The Protective Effects of a Healthy Spouse: Medicare as the Family Member of Last Resort*

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Abstract

The aging of the US population has been a major source of concern, in part due to the rising costs of long-term care. We study the demand for long-term care among elderly American couples, both formally (provided in nursing facilities) and informally (provided by family members at home). Using administrative Medicare claims data and a novel spousal linkage, we analyze how the health of one spouse affects the need for formal long-term care of the other. In the weeks following a wife's incapacitation (for a heart attack or stroke), husbands are 55% more likely to visit an emergency department, 16% more likely to be hospitalized, and 23% more likely to be admitted to a skilled-nursing facility. We show that these effects appear to be caused by both direct health effects from losing informal care and changes in the use of formal care conditional on health. We offer revealed preference methods to evaluate households' valuation of formal and informal care, leveraging our findings that affected husbands are much less sensitive to the price of formal care than unaffected husbands that indicates their higher valuation. We discuss the implications of these results for optimal health insurance contracts, showing that these types of within-household spillovers can provide justification for household-level deductibles and out-of-pocket maximums. Overall, our analysis provides new evidence on the interaction between formal and informal care and on the value of long-term care among elderly American couples.

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1 Introduction

One of the challenges that an aging population presents is the growing need for long-term care (Johnson et al., 2021). When the elderly cannot care for themselves, then care must be provided, either formally or informally. Formal long-term care consists of nursing homes, home health aids, and other types of care often paid by Medicare or Medicaid. Informal long-term care consists of the time and resources that an older individual's family members invest to care for them.

The measurement of formal long-term care is straightforward – it can be directly observed in insurance claims and financial statements. Informal care, by contrast, is difficult to measure and even more difficult to value. When providing care, family members do not clock in, track their hours, or log their effort, so that informal care is typically unobserved and unmeasured.[1] Further, the opportunity cost of the time informal caregivers devote to caregiving activities is even more opaque, and differences in the quality and valuation of formal versus informal care are hard to assess. This has led to a strikingly wide range of estimates of the value of informal care, ranging from $86 billion (Gruber and McGarry, 2023) to over $500 billion (Chari et al., 2015).

In this paper, we study one of the most important sources of informal care: care from a healthy spouse. Spouses provide the vast majority of informal care and, overall, care delivered by spouses accounts for roughly one-third of all informal care (Gruber and McGarry, 2023). We identify the effects of receiving informal care from a healthy spouse and its valuation by leveraging plausibly exogenous changes in the availability of that care. Specifically, we identify Medicare beneficiaries who are hospitalized for a heart attack or stroke after a lengthy period with no hospitalizations, and we then use event-study methods to identify the effects of that spouse's incapacitation on their partners. Our analysis relies on novel data that allow us to link American couples covered by Medicare and study formal long-term-care outcomes using administrative Medicare claims.

We find large effects of the incapacitation of a wife on her husband's utilization of formal care.[2] Specifically, we find that in the weeks following a wife's health shock, husbands are 23% more likely to be admitted to a skilled-nursing facility (SNF). To interpret this finding, we offer a simple conceptual framework that incorporates a

[1] Some household surveys, such as the Health and Retirement Survey, collect self-reported measures of informal care among the surveyed households.

[2] We focus on opposite-sex couples in which the wife has a health shock. We find fairly similar effects when it is the husband who experiences the index event, as discussed in Section 4.

health effect and a substitution effect as two potential channels for the increased demand for formal care. First, the wife's health shock can directly lead to a worsening of their husband health that in turn raises their need for care. In support of this channel, we find that affected husbands exhibit a 55% increase in emergency department visits and are 16% more likely to be hospitalized. Second, there could be a substitution effect, whereby husbands shift from receiving informal care to receiving formal care because informal care is no longer available. In support of this channel, we find that the effects are larger for husbands with chronic conditions (prior to the wife's event) and when the spousal incapacitation is more severe. These findings highlight the protective role of a healthy spouse and that the overall increase in formal care that we observe upon a spouse's health shock is a combination of these effects. We approximate that the share of the increased demand attributable to the health effect is on the order of 30%.

We then move on to assess the welfare implications of our findings. Social welfare is composed of two components: the implications for the government's budget, that is, the "fiscal externality"; and the household's valuation of formal and informal care. To assess the fiscal externality—i.e., the expenditures that would have been spent on formal care in the absence of the informal care—we estimate the effects of the wife's health shock on total Medicare spending by the husband. We find that the wife's incapacitation leads to a 13% increase in spending for husbands in the year of the event, or \$1,364 on a baseline of \$10,536. Thus, from a purely fiscal perspective, the value of a healthy spouse is \$1,364 per person per year.

To measure the household's valuation of the availability of spousal informal care, we offer two complementary methods that assess the option value of a healthy spouse via households' "willingness to pay." The two methods offer revealed preference exercises that leverage households' choices of formal care across the two states of the world, when the wife becomes incapacitated versus the counterfactual in which the wife remains healthy and can provide care. The first method evaluates how the marginal valuation of SNF days varies across states of the world. It relies on within-state first order conditions of SNF days and the fact the price schedule is invariant to the wife's incapacitation. For a plausible range of the relative risk aversion parameter, we find that an additional day of SNF is valued (relative to income) by 30% to 120% more after the event.

The second method evaluates the overall willingness to pay for formal care across the two state of the world. We leverage a discontinuous change in the out-of-pocket

price of SNF stays. On the 20th day of a SNF visit, Medicare recipients' out-of-pocket costs shift from 0% to 20% coinsurance. We find that treatment households are much more inelastic, with patients whose spouses recently experienced a health shock being 74% less likely to leave SNFs immediately upon facing co-payments. These patterns imply a higher willingness to pay for formal care in the absence of a healthy spouse, which in turn reveals the option value of the availability of spousal informal care. We use these estimates to plot demand curves for SNF care and evaluate consumer surplus. This leads us to assess that husbands whose wives have been incapacitated are willing to pay 5 times more for formal care than control patients.

Finally, we consider the implications for the design of optimal healthcare policies. The differential slopes of the demand curves across states of nature map directly to the magnitude of moral hazard in the consumption of SNF stays. In other words, the ratio of elasticities governs the relative deadweight loss from subsidies to formal long-term care across households with and without healthy spouses. With this assessment, we evaluate that there is a 63% reduction in efficiency loss among affected households. This implies that Medicare can provide higher levels of coverage for SNF care with lower deadweight loss due to moral hazard when a beneficiary's spouse is incapacitated versus when the spouse is healthy. This in turn provides strong support for the design of insurance contracts with family-level deductibles or a shared out-of-pocket maximum.

Our work contributes to three areas of inquiry. First and foremost, we contribute to research on long-term care in the US, particularly informal care. In their recent review of the literature on long-term care, Gruber and McGarry (2023) estimate that formal-care expenditures totaled $280 billion in 2018, that the public sector finances the majority of long-term-care spending, and that informal care plays a critical role. Indeed, they show that the elderly at every age and disability level receive informal care more frequently than formal care, and that informal care may delay entry into formal care (Bergeot and Tenand, 2023; Bonsang, 2009; Charles and Sevak, 2005). We contribute to this literature by providing, to the best of our knowledge, the first analysis of intra-family interactions in the demand for long-term care in the US using administrative data at the population level. We estimate the value of informal care by isolating the causal relationships in these interactions, evaluating the monetary value of the spousal relationship in long-term care, and assessing beneficiaries' valuation of formal long-term care when their spouse becomes incapacitated.

Second, this paper contributes to a broad academic literature on the economics

of risk sharing within the household. Since the pioneering work of Becker (1974), there has been significant progress in understanding the dynamics of risk-sharing within families, particularly how health shocks to one member of the family can affect the others. This body of research has explored joint learning about health risks (Hoagland, 2024), the interdependence of family members' risks (Fadlon and Nielsen, 2019a), and the implications for public policy (Fadlon and Nielsen, 2019b; Gross et al., 2024). Additional work has highlighted the role of economic and health shocks on household labor supply and family stability (Fadlon and Nielsen, 2021; Hodor, 2021; Arteaga et al., 2024; Fontes et al., 2024). We contribute to this literature by providing novel evidence on the value of a healthy spouse via the intra-household interactions between formal and informal care among elderly American couples.

Third, this paper uncovers healthcare dynamics that can inform how health insurance contracts ought to be structured. When one person is experiences a health shock, the risks that their spouse faces change. And yet, the Medicare program offers individual health insurance plans that make no adjustment for the rest of the household. Many employer-provided plans also feature individual-specific rather than household-specific out-of-pocket limits or deductibles. This paper provides new evidence that can help assess the optimality of such arrangements. Our work is therefore related to previous work estimating optimal levels of social insurance (Baily, 1978; Chetty, 2006; Chetty and Finkelstein, 2013), where we provide novel findings with respect to the design of healthcare policies which are large and growing.

The remainder of the paper proceeds as follows. Section 2 provides our empirical framework by describing the data we use and our identification strategy. Section 3 provides a conceptual framework that organizes our empirical analysis of the causal effects of spousal shocks and their implied effects on welfare. Section 4 provides the main empirical evidence of the effects of a wife's health shock on the husbands' health and healthcare utilization. Section 5 provides our welfare analysis of households' valuation of informal care and the optimal design of healthcare policies. Section 6 concludes.

