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Spousal Labor Supply, Caregiving, and the Value of Disability Insurance

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Abstract

For married couples, spousal labor supply can act as a household insurance mechanism against one spouse's earnings shock. This paper examines married women's time allocation to market hours and spousal care in the event of their husbands' disability and its implications for evaluating the insurance value of the Social Security Disability Insurance (SSDI) program. Using an event study approach, I find that while there is a sizable increase in wives' working hours after their husbands' job displacement, wives' labor supply responses to their husbands' disability are small, and instead, a considerable amount of time is spent in spousal care. I develop and estimate a dynamic model of married households and find that incorporating time loss due to spousal care increases the insurance value of SSDI relative to its costs. Furthermore, budget-neutral policy reforms that subsidize the cost of care can improve social welfare.

Keywords: disability, social security, added worker effect, caregiving

JEL codes: D13, D15, H53, H55, I38, J22

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1 Introduction

An important aspect of household labor supply is that idiosyncratic wage shocks of one spouse can be mitigated by an increase in the labor supply of the other spouse. Indeed, previous studies have shown that spousal labor supply acts as an important household insurance mechanism, mainly in the context of husbands' permanent wage shocks or job displacement shocks.[1] However, as I show in this paper, wives' labor supply responses in the event of their husbands' disability are close to zero despite disability shocks being persistent negative shocks to husbands' earnings.

A crucial difference between a job displacement and a disability shock that has not received much attention in previous studies is that disability shocks can reduce spouses' labor market hours due to time spent caring for their disabled spouses. This paper studies married women's time allocation to market hours and spousal care when their husbands become disabled and evaluates its implications for measuring the welfare benefits of social disability insurance programs. I focus on the Social Security Disability Insurance (SSDI) program as SSDI is one of the largest social insurance programs in the U.S. with 9 million working-age beneficiaries in 2016. Despite the rapid growth in program size over the past two decades, little is known about the consumption-smoothing benefits of SSDI relative to its costs. Furthermore, most studies have analyzed social disability insurance programs by modeling households as individual workers although married couples account for the majority of the labor force. This paper fills these gaps by quantifying the welfare benefits of SSDI for married households when taking into account that some of the household insurance that spousal labor supply provides is reduced due to time spent in caregiving.

Using data from the Health and Retirement Study (HRS), I perform a set of event study analyses and show that although husbands' job displacement and disability shocks both lead to a persistent drop in husbands' working hours, wives' responses differ considerably. I find that on average, wives' weekly working hours increase by 3 hours (a 12% increase) following their husbands' displacement, whereas wives' labor supply responses are close to zero when their husbands become disabled. The most novel finding from the event study analyses is

[1] Earlier studies on the added worker effect (i.e., the extent to which one spouse's labor supply increases in response to a negative earnings shock of the other spouse) have focused on female labor supply responses to husbands' unemployment shocks and found added worker effects to be small (Mincer, 1962; Heckman and MaCurdy, 1980; Layard et al., 1980; Lundberg, 1985; Maloney, 1987, 1991; Spletzer, 1997; Cullen and Gruber, 2000). In contrast, more recent works have attempted to distinguish between transitory and permanent wage shocks and found that female labor supply plays an important role in insuring against husbands' permanent wage shocks (Hyslop, 2001; Stephens, 2002; Juhn and Potter, 2007; Merkurieva, 2014; Haan and Prowse, 2015; Blundell et al., 2016; Garcia-Perez and Rendon, 2020).

that wives increase their time spent caring for their husbands by 2 to 3 hours per week and that this magnitude is similar to the increase in wives' labor supply responses to their husbands' job displacement.

To measure the welfare benefits of current and counterfactual SSDI policies relative to its costs, I develop and estimate a dynamic programming model of married households where households are single decision-making units (i.e., unitary household model) and husbands face both job displacement and disability shocks. The model accounts for three crucial mechanisms that affect spousal labor supply responses to a husband's job displacement or disability shock: 1) wives' time allocation to caregiving, 2) the interaction with social welfare programs including SSDI, unemployment insurance, and means-tested government transfers, and 3) health state dependent utility where health status enters the utility function in a non-separable way.[2] Additionally, the model allows households to purchase formal care (i.e., paid caregivers) from the market. I estimate the model parameters by indirect inference and use the sensitivity measure proposed by Andrews et al. (2017) to show that the data patterns from the event study analyses are informative of the key preference parameters of the model.

Using my estimated model, I perform three counterfactual exercises. First, I show that the extent to which spousal care attenuates wives' labor supply responses varies by husbands' disability severity. In the absence of time lost to spousal care, I find that wives' labor supply responses are small when husbands become moderately disabled. However, wives of severely disabled husbands would have increased their weekly working hours by 1.5 hours (a 5.9% increase), which is comparable to the increase in wives' labor supply in the event of their husbands' death (Fadlon and Nielsen, 2021).

