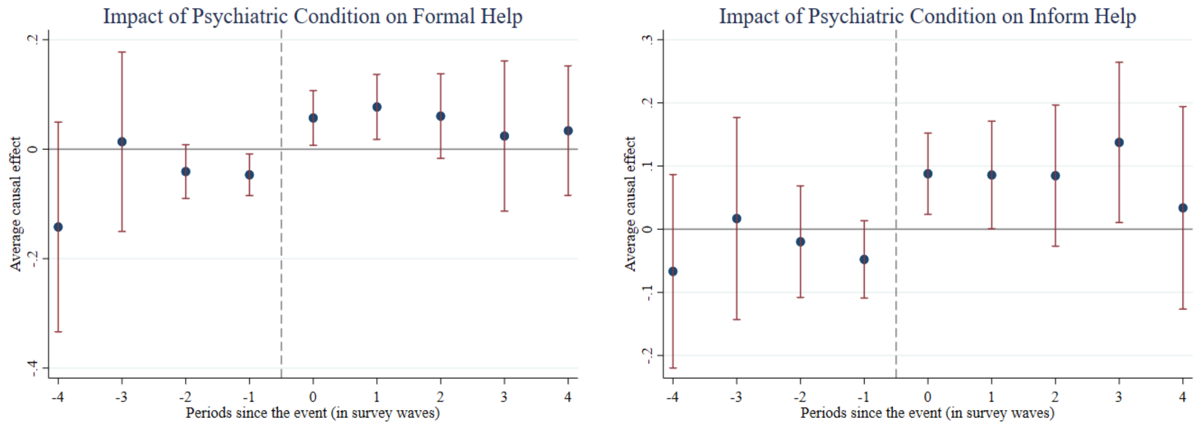


Figure A13: Psychiatric Shock

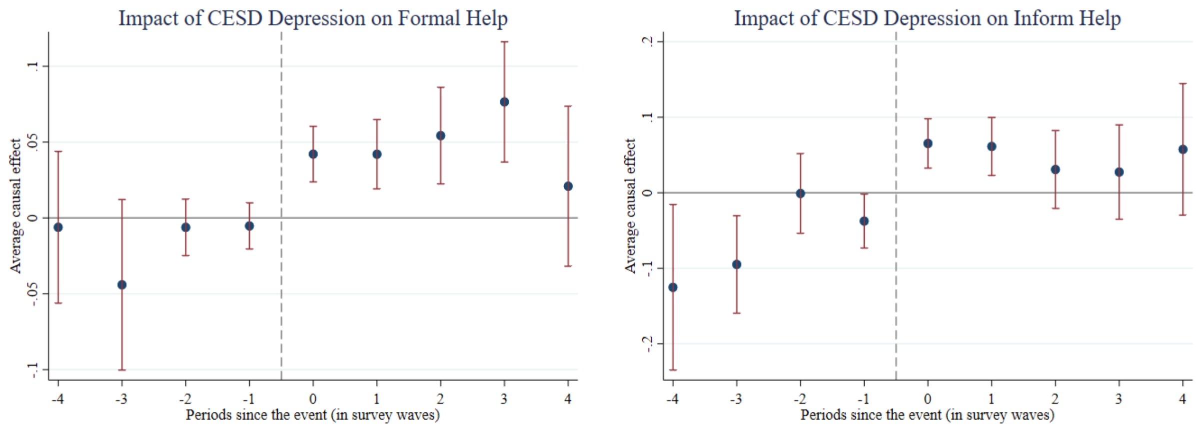


Figure A14: CESD Depression Shock

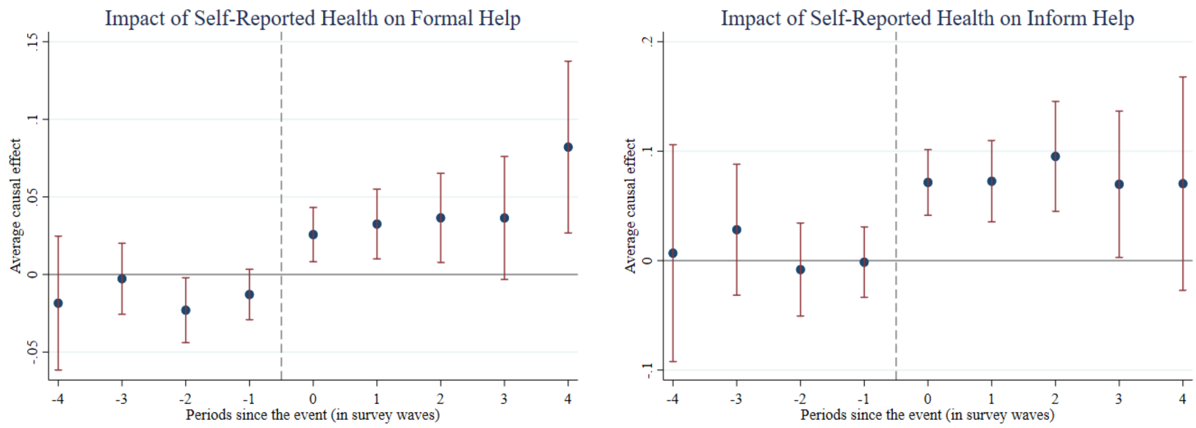


Figure A15: Self-Reported Health Shock

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.