2 Empirical Framework

2.1 Data

We use Medicare claims data that cover all types of care: primary and specialty care, inpatient and outpatient care, and long-term care. We have created a dataset

of couples in Medicare using a custom crosswalk from the Centers for Medicare and Medicaid Services (CMS). The dataset includes beneficiaries' addresses, as tracked by CMS. We then group beneficiaries who live at the same address and identify spouses by selecting residences with a maximum of two Medicare recipients of opposite sexes living at the same address. This allows us to study Medicare-covered healthcare among American couples with large scale administrative data. Gross et al. (2024) validate this identification of spouses, specifically by comparing the gaps in ages for spouses identified with this crosswalk to spouses identified in the American Community Survey.

Our outcome measures are drawn from fee-for-service claims for traditional Medicare enrollees from 2010 to 2017. We use information on 100% of hospital inpatient stays and qualifying SNF stays using the Medicare Provider Analysis and Review (MedPAR) file, as well as beneficiary summary information and annual measures of utilization for each enrollee. In addition, we observe detailed outpatient, carrier claims, and Part D (pharmaceutical) events for 20% of enrollees.

In our analysis, we require households to have full Medicare eligibility throughout the window of observation, and assign spouses in the year prior to the index health event. We also exclude households where the index event has accompanying external injuries so as to avoid capturing joint events affecting both members of the household (for example, vehicle accidents). Finally, in keeping with previous work, we require the spouse who has the health shock to have not had a prior hospital admission in the three years preceding their index admission (Dobkin et al., 2018).

2.2 Research Design

A macabre thought experiment that would identify the impacts of a spouse's health shock would randomly assign such shocks to couples and track the responses and outcomes of partners over time. We take a quasi-experimental approach that aims to approximate this thought experiment. We compare the responses to events by affected couples to counterfactual outcomes of not-yet-affected couples. We restrict the analysis to couples that have experienced a health event—a heart attack or stroke—and we identify the treatment effect using variation in the timing of when the event was realized. Similar approaches have been used by Dobkin et al. (2018) and Fadlon and Nielsen (2019a, 2021). We follow the work of Fadlon and Nielsen (2019a, 2021) to construct counterfactual trends for affected families using families that experience the same event but several periods in the future.

As such, we construct a treatment group, composed of spouses in households that experience the event in period τ, and a matched control group (based on event time), composed of spouses in households that also experience the event, but in period $\tau+\Delta$. We assign a placebo event to control households in period τ. We then recover the treatment effect by using a dynamic difference-in-differences estimator, identifying the event's impact purely from the change in the differences in outcomes across the two groups over time. We require full eligibility over the sample period, meaning that our results are not affected by potential challenges involved in units that switch in and out of experimental arms. Similarly, our results are also robust to using estimators that explicitly model heterogeneous treatment effects, specifically the local-projection difference-in-differences estimator developed by Dube et al. (2023).

Our empirical strategy rests on the standard parallel-trends identifying assumption. It assumes that, absent the realization of the health shock, the outcomes of the treatment and control groups would evolve in parallel. To test the validity of this assumption, we study the evolution of the treatment and the control groups' outcomes in the periods prior to the event. Our choice of Δ is one year, so that we match households that experience health shocks 12 months apart. This implies that we can estimate the effects of shocks up to 12 months after the event, since the control group becomes "treated" 12 months later. Using a weekly frequency, we normalize the time of observation such that event-time period n is measured with respect to the assigned event period. That is, $n \equiv$ calendar week $- \tau$, where $n = 0$ is when the assigned event occurs (the actual event for the treatment group and the placebo event for the control group).

We then run the following event-study regressions for the dynamic difference-in-differences estimator:

$$y_{i,t} = \alpha_i + \theta_n + \sum_{n \neq -1} \delta_n \times I_n \times \text{treat}_i + \lambda X_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where $y_{i,t}$ denotes an outcome for household i at calendar time t, treat_i denotes an indicator for whether a household belongs to the treatment group, and I_n are indicators for weeks relative to the assigned event period. Equation (1) includes household fixed effects (α_i) and relative-time fixed effect (θ_n) level, and can flexibly accommodate a vector of controls $X_{i,t}$. The key parameters of interest are the δ_n coefficients, which estimate the period n treatment effects relative to the pre-period $n = -1$. In order to calculate average effects over several periods, we estimate a

standard difference-in-differences specification of the following form:

$$y_{i,t} = \alpha_i + \theta \times \text{post} + \delta \times \text{treat}_i \times \text{post}_{i,t} + \lambda X_{i,t} + \varepsilon_{i,t}, \tag{2}$$

where $\text{post}_{i,t}$ is an indicator for whether the observation belongs to a period after the shock occurred, and δ is the estimate for the average treatment effect.

Table 1 presents summary statistics for our analysis sample. The treatment and matched control groups are closely similar in terms of patient demographics and healthcare utilization at the baseline year prior to the event (the actual event for the treated group and the placebo event for the matched control group).

Table 1. Summary Statistics

	Affected Husbands	**Matched Control Husbands**
Panel A: Demographics		
Male	1.00 (—)	1.00 (—)
Age	78.57 (7.71)	78.51 (7.69)
White	0.641 (0.480)	0.634 (0.482)
Black	0.048 (0.214)	0.054 (0.225)
Hispanic	0.008 (0.091)	0.009 (0.96)
Dual Eligibility Status	0.103 (0.304)	0.096 (0.294)
FFS Status	0.631 (0.483)	0.637 (0.481)
HMO Status	0.285 (0.451)	0.280 (0.449)
Panel B: Healthcare Utilization		
SNF	0.130 (0.336)	0.132 (0.339)
Hospitalization	0.871 (0.336)	0.868 (0.339)
#, SNF Stays	0.230 (0.615)	0.237 (0.635)
#, Hospitalizations	1.544 (1.072)	1.551 (1.092)
Year	2013.22 (2.058)	2013.23 (2.064)
N	297,340	298,440

Notes: This table presents summary statistics for the analytical sample. Following the design discussed in Section 2.2, we identify husbands affected by their wives' health events, and construct a matched control group of the same husbands a year prior to the event. Table shows averages with standard deviations in parentheses.

3 Conceptual Framework

This section presents a framework to conceptualize the effects of a spouse health shock and their potential consequences.

3.1 Decomposing the Effects of Spousal Health Shocks

Consider two time periods, $t \in \{0, 1\}$, where $t = 0$ represents time prior to a spouse's health event and $t = 1$ represents time after a spouse's health event. The spouse whose outcomes we study, the "focal spouse," experiences two possible states: healthy and sick. Denote h_t as an indicator for whether the focal spouse is sick in period t, such that $h_t = 0$ indicates the healthy baseline at time t and $h_t = 1$ indicates a health condition that requires care at time t. Conditional on being sick, the focal spouse's mode of receiving treatment is denoted by c_t, with $c_t = 0$ indicating informal care and $c_t = 1$ indicating formal care. We can include in the "0" a fallback option or extend framework to model it directly (e.g., self-care and care from other members).

The focal spouse transitions across states via the following matrix. Each row represents the conditional probability of moving to the given column.

	Healthy in $t = 1$	Sick in $t = 1$	
		Informal care	Formal care
	$(h_1 = 0)$	$(h_1 = 1, c_1 = 0)$	$(h_1 = 1, c_1 = 1)$
$(h_0 = 0)$	$p_{0,0}$	0	$p_{0,(1,1)}$
$(h_0 = 1, c_0 = 0)$	0	0	1
$(h_0 = 1, c_0 = 1)$	0	0	1

In period 1, informal care is not available to a sick focal spouse following their spouse's health event. Hence, the transition probabilities for the second column are all 0, and previously sick husbands relying on either informal or formal care are assumed to move to formal care after their wives' health shocks. We model sickness as an absorbing state since we focus on long-term care. The transition matrix above therefore assumes that once $h_t = 1$ the person cannot transition back to $h_t = 0$, which restricts the transition probabilities in the first column. Note that by construction, $p_{0,0} + p_{0,(1,1)} = 1$.

One goal of our empirical strategy is to identify the impact of spousal incapacitation on the demand for formal care. We denote this parameter by τ, where

$$\tau \equiv \Pr(c_1 = 1) - \Pr(c_0 = 1).$$

Note that we can interpret τ as the option value of a healthy spouse based on the causal effect of losing that option.

This then lends itself to a straightforward decomposition. Since

$$\begin{aligned}
\Pr(c_0 = 1) &= \Pr(h_0 = 1, c_0 = 1), \\
\Pr(c_1 = 1) &= \Pr(h_1 = 1, c_1 = 1) \\
&= \Pr(h_0 = 0) \times p_{0,(1,1)} + \Pr(h_0 = 1, c_0 = 0) + \Pr(h_0 = 1, c_0 = 1),
\end{aligned}$$

it follows that

$$\tau = \underbrace{\Pr(h_0 = 0) \times p_{0,(1,1)}}_{\text{Health Effect} \equiv \tau_H} + \underbrace{\Pr(h_0 = 1, c_0 = 0)}_{\text{Substitution Effect} \equiv \tau_S}. \tag{3}$$

That is, we can decompose the overall effect of the spouse's health shock on the focal spouse's care into two components. The shock directly worsens the focal spouse's health, τ_H, and it also leads him to be more likely to consume formal care instead of informal care conditional on needing care, τ_S.