Second, I find that accounting for time spent in spousal care increases the ex-ante insurance value of SSDI for married households. Using compensating variation measures, I find that married households value each dollar of SSDI benefits as \$0.99 when I ignore that disability shocks entail care needs (and thus, wives only spend time in leisure and market work). However, the ex-ante insurance value of SSDI increases to \$1.04 per each dollar of

[2]Regarding the third mechanism, the model allows the marginal utility of consumption in the disabled state to differ from that in the healthy state. For example, if consumption goods (such as vacations or recreational activities) are complements to good health, the marginal utility of consumption would be lower in the disabled states. On the other hand, the marginal utility of consumption would be higher in the disabled states if consumption goods (such as household services) are substitutes for good health. While it has been long recognized that health state dependence in the utility function has important economic implications (e.g., the optimal structure of insurance depends on making transfers from the "good" state to the "bad" state such that the marginal utilities of consumption in the two states are equated), there is little empirical consensus on its direction and magnitude. See Finkelstein et al. (2009) for a survey of this literature.

benefits once wives' time spent in spousal care is accounted for. In terms of magnitude, this is equivalent to the difference in the insurance value between the current SSDI program and a reformed SSDI program where benefits are 4.7% higher than current levels. This implies that once we take into account that spousal care reduces the insurance role of wives' labor supply, SSDI benefits for married households need to be higher compared to when we assume that spouses allocate their time to market work and leisure only.

Finally, I find that it is possible to improve utilitarian social welfare given the same government budget by reducing SSDI benefits but subsidizing care for eligible SSDI beneficiaries in the form of either flat supplemental caregiver benefits or in-kind transfers that cover formal care costs. In particular, in-kind transfers provide larger welfare gains than flat caregiver benefits with low-income couples benefiting the most from the introduction of in-kind transfers. These findings suggest that varying the amount of transfers based on the degree of required care is one possible modification of the current SSDI system to provide households with the welfare benefits of SSDI while managing the rapid growth of SSDI rolls.

This paper contributes to the large literature on social disability insurance programs (DI) by being the first to explicitly model both the labor supply and caregiving decisions of spouses to quantify the welfare benefits of current and counterfactual SSDI policies. Although this literature has largely evolved around exploring the disincentive effect of the receipt of disability benefits (Parsons, 1980; Bound, 1989; Gruber, 2000; Chen and van der Klaauw, 2008; von Wachter et al., 2011; Maestas et al., 2013; French and Song, 2014), more recent works have focused on the economic consequences of disability and welfare implications of existing or counterfactual disability insurance policies (Bound et al., 2004; Chandra and Samwick, 2005; Bound et al., 2010; Gallipoli and Turner, 2011; Kitao, 2014; Jacobs, 2021; Kostøl and Mogstad, 2015; Low and Pistaferri, 2015; Meyer and Mok, 2019; Autor et al., 2019; Rhee, 2020; Kellogg, 2022). Most of these works model households as individual workers and do not explicitly model spouses.[3] This paper extends the models proposed by

[3]Studies by Gallipoli and Turner (2011), Autor et al. (2019), and Kellogg (2022) are exceptions. Using Canadian data, Gallipoli and Turner (2011) focus on the role of endogenous marriage and human capital accumulation in explaining the small spousal labor supply responses to husbands' disability. Autor et al. (2019) study the Norwegian DI program and find that households' valuation of DI receipt at appeal is considerably greater for singles than for married couples as spousal labor supply responses offset the loss in household income due to DI denial at appeal. An important caveat of their results is that their analysis is based on DI appellants (i.e., applicants who appeal their initial DI denial) who are more likely to be marginally disabled and thus less likely to require spousal care. Furthermore, their welfare analyses do not account for the ex-ante insurance value of DI prior to disability onset. Kellogg (2022) develops a dynamic life-cycle model and evaluates the welfare benefits of the U.S. DI system given the difference in the self-insurance capacity between single and partnered households. My paper differs by focusing on a different mechanism (namely, wives' trade-off between caregiving and market work) and explicitly modeling the household's time

earlier works. By explicitly accounting for the trade-off between time spent in market work and caregiving, this paper is able to analyze the welfare effects of novel policy reforms such as the introduction of supplemental caregiver benefits and in-kind transfers for formal care expenses.

Also, this paper is the first to empirically quantify the extent to which caregiving activities attenuate spousal labor supply responses. My finding that husbands' disability shock has a negligible effect on wives' labor supply is consistent with most studies that examine the effect of health shocks on spousal labor supply responses (Berger and Fleisher, 1984; Haurin, 1989; Coile, 2004; Gallipoli and Turner, 2011; Fadlon and Nielsen, 2021).[4] By jointly modeling spousal care and labor supply responses to disability and utilizing the rich information on caregiving hours in the HRS, I show that spousal care is an important mechanism in understanding the small spousal labor supply responses documented by previous works.