D 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 CESD 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)
CESD 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)
CESD 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)
CESD 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 A16 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 A16 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)
CESD 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

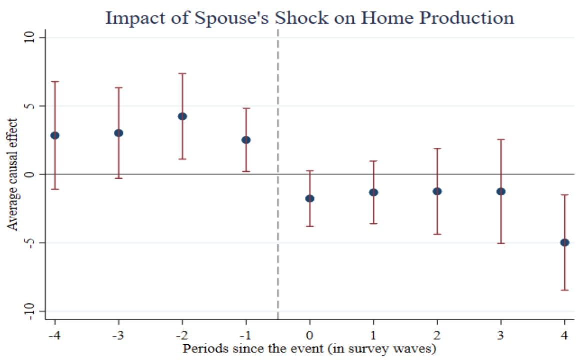
	(1) HP	(2) Meal Prep	(3) Housekeeping	(4) Shopping	(5) Home Maint.	(6) Yard work
Psychiatric	-1.766^{+}	-0.806^{+}	-1.042*	-0.312	0.00428	0.00340
	(1.038)	(0.429)	(0.473)	(0.205)	(0.0681)	(0.164)
CESD Depression	-1.506	-0.614	-0.835	-0.156	0.0636	0.206
	(0.970)	(0.398)	(0.514)	(0.196)	(0.0634)	(0.156)
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)
	(0.952)	(0.406)	(0.484)	(0.208)	(0.0618)	(0.170)

Control group includes not yet + never treated.

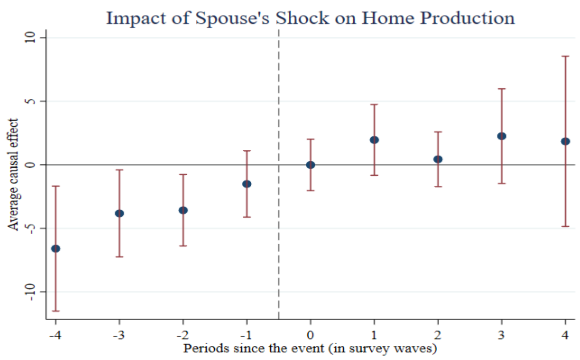
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Psychiatric Condition

Wife's HP

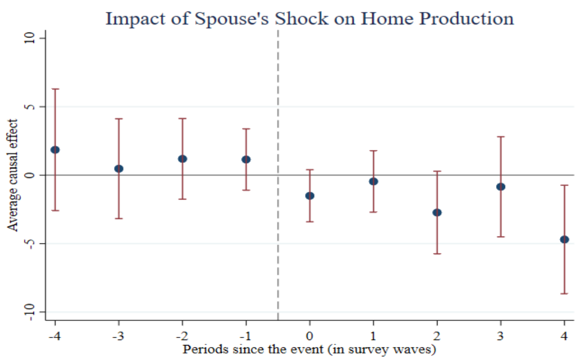


Husband's HP

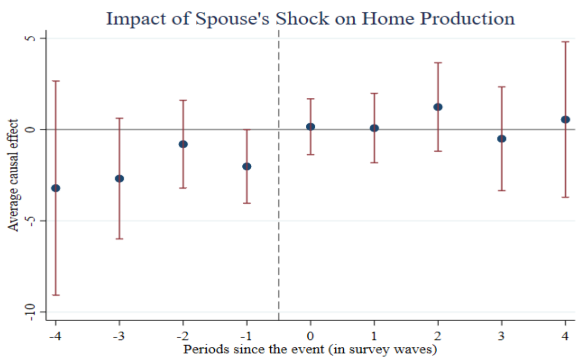


CESD Depression

Wife's HP

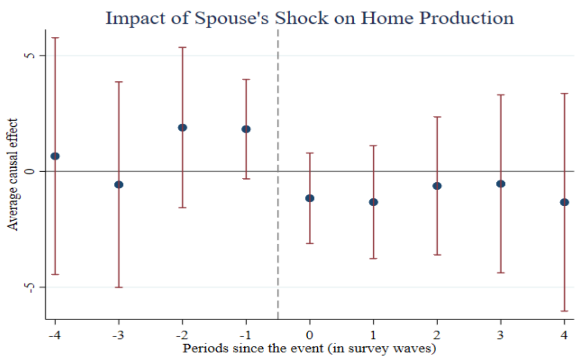


Husband's HP



Self-Reported Health

Wife's HP



Husband's HP

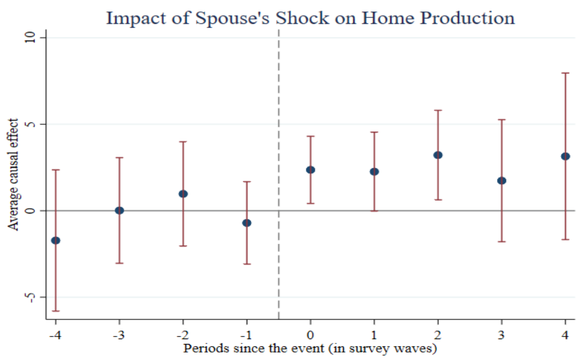


Figure A16