3.2 Social Welfare Effects

To assess social welfare, we consider the differentials in the household's value function across states, $V(h, c)$. We define $V_S \equiv V(1, 0) - V(1, 1)$ as the value of informal care versus formal care for sick partners who chose informal care at baseline. We define $V_H \equiv V(0, \cdot) - V(1, 1)$ as the value of being healthy. We further denote by μ the marginal value of public funds, which corresponds to the shadow value of government resources, which we denote by R_t. With this formulation, we can represent social welfare by:

$$W_t = E_t(V) + \mu E_t,$$

where $E_t(V) = \Pr(h_t = 0) \times V(0) + \Pr(h_t = 1, c_t = 0) \times V(1, 0) + \Pr(h_t = 1, c_t = 1) \times V(1, 1)$.

We normalize the utility valuations by μ so that they are represented in their money-metric dollar equivalent, defining $v_S \equiv V_S/\mu$ and $v_H \equiv V_H/\mu$. We further denote by e_H the average expenditure per beneficiary who experiences a health condition, and we denote by e_F the average expenditure per beneficiary who utilizes formal care. Defining $w_t \equiv W_t/\mu$, the money-metric change in welfare following the

event is:

$$\triangle w \equiv w_1 - w_0 = \underbrace{-v_H \tau_H - v_S \tau_S}_{\text{Household Welfare Effect}} + \underbrace{-(e_H + e_F)\tau_H - e_F \tau_S}_{\text{Fiscal Externality} = (R_1 - R_0)}.$$

This first component is the loss in household welfare from the health effect and from the imposed substitution away from informal care. The second component is the change in expenditure $(R_1 - R_0)$, which represents the fiscal externality on Medicare costs.

3.3 Parameter Estimation

Our analytical approach allows us to directly identify τ, the effect of a spousal health shock on the takeup of formal care, measured using SNF stays. In addition, our framework motivates a decomposition of τ into a health effect and a substitution effect. We will identify the health effects by measuring changes in underlying health conditions and proxies for poor husband health, such as the predicted probability of a SNF stay as a function of husband demographics and health conditions. We will identify the substitution effect by examining differences in responses to a health shock across husbands with pre-existing conditions or across responses to initial shocks with differing levels of underlying severity.

We can also directly estimate $(R_1 - R_0)$ by measuring the change changes in total Medicare spending for affected husbands compared to their matched control group. This allows us to evaluate the fiscal externality associated with losing the option of a healthy spouse to provide informal care.

Finally, in Section 5.2, we develop our two revealed preference approaches to infer measures of v_S. We will infer the average dollar valuation of informal care from spouses by excess valuation of formal care when informal care becomes absent.

4 Empirical Evidence: Event-Study Analysis

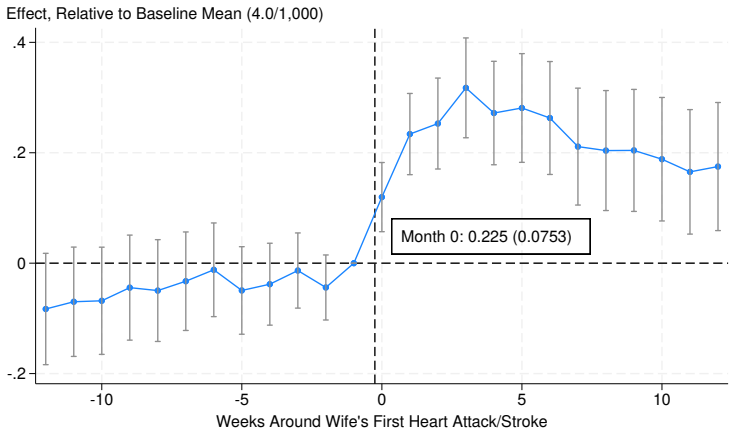
We now turn to our main empirical analysis of the effects of a spousal health shock on healthcare utilization and health. Our current analysis focuses on households in which the wife experiences the event (being the index spouse) and the husband is the spouse whose outcomes we study (being the focal spouse). Appendix Figure A1 compares those effects to households in which the husband experiences the initial

health shock.[3] In general, the responses are qualitatively similar across gender but we focus on one gender (here the wife as the index spouse) for simplicity.

4.1 Dynamic Impacts on formal care

Figure 1 examines the risk of a husband visiting a Skilled Nursing Facility (SNF) after his wife's index event. This figure, and subsequent dynamic figures, plot the δ_n coefficients from estimates of equation (1). The x-axis represents time relative to the wife's index event. Average baseline levels in the pre-event period are reported in the label of the y-axis and the outcome variables are normalized such that coefficient are in percent relative to baseline.

Figure 1. Change in the Risk of Visit to a SNF After a Wife's Index Event



Notes: This figure plots estimates of the δ_n coefficients from equation (1), difference-in-differences estimates that track the weeks since a wife's first heart attack or stroke. The outcome of interest is an indicator for whether the husband visited a SNF. We re-scale all coefficients such that they indicate the change relative to the initial baseline risk of hospitalization or SNF stay. The error bars plot 95-percent confidence intervals based on standard errors clustered at the household level. The estimation includes calendar-time fixed effects and person-specific fixed effects.

The figure first shows no systemic differentials across experimental groups in the periods prior to the event, in support of our research design. Then, we see a sharp increase in the risk of a husband's visit to a SNF upon a wife's health shock, which remain persistent throughout the analysis horzion of 12 weeks. Column 1 of Table 2 summarizes the effects over the over the month immediately following the wife's shock using equation (2). We find that the husband's propensity to visit a SNF increases

[3]In our main specification with an affected spouse's visit to a SNF as the outcome variable, the associated p-value for differences in pooled effects across the two groups (one where husbands experience the focal event, and the other where wives are affected) is 0.073.

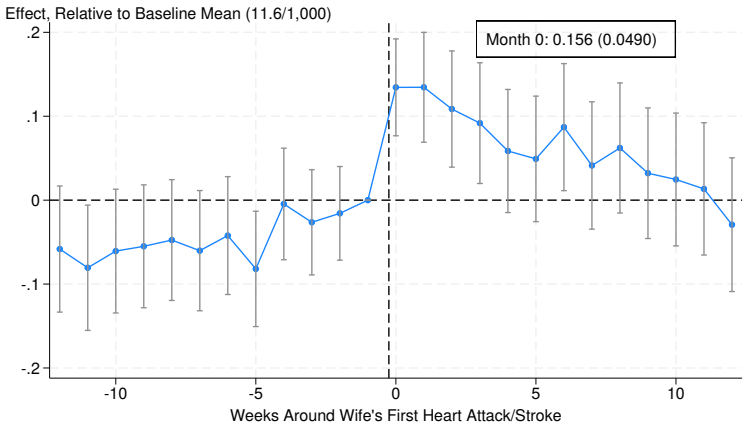
by over 22%. Appendix Figure A2 presents estimates over the full year following the wife's shock.

The increased risk of a visit to a SNF could be driven by several potential mechanisms. We focus on two leading candidates. First, motivated by prior work (Arteaga et al., 2024; Bünnings et al., 2021), there could be a *health effect*: adverse health shocks to wives can lead to worsening of husbands' own health and thus translate to a greater need for care. Second, there could be a *substitution effect*: husbands with existing long-term care needs may switch from receiving informal care from their wives to utilizing formal care. We now turn to provide tests for the presence of these channels.

4.2 Health Effect

We first assess the possibility of an effect on health. We study a husband's probability of being hospitalized following the wife's health shock. Figure 2 plots estimates of equation (1) when the outcome is an indicator for visiting a hospital in the given period. We find clear increases in the probability of hospitalization immediately upon a wife's health shock. The increased risk is elevated over the first month—and amount to 15.6%—and it then reverts back to baseline in the follow-on periods.

Figure 2. Change in the Risk of Hospitalization After a Wife's Index Event



Notes: This figure plots event-study coefficients that track the weeks since a wife's first heart attack or stroke. The outcome of interest is an indicator for whether the husband was hospitalized, and we re-scale all coefficients such that they indicate the change relative to the initial baseline risk of hospitalization. The error bars plot 95-percent confidence intervals based on standard errors clustered at the household level. The regression includes calendar-time fixed effects and person-specific fixed effects.

Table 2 summarizes the results and further digs into health proxies. In column

Table 2. Change in Risk of Husband Health Events After a Wife's Index Event

	(1) SNF	(2) Hospitalization	(3) ED Visits	(4) Hospitalization & SNF
Treatment Effect, Month 0	0.225***	0.156***	0.553***	0.303***
	(0.0753)	(0.0490)	(0.1675)	(0.1097)
Baseline Rate/1,000	4.0	11.6	8.1	2.8
N	3,353,626	3,353,626	618,242	3,353,626

Notes: This table presents pooled difference-in-differences coefficients estimating the effect of a wife's first heart attack or stroke on husband health outcomes (indicated in each column). "Hospitalization & SNF" indicates that a husband both was hospitalized and visited a SNF in the same period. ED Visits are measured as total number of visits. All other outcomes are binary. Note that ED visits are measured using the 20% sample of Medicare beneficiaries, hence the reduced sample size. Treatment effects are estimated in month 0, capturing the effect for the first four weeks post-event. We re-scale all coefficient such that they indicate the change relative to the initial baseline risk of diagnosis in each category, and we cluster standard errors at the household level. Regressions include calendar-time fixed effects and person-specific fixed effects. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3, we study a husband's Emergency Department (ED) encounters as the outcome of interest tracks . The risk of an ED visit increases by over 50% in the month of a wife's health shock. Finally, column 4 looks directly at the health effect in increased SNF stays by studying the probability of the joint event of a hospitalization and a SNF stay. In the weeks after a wife's health shock, husbands are 30% more likely to be hospitalized and then consume formal care at a SNF.

These findings suggest that part of the increased utilization of formal care after wives' health shocks is driven by changes in their husbands' health. It is that diminished health that then leads to the increase in hospitalizations and ED visits.

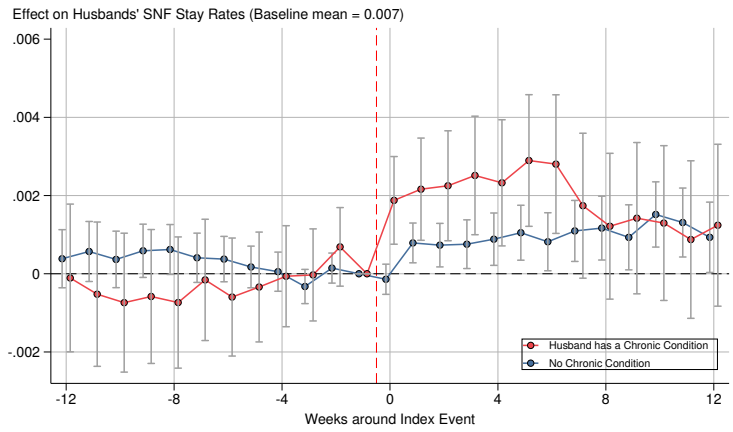
4.3 Substitution effect

We next assess the presence of a substitution effect: whether husbands substitute formal care for informal care due to their wives' incapacitation. We provide two exercises to test for such an effect. First, we stratify households based on the husband's underlying needs before the wife's index event. Second, we stratify households based on the degree of incapacitation of the wife.

For the first exercise, Figure 3 plots estimates of equation (1) for visits to SNFs separately by whether the husband suffered from a chronic condition before the index

event. For this measure, we rely on Medicare's Chronic Conditions file, which catalogs for each Medicare beneficiary the presence of one of 27 chronic conditions. The figure shows that husbands with chronic conditions are more likely to visit a SNF after their wives' index event as compared to husbands without a chronic condition. Importantly, both groups of husbands exhibit an increases in SNF visits, but the increase is meaningfully larger for less-healthy husbands.

Figure 3. SNF Effects Stratified by Husband's Pre-Event Chronic Condition Status



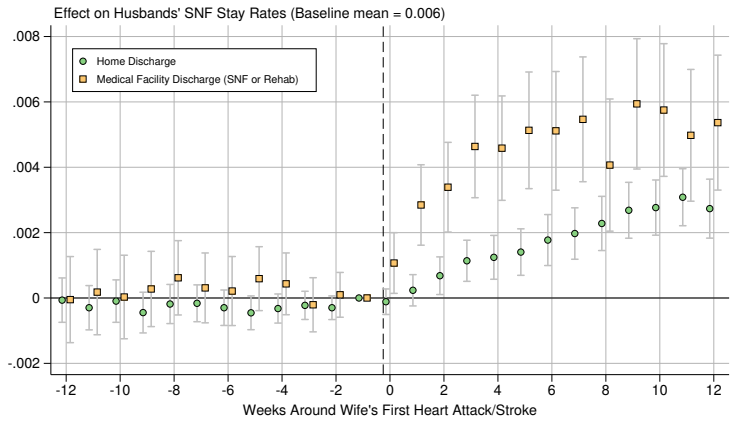
Notes: This figure plots estimates of the δ_n coefficients from equation (1), difference-in-differences estimates that track the weeks since a wife's first heart attack or stroke. The outcome of interest is an indicator for whether the husband visited a SNF. We stratify the sample based on whether a husband had a documented chronic condition at least one year prior to the wife's event. Chronic conditions include ADRD, AMI, anemia, cancer (colorectal, lung, or prostate), chronic kidney disease, chronic heart failure, COPD, depression, diabetes, hip fractures, osteoporosis, and strokes. The error bars plot 95-percent confidence intervals based on standard errors clustered at the household level. Regressions include calendar-time fixed effects and person-specific fixed effects.

For the second exercise, in which we study husbands' risk of a SNF stay by the severity of the wife's health shock, we focus on non-fatal events since spousal death has been shown to more likely lead to health effects (Fadlon and Nielsen, 2019a). To split households by the degree of wife's incapacitation due to the shock, we use the discharge destination. Specifically, we stratify households by the wife was discharged home or to a medical facility which include rehabilitation facilities and Skilled Nursing Facilities.[4] The figure clearly shows that index events in which the wife is incapaci-

[4]We limit this sample to husbands who did not recently experience a health event: those who have not been hospitalized in weeks -12 to -1. That restriction addresses potential contamination from reverse causality: the severity of a wife's health event could be worse due to a recent health event inflicted on the husband.

tated have a much larger impact on the husband's demand for formal care than index events in which the wife is simply discharged home. In combination, these patterns provide strong support for a substitution effect in the increased risk of SNF stays following the wife's event.

Figure 4. SNF Effects Stratified by Severity of Wife's Index Event



Notes: This figure plots estimates of the δ_n coefficients from equation (1), difference-in-differences estimates that track the weeks since a wife's first heart attack or stroke. Here, analysis is restricted to non-fatal index events only. We also exclude households whose husbands experienced a hospitalization in the 12 weeks prior to the wife's event to avoid bias from anticipatory SNF stays from precedent hospitalizations. The outcome of interest is an indicator for whether the husband visited a SNF during that week, where effects are split based on the discharge status of the wife. The error bars plot 95-percent confidence intervals based on standard errors clustered at the household level. Regression include calendar-time fixed effects and person-specific fixed effects.

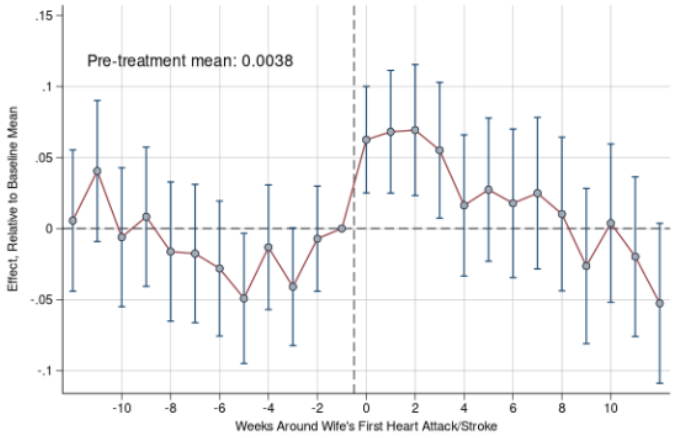
4.4 Effect Decomposition

To offer a decomposition exercise in line with equation (3), we proceed as follows. We predict the probability that a husband will be discharged to a SNF following a hospitalization, and we then evaluate how those predicted probabilities evolve around a health shock to their wives.

We split the full set of hospitalizations in the MedPAR file into a 90% estimation sample and a 10% validation sample. We then predict a binary indicator for any SNF discharge using a Lasso model based on patient age, sex, race, Medicaid eligibility, Medicare enrollment type, and the Diagnostic Resource Groups (DRGs) for the hospitalization (Ellis et al., 2022). We rely on a Lasso regression given the moderate dimensionality of our covariate space (Abadie and Kasy, 2019). Appendix Figure A3 shows the predicted values on the 10% validation sample of hospitalizations. Those

ending in SNF stays have considerably higher predicted values than those ending in another form of discharge.

Figure 5. Change in Husband's Predicted Probability of SNF Discharge



Notes: This figure plots estimates of the δ_n coefficients from equation (1), difference-in-differences estimates that track the weeks since a wife's first heart attack or stroke. The outcome of interest is the predicted probability of a SNF discharge based on hospitalization and patient characteristics using LASSO regression; see Section 4.2 and Appendix Figure A3 for more discusion. We re-scale all coefficient such that they indicated the change relative to the pre-treatment average predicted probabilities. The error bars plot 95-percent confidence intervals based on standard errors that have been clustered on each Medicare household. The regression includes calendar-time fixed effects and person-specific fixed effects.

We then evaluate how the predicted probabilities change over time for a husband following a wife's health shock. Figure 5 presents the results. In the month following a wife's health shock, a husband's predicted probability of having a SNF stay increases by roughly 6.5%, up from a baseline risk of 0.38%. This can be interpreted as indicating that we would expect 30% ($= 0.065/0.225 = 0.3$) of the marginal SNF stays to have occurred solely based on the increase in hospitalizations (i.e., deterioration of husband health). This leaves 70% of the SNF stays to potentially come from substitution.

4.5 New Diagnoses

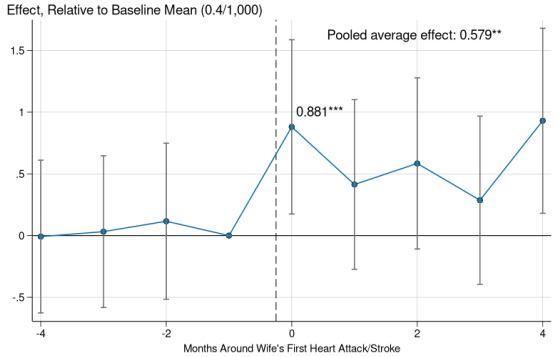
The results imply that husbands' mode of care changes following the spousal shock. Specifically, it shifts from informal to formal care and there could be also changes in the provision of informal care service (e.g., from spouse to child). This can lead to reevaluation of husbands' needs so that existing conditions may be more likely detected. In this sense, we would expect new diagnoses of existing to occur when:

(1) the conditions develop over time, so that their diagnoses cannot be attributed to a direct health effect; (2) the diagnoses and detection of these conditions are more uncertain and less straightforward to establish with objective tests.

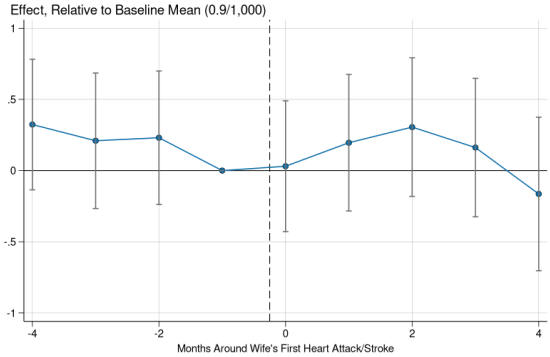
Two main classes of diseases that often require long-term care are Alzheimer's Disease Related Dementias (ADRD) and cancer. Both ADRD and cancer are serious conditions that develop over time, so we would not expect a wife's heart attack or stroke to immediately result in these conditions. In addition, the two conditions substantially differ by the degree to which they can be directly and accurately diagnosed. Diagnosis of ADRD is notoriously uncertain and requires multiple mental and physical tests, whereas cancer can be accurately diagnosed via biopsy.

Figure 6. Change in the Probability of New Diagnoses After a Wife's Index Event

(a) New ADRD Diagnoses for Husband



(b) New Cancer Diagnoses for Husband



Notes: These figures plot estimates of the δ_n coefficients from equation (1), difference-in-differences estimates that track the weeks since a wife's first heart attack or stroke. The outcomes of interest are indicators for whether the husband has a new diagnosis for Alzheimer's Disease and Related Dementias (ADRD) in panel (a) and cancer in panel (b). We re-scale all coefficients such that they indicate the change relative to the initial baseline risk of diagnosis in each category. The error bars plot 95-percent confidence intervals based on standard errors clustered at the household level. Regressions include calendar-time fixed effects and person-specific fixed effects.

Figure 6 plots estimates of equation (1) when the outcomes of interest are new diagnoses of ADRD and cancer. Given the infrequent appearance of new diagnoses, we shift from a weekly frequency to a monthly frequency. We find that the likelihood of a husband being diagnosed with ADRD increases by 88% in the immediate month that follows a wife's health shock. By contrast, we observe no statistically significant effect on cancer diagnoses. These patterns suggest that husbands may be living with latent, undiagnosed conditions such as ADRD, whose detection is triggered by the changes in care following the spousal event. ADRD symptoms typically involve

a process of cognitive decline and behavioral changes that may not be immediately linked to a medical condition. In contrast, cancer typically has more clear-cut physical symptoms and diagnostic tools (biopsies, imaging) provide definitive results quickly.

5 Welfare Analysis

In this section, we analyze the welfare implications of our findings. We assess the fiscal externality, offer methods to recover household's valuation of different modes of care, and discuss angles of optimal policy design.

5.1 Government Fiscal Value of a Healthy Spouse

Our findings show significant increases in husbands' healthcare utilization, including SNF admissions, hospitalizations, and ED visits. Accordingly, we explores how the effects of spousal health events translate into overall healthcare expenditures, which directly estimates the fiscal externality ($R_1 - R_0$).

We assess the overall impacts of a health shock on spending for the full sample of enrollees using the annual summary measures recorded for each Medicare enrollee. These data also allow for a disaggregation of spending into various categories such as long-term care usage (including hospice and home health care).[5]

Table 3 presents estimates for overall spending and by spending category. We find that total spending increases by roughly 11% in the year of the health shock, and by an average of 7% for all years. The table suggests increases in healthcare expenditure across categories that are large in both absolute and relative terms. For instance, spending on SNFs increases by $218 in the year of the event, roughly a 50% increase over the baseline mean.[6] We observe similarly large increases in the use of home health and hospice care, as well as across various measures of hospitalizations.

Our results further suggest that increased use of inpatient and long-term care crowds out use of other types of health expenditures that are less urgent. We observe declines in spending for elective surgeries (8%) and outpatient payments to physicians (4%). We also find declines in spending on prescription medication (3%), but part

[5]We note that are current results for spending are obtained by estimating a regression of spending only on indicator variables for year relative to the true event and adjusting for household and calendar time fixed effects.

[6]We present estimates from Poisson regressions as well as regressions estimated in dollars to accommodate the potentially skewed nature of the spending data at the annual level (Mullahy and Norton, 2022). These estimates can be interpreted as approximate percentage changes relative to the pre-treatment median.

Table 3. Effect of Wife Index Event on Husband Spending, Annual Level

		Levels		Poisson	
Spending Measure	Pre-Treatment Median	All Post	Year 0	All Post	Year 0
Panel A: Total Spending					
	$8,287	$793***	$1,364***	0.07***	0.11***
		(71.56)	(78.69)	(0.007)	(0.008)
Panel B: Long-term Care					
SNF	$ 444	$ 99***	$ 218***	0.09***	0.08**
		(18.47)	(21.43)	(0.027)	(0.034)
Home Health	$ 306	$ 10	$ 28***	0.05***	-0.00
		(6.61)	(7.07)	(0.017)	(0.019)
Hospice	$ 85	$ 89***	$ 209***	0.05	0.13
		(10.88)	(10.41)	(0.057)	(0.085)
Panel C: Hospital & Surgical Care					
Acute Inpatient	$ 2,041	$ 425***	$ 742***	0.14***	0.24***
		(36.96)	(43.34)	(0.014)	(0.017)
Other Inpatient	$ 209	$ 58***	$ 106***	0.15***	0.24***
		(13.96)	(16.42)	(0.046)	(0.056)
Hospital Outpatient	$ 1,365	$ 35**	$ 18	0.02*	-0.01
		(17.99)	(19.58)	(0.011)	(0.013)
Ambulatory Surgical Center	$ 90	$ -3	$ -7***	-0.03	-0.08***
		(1.88)	(2.12)	(0.022)	(0.024)
Panel D: Other Care					
Physician Payments	$ 470	$ 0	$ -17***	0.00	-0.04***
		(1.64)	(1.75)	(0.003)	(0.004)
Evaluation & Management	$ 319	$ 63***	$ 114***	0.13***	0.21***
		(4.86)	(5.45)	(0.011)	(0.013)
Part D Spending	$ 1,290	$ -11	$ -36***	-0.01	-0.03***
		(17.05)	(12.88)	(0.011)	(0.009)

Notes: This table plots results from an interrupted time series regression adjusting for household-specific and year-specific fixed effects and a linear time trend in time relative to individual events. The first two columns present models estimated via OLS and the second two columns present models estimate via poisson regression. Columns (1) and (3) report the estimate of a Post_{it} coefficient for the full post-treatment period, while columns (2) and (4) report the estimate just for the initial year of the index event. Standard errors are clustered at the household level.

of this may be mechanical to the extent that a patient receives medications directly while in a SNF. However, these results suggest that a wife's health shock causes husbands to alter the type of care they receive, postponing elective care in favor of treating more urgent conditions.

Overall, these results shed light on the fiscal value of a healthy spouse. The fiscal externality of a spousal health shock amount to $1,364 per person per year, which presents a 13% in total spending.

5.2 Household Valuation of Care

We now turn to develop our two revealed preference approaches to infer measures of v_S, i.e., the average money-metric valuation of informal care. We assess the option value of a healthy spouse via households' "willingness to pay," based on revealed preference exercises that leverage households' choices of formal care across the two states of the world.

5.2.1 Marginal Rate of Substitution

The first method evaluates how the marginal valuation of SNF days relative to $1 varies across states of the world. It relies on within-state first order condition of SNF days and the fact the price schedule is invariant to the wife's incapacitation.

We write the utility in state $j \in (H, S)$ (reflecting the index spouse's state of being healthy or sick) as

$$U_j(x_j, m_j) = u_j(x_j) + m_j,$$

where x_j is the consumption of care and m_j is "money" so that the utility from care $u_j(x_j)$ is relative to the within-state valuation of resources.

The within-state optimality condition implies that

$$u'_j(x_j) = P(x_j)$$

where $P(x_j)$ is the marginal price of a SNF days (which capture the non-linear pricing of SNF days). A similar formulation can be obtained by writing the Lagrangian and normalizing the problem by the shadow value of household resources. The optimality condition within each state implies across states that:

$$u'_H(x_H) = u'_S(x_S)$$

since the marginal price is similar across states of nature. A first-order expansion of the left-hand leads to the following welfare formula:

$$1 + \gamma(x_S)\frac{x_S - x_H}{x_S} = \sigma(x_S)$$

where $\gamma(x_S) \equiv -\frac{u''_H(x_S)}{u'_H(x_S)}x_S$ represents relative risk aversion, which can be calibrated from previous work to vary from 1 to 4. The parameter $\sigma(x_S) \equiv \frac{u'_S(x_S)}{u'_H(x_S)}$represents the state-dependence valuation parameter we want to assess. It captures how the marginal (money-metric) valuation of a SNF day changes across states of nature. As such, it represents the ratio of the willingness to pay for care across the two states, which can alternatively be thought of as the marginal rate of substitution of care across states.

This approach evaluates welfare based on changes in the curvature of the indirect utility from care. When an input into the household production function is missing, it would lead to higher curvature of the indirect utility from any other input since there are fewer choice variables to smooth across marginal decisions. It has a similar effect as in consumption commitments, where there is a margin you cannot freely adjust on (Chetty and Szeidl, 2016). This approach does not require price variation, but it is constrained to marginal assessments and requires calibration of risk aversion.

Based on our findings, we have that $\frac{x_S - x_H}{x_S} = 0.30$. For a range of relative risk aversion from 1 to 4, this implies that an additional day of SNF is valued (relative to income) by 30% to 120% more after the event. The following table summarizes the calibration:

γ	1	2	3	4
σ	1.3	1.6	1.9	2.2

5.2.2 Consumer Surplus

The second method evaluates the overall willingness to pay for formal care across the two state of the world. It evaluates the option value of spousal informal care by the excess valuation of formal care when this option vanishes. We explicitly model willingness to pay for formal care compared to the alternative, Where set of alternatives changes across states. Specifically, we leverage price variation from the non-linear schedule of the cost of SNF days. We use the responses to the price variation to back out demand curves in each state and impute the excess valuation of formal in a given day due to the spousal event. We then calculate the change in consumer surplus for

each SNF day and aggregate over days to get at the total option value of spousal informal care.

We let beneficiaries be indexed by $s_j \in [0,1]$ where s_j orders consumers according to differential willingness-to-pay for formal care relative to informal care in state of the world j. We again let $j = H$ indicate a healthy spouse and $h = S$ indicate a sick spouse. We order consumers such that $s_j = 0$ is the consumer with highest willingness-to-pay and $s_j = 1$ is the consumer with lowest willingness-to-pay, which will simplify the formulas. We denote the willingness-to-pay for formal care (relative to the available alternative) by $u_j(s_j)$ for an s_j-type consumer. Let P be the daily out-of-pocket price charged for formal care, which is similar across states of nature but can vary for based on the length of stay. Finally, let $s_j^*(P)$ represent the s_j-type consumer who is on the margin between purchasing and not purchasing formal care at price P so that $u_j(s_j^*(P)) = P$.

With this setup, we can write the consumer surplus as:

$$CS_j(P) = \int_0^{s_j^*(P)} \left[u_j(s_j(P)) - P\right] f_j(s_j)\, ds_j$$

We note that since the probability density function is not conditional on takeup, it captures the option value of the alternative mode of care. Calculation of $CS_j(P)$ relies on the known fact that it is the integral of the inverse demand function since:

$$\frac{dCS_j}{dP} = \frac{ds_j^*(P)}{dP}\left[u_j(s_j^*(P)) - P\right] f_j(s_j^*(P)) - \int_0^{s_j^*(P)} f_j(s_j)\, ds_j = -F_j(s_j^*(P)).$$

We then infer the mean valuation of spousal informal care by

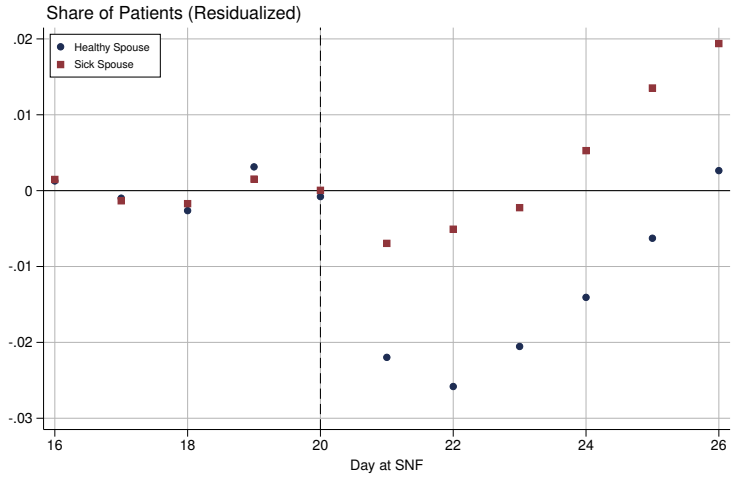
$$v_S = CS_S(0) - CS_H(0).$$

That it, we use the excess valuation of formal care in the absence of the option of spousal care to infer the option value of spousal care.

We recover the inverse demand curves using local price variation and a linear approximation. Specifically, leverage the fact that Medicare coverage of SNF stays is limited to 100 days and patients face a discontinuous change in their coinsurance from 0% to 20% after 20 days. We study responses to these discontinuous changes in a regression discontinuity (RD) framework, and we recover the difference in the RD parameter across the wife's health shock in a difference-in-discontinuities design

(Grembi et al., 2016). In Figure 7 we illustrate the variation we exploit. In the figure, we plot the residuals after adjusting for the day of the week and the days a husband has been covered by Medicare for their SNF stays. We find visually clear evidence that husbands with a healthy wife appear to be much more price sensitive than those whose wife has just experienced a major health event.[7]

Figure 7. Responses to Cost-Sharing for SNF Stays By Wife Health Status



Notes: This figure plots binscatter coefficients for the average share of patients in a SNF on a given day. We plot residual means in this figure after adjusting for the day of the week and a measure of days covered by Medicare previously. Averages for the group with healthy wives are shown in blue circles, while those whose wife has experienced an adverse health shock are shown in red squares. The vertical line indicates the day after which 20% coinsurance is applied to each additional day the husband remains in the SNF. The selected bandwidth in the figure is chosen to match the optimal bandwidth used in estimating Equation 4. See Appendix Figure A4 for a non-residualized histogram of the LOS for SNF stays across groups.

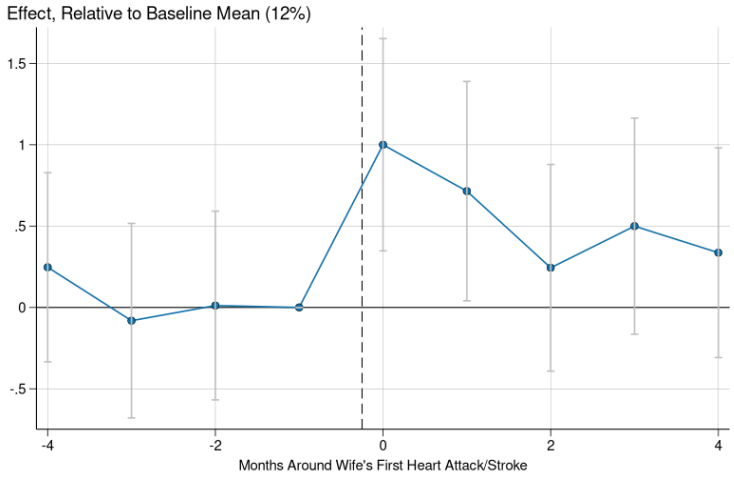
In support of these patterns, we look at the likelihood that a husband stays in a SNF for longer than Medicare fully covers. In Figure 8 we observe a doubling in the likelihood that husbands stayed in a SNF beyond 20 days in to the spousal health event, implying that nearly one-quarter of husband SNF stays following a wife's event required some patient cost-sharing.

We estimate the difference in responses from Figure 7 using an RD design around the 20-day cutoff with the following specification:

$$y_{i,t} = \delta_0 + \delta_1 D^*_{i,t} + S_{i,t}(\gamma_0 + \gamma_1 D^*_{i,t}) + T_{i,t}\left[\alpha_0 + \alpha_1 D^*_{i,t} + S_{i,t}(\beta_0^{\text{D-Disc}} + \beta_1 D^*_{i,t})\right] + \varepsilon_{i,t}, \quad (4)$$

[7]This bunching can also be seen directly when plotting the distribution of LOS conditional on SNF stays, as shown in Appendix Figure A4.

Figure 8. Effect of Wife's Hospitalization on Husband SNF Stays Not Fully Covered by Medicare



Notes: This figure plots estimates of the δ_n coefficients from equation (1), difference-in-differences estimates that track the weeks since a wife's first heart attack or stroke. The outcome of interest is an indicator that equals one if at least part of that SNF stay was not fully covered by Medicare. All husbands without SNF stays in both treatment and control groups are assigned values of 0 when no SNF admission occurred in a month. We re-scale all coefficients such that they indicate the change relative to the initial unconditional mean values. Error bars plot 95-percent confidence intervals based on standard errors clustered on each Medicare household. The regression includes calendar-time fixed effects and person-specific fixed effects.

where $y_{i,t}$ is an indicator for whether husband i is in a SNF on day t, $D^*_{i,t}$ is the re-centered running variable of SNF days relative to the 21-day cutoff, $S_{i,t}$ indicates a post-cutoff dummy, and $T_{i,t}$ indicates a post-treatment dummy of a wife's health shock. Equation (4) is estimated only for SNF stays of duration within a certain bandwidth of the cutoff, $D^* \in [-h, h]$, and uses a triangular kernel to weight observations more heavily closer to the cutoff. The parameter β_0 indicates the difference in responses across the experimental groups.

We estimate equation (4) on the sample of SNF stays within four months of both the treated and placebo index events and adjust for Medicare couple and time of event fixed effects. Table 4 presents the results. Prior to the wife's event, the discontinuous change in Medicare payment for SNF stays induces a significant negative effect on the length of a husband's stay, decreasing the probability that he will remain in the SNF on the first day he will face copayments by 1.9 percentage points. In contrast, we do not observe responses to this cutoff when a husband has been admitted following his wife's heart attack or stroke. Comparing the differences in the estimated responses,

we find that households affected by a wife's shock are 1.4 percentage points more likely to remain in care across this threshold, absorbing nearly all of the pre-treatment price responses.

Table 4. Effects of Losing Medicare Coverage on Husband's SNF Stay Decision

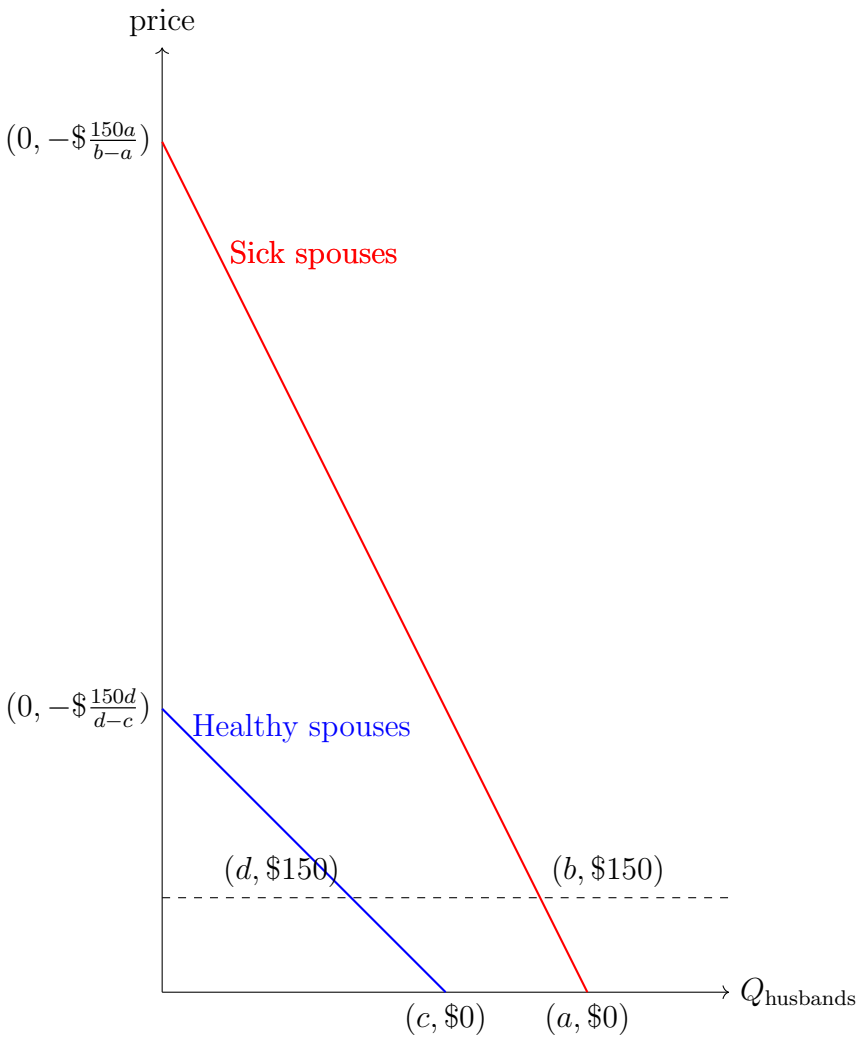
	(1)	(2)
τ_{pre}	-0.019*	-0.019***
	(0.0101)	(0.0054)
τ_{post}	-0.007	-0.007
	(0.0121)	(0.0064)
$\beta_{\text{D-Disc}}$	0.014	0.014*
	(0.0114)	(0.0067)
Couple FEs		✓
Time FEs		✓
Bandwidth	8.474	8.474
N	158,916	158,916

Notes: This table presents regression-discontinuity and differences-in-discontinuities estimators identifying the effect of ending Medicare coverage for SNF stays, which ends on day 21 for qualifying stays. The first two rows present the estimated effect of losing coverage on the probability a husband will remain in the SNF, stratified by before or after the wife's index event. The third row presents the difference-in-discotinuities estimator as discussed in the text. SNF stays within 4 months of the treatment and placebo events are included in the regression.

Figure 9 illustrates the intuition of the approach. In our data, we can observe level differences in the demand for SNF care among husbands with spouses either affected or unaffected by health events. By identifying the fraction of husbands in a SNF at day 20 (the day before the price change) in each group, we identify the x-intercepts for each demand curve (points $(c, \$0)$ and $(a, \$0)$). The slope of the demand curve is then identified based on the estimated percentage change in demand for formal care between days 20 and 21 when cost-sharing for formal care increases discontinuously. The RD estimates allow us to identify the values b and d. Demand curves are then extrapolated using linear approximation based on these two points for each group.

From these estimated inverse demand curves, we estimate consumer surplus for each additional day of SNF coverage. For day 20, we estimate that $CS_H(0) = \$1,038$ for the healthy spouse group, and $CS_S(0) = \$5,616$ for the sick spouse group. That is, husbands whose wives are less available to provide informal care derive roughly 5.4 times the consumer surplus from receiving formal care at a given price. Appendix

Figure 9. Estimating Demand for LTC Across Groups



Notes: This figure shows the intuition for estimating linear inverse demand curves using variation in prices that husbands face for formal long-term care. Demand curve estimation relies on identifying differences in levels of demand (values a and c) and the relative change in this demand as a function of the RD estimates presented in Section 5.2. These changes identify b and d.

Figure A5 illustrates how these differences in consumer surplus accumulate over days in a SNF. By the end of day 100—the day at which consumers face full cost-sharing for a SNF stay—husbands with an incapacitated spouse have a total consumer surplus of $319,779, roughly 4.8 times larger than the estimated consumer surplus of the group with healthy spouses.

5.3 Design of Optimal Insurance Policies

Optimal health insurance involves a trade-off between the welfare benefits of risk protection and the deadweight loss from moral hazard (Zeckhauser, 1970). Increasing insurance coverage induces welfare gains from equalizing marginal utility between the healthy and sick states of the world, but comes at the cost of the over-consumption of medical care.

In the current setup, we can represent welfare using

$$W_j(P) = \int_0^{s_j^*(P)} \left[u_j(s_j(P)) - P\right] f_j(s_j)\, ds_j + P \int_0^{s_j^*(P)} f_j(s_j)\, ds_j.$$

Accordingly, the welfare cost of a price change, the deadweight loss (DWL), is captured by

$$\frac{dW_j(P)}{dP} = P \frac{dF_j(s_j^*(P))}{dP}.$$

Importantly, this implies that the ratio of elasticities governs the relative DWL from subsidies to formal long-term care across households with and without healthy spouses.

Given the demand elasticities identified above, we estimate a ratio of 63%. This implies that efficiency losses are reduced by 63% when subsidizing formal long-term care for individuals without readily available informal care provided by a spouse. This captures that idea that people whose partners just experienced a shock have less access to informal care, and so exhibit a less elastic demand for formal care. As a result, generous coverage leads to less moral hazard among them.

This estimated difference in efficiency loss effectively motivates differential pricing for long-term care insurance based on household structure. In particular, policymakers may consider family deductibles—which are more likely to bind if a spouse becomes incapacitated—as a means to charge different out-of-pocket costs to consumers with and without the option of informal care provided by a spouse or a family member.

6 Conclusion

We use Medicare claims data to study the long-term care valuation of a healthy spouse. We find strong evidence of a protective role of a healthy spouse, with a negative health shock adversely affecting a husband's health as well as their substitution across formal and informal care options. The large estimated effects of a wife's incapacitation on husband's formal long-term care and health outcomes impose significant fiscal externalities. We also estimate a high option value of informal care: affected husbands are willing to pay 5 times more for formal care than those with unaffected wives. This suggests that a family deductibles may be a welfare-improving tool for differential pricing of formal care. In particular, such policies could provide formal long-term care at lower prices to households with an incapacitated spouse with reduced moral hazard from inelastic demand.

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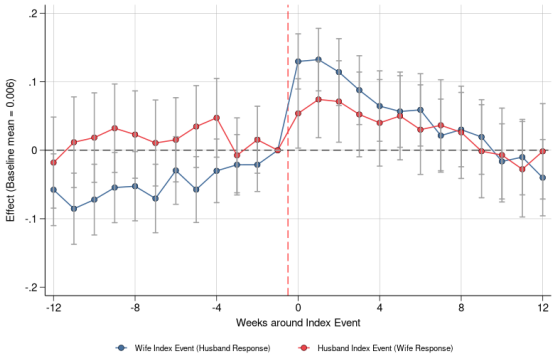
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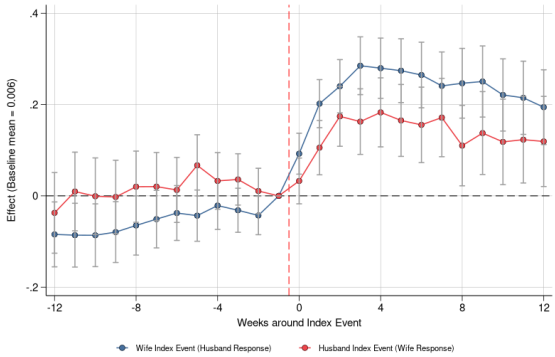
A Appendix Tables and Figures

Appendix Figure A1. Spillover Effects by Gender

(a) Inpatient Hospitalizations

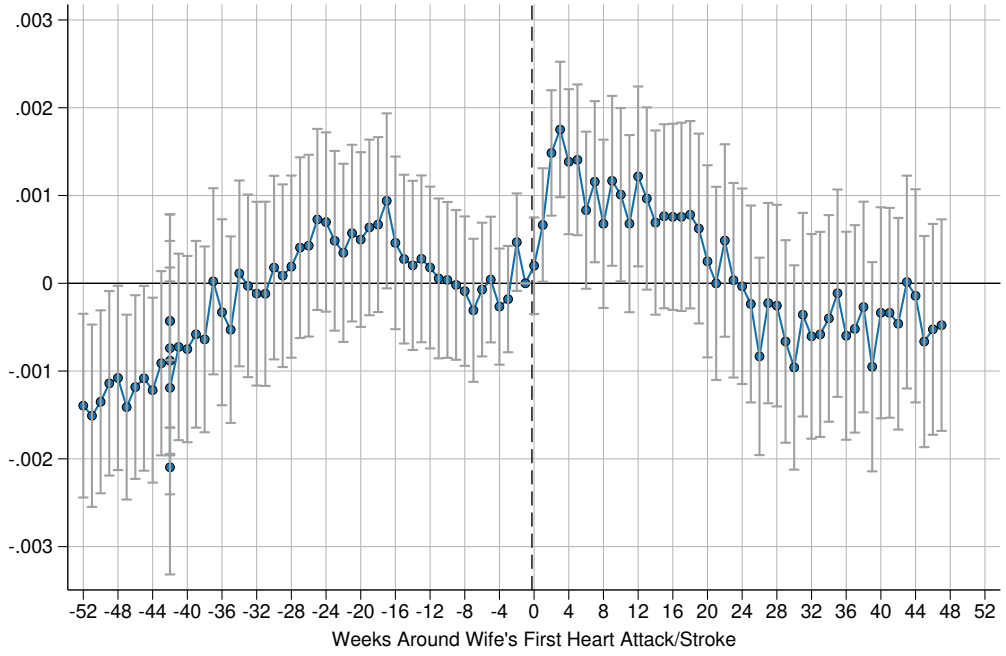


(b) Visits to Skilled Nursing Facilities



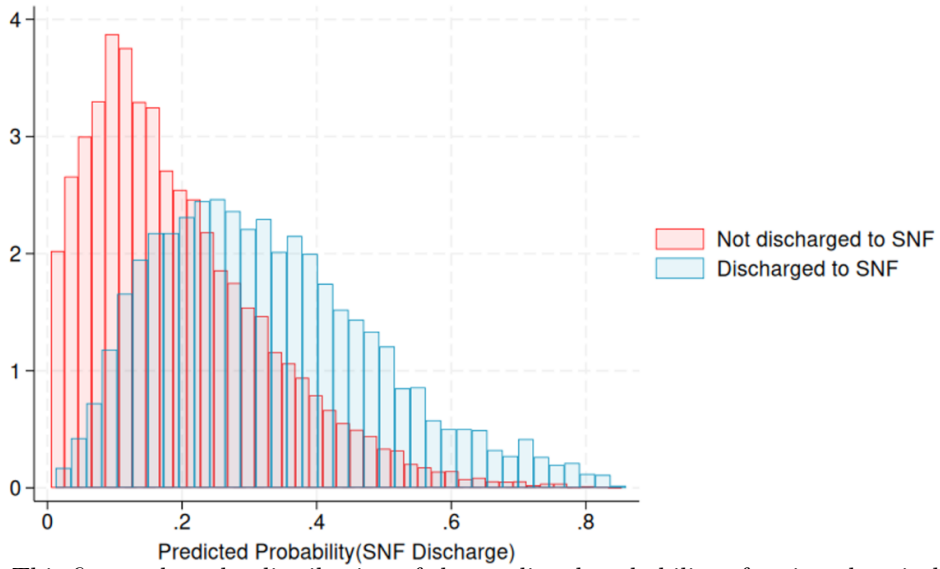
Notes: This figure plots dynamic difference-in-differences coefficients that track the weeks since the index event of a heart attack or stroke in the household, stratified by whether the event occurred to a husband or wife. The outcome of interest is an indicator for whether the other partner was hospitalized or visited a SNF, and we re-scale all coefficients such that they indicated the change relative to the initial baseline risk of hospitalization or SNF stay. The error bars plot 95-percent confidence intervals based on standard errors clustered at the household lever. Regressions include calendar-time fixed effects and person-specific fixed effects.

Appendix Figure A2. Change in the Risk of SNF Stay After a Wife's Index Event, Full Year



This figure plots dynamic difference-in-differences coefficients that track the weeks since a wife's first heart attack or stroke. The outcome of interest is an indicator function equal to one if the husband visited a SNF. Compare with Figure 1.

Appendix Figure A3. Predicted Probability of Discharge to SNF: Validation on 10% Sample

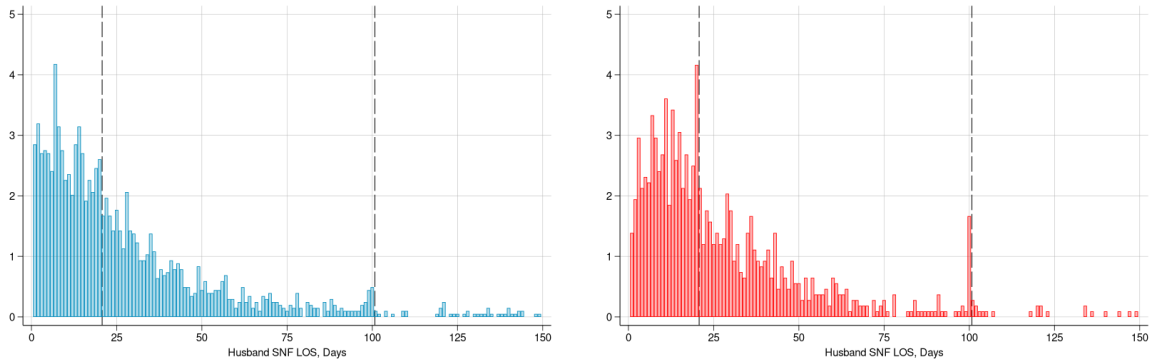


Notes: This figure plots the distribution of the predicted probability of a given hospitalization ending in a discharge to a SNF across a 10% validation sample of husband hospitalizations in the Medicare data, for two groups: those that did not end with a discharge to a SNF (in red), and those which did (in blue). Predicted values are modeled using LASSO prediction, with a binary predicted outcome for all hospital stays in the 100% Inpatient claims files from 2011 to 2017. Covariates include patient age, sex, race, dual Medicaid eligibility, Medicare enrollment type, and DRG indicators.

Appendix Figure A4. Distribution of SNF Visit Lengths of Stay Following a Wife's Index Event

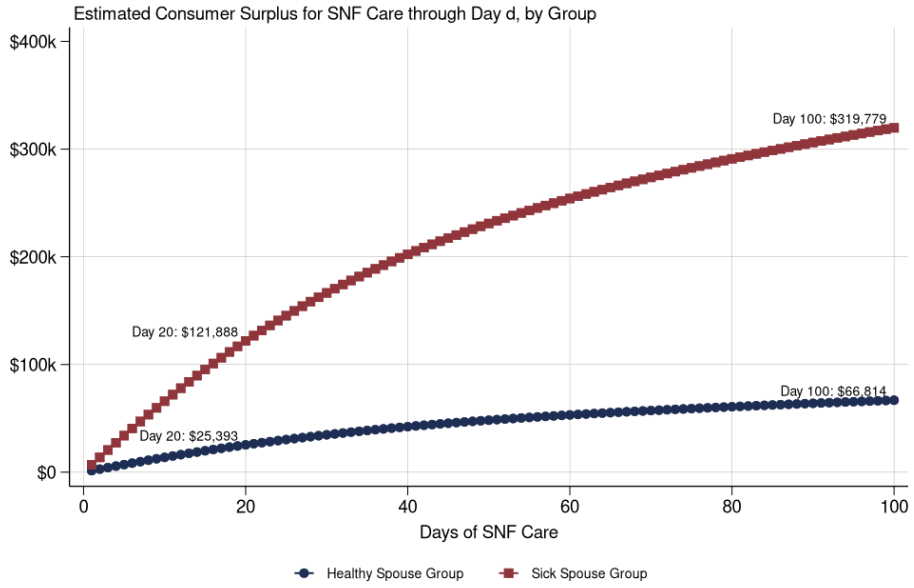
(a) Treated Group

(b) Control Group



Notes: This figure plots histograms showing the distribution of length of stay (LOS) for husbands visiting SNFs around the time of their wife's initial heart attack or stroke. Panel A provides the distribution among beneficiary observations from the first 12 weeks following an actual spousal event (from the treatment group), and panel B provides the distribution among beneficiary observations from the first 12 weeks following a placebo spousal event (from the control group). Vertical lines indicate the days at which Medicare payment rates for SNF stays change discontinuously.

Appendix Figure A5. Differences in Cumulative Consumer Surplus, by Wife's Health Status



Notes: This figure plots estimated cumulative consumer surplus following the methodology of Section 5.2.2 and the framework presented in Section 3. The cumulative consumer surplus from a SNF stay for husbands with a healthy spouse is plotted in blue; the same values for those with a sick spouse (for whom demand curves have shifted) are plotted in red.