It is important to note that while SSDI beneficiaries are eligible for Medicare benefits after a two-year waiting period, this paper only analyzes the insurance value of SSDI's cash benefits and does not model the Medicare benefits provided to SSDI beneficiaries.[5] This modeling choice is partly driven by the fact that 1) Medicare does not cover most home care costs, 2) in my sample, the amount of spousal care that SSDI beneficiaries receive do not vary by whether they are in the two-year waiting period or not, and 3) private long-term care insurance coverage is very low in my sample (about 5%) and does not depend on whether SSDI beneficiaries have Medicare benefits or not.[6] As robustness, I also perform a "back-of-the-envelope" counterfactual exercise where I assume that all SSDI beneficiaries immediately receive an average amount of Medicare benefits and show that this robustness exercise produces similar results.

The rest of the paper is organized as follows. Section 2 provides empirical evidence

allocation to spousal care.

[4]Some papers find different results. Parsons (1977) and Charles (1999) find that wives increase their labor supply in response to their husbands' bad health. Jeon and Pohl (2017) find that individuals decrease their labor supply when their spouses are diagnosed with cancer.

[5]To the best of my knowledge, Kitao (2014) is the only paper that considers both cash and in-kind Medicare benefits of the SSDI program using a dynamic life-cycle model of individual agents. Kitao (2014) finds that SSDI coverage would fall by one-third when Medicare benefits for SSDI beneficiaries are removed, which implies that the insurance value of in-kind Medicare benefits can be sizable.

[6]Another complication of analyzing the insurance value of in-kind Medicare benefits for married couples is that the insurance value would not only depend on the individual's access to their own (employer-sponsored) health insurance, but also on whether they are covered by their spouse's health insurance (in my data sample, about 30% of working wives provide health insurance coverage for their husbands and 50% of working husbands provide health insurance coverage for their wives). Although an important question, jointly measuring the insurance value of SSDI cash benefits and in-kind Medicare benefits for married households is left for future research.

on wives' labor supply and caregiving responses to their husbands' disability shock using an event study framework. Section 3 describes a dynamic programming model of married households, and Section 4 discusses the estimation method of the model parameters. Section 5 reports the estimates of the model parameters and presents the key findings from the welfare analyses using the estimated model. Section 6 concludes.

2 Empirical Evidence

This section provides empirical evidence on how wives' labor market and caregiving hours respond to their husbands' disability and job displacement shocks. All analyses are restricted to the event of husbands' wage shocks since husbands are the "main earners" for most married households in my data sample.[7]

2.1 Background

Before presenting the empirical patterns regarding wives' time allocation to market work and caregiving, I discuss the dataset that is used throughout this paper and how "disability" is defined. I also provide a brief overview of the institutional settings of SSDI and report summary statistics of my data.

2.1.1 Data

Data from the Health and Retirement Study (HRS) are used for all analyses. The HRS is a biennial panel of a representative sample of Americans aged 50 and over and their spouses. I merge three HRS data products to create a unique panel dataset that contains rich information on respondents' disability status, labor market outcomes, non-market time use, and interactions with disability insurance programs.

First, the Core survey includes data on respondents' health, assets, marital status, labor market outcomes, disability benefits, and caregivers. Twelve survey waves from 1992 to 2014 are used. The caregiver data are especially useful since they report whether the respondent receives help from someone else to perform a set of (Instrumental) Activities of Daily Living

[7]Based on the dataset described in Section 2.1.1, I use various definitions of "main earner" (e.g., the share of total earnings during the marriage, number of years in which one spouse earned more than the other spouse, the share of earnings at a given point in time) and find that 80–85% of married households can be classified as husbands being the main earner. Also, these measures of "main earner" are highly correlated and therefore robust to how they are defined.

(ADLs/IADLs), the caregiver's relationship to the respondent (e.g., spouse, daughter, son, other relative, non-relative), the number of hours they provide help, whether they are paid, and if so, the amount they are paid. Six ADLs (walking across a room, dressing, bathing or showering, eating, getting in and out of bed, and using the toilet) and five IADLs (preparing hot meals, shopping for groceries, making phone calls, taking medications, and managing money) are included. Due to inconsistencies in earlier survey waves, I use information from 2000 to 2014 (8 waves) to identify wives who provide care for their husbands.

Next, I merge Social Security administrative data with the HRS Core survey to obtain information on respondents' Social Security earnings history and disability benefit claims. Social Security earnings are reported annually and date back to 1954. The disability benefit claims data (Form 831 Disability Records) include detailed information on SSDI applications and their outcomes.

Finally, I use the Consumption and Activities Mail Survey (CAMS) as a supplementary data source. The CAMS consists of a subsample of the HRS Core respondents and has comprehensive information on household expenditures and non-market time use (including time spent in spousal care). Six survey waves from 2005 to 2015 are used with information on time spent in spousal care being available from 2007. I exclude the first two waves of CAMS (2001 and 2003) due to inconsistencies in the measurement of household expenditures.

2.1.2 Definition of "Disability"

Throughout this paper, a respondent is classified as "disabled" if the individual answered 'yes' to the HRS question of "having a health condition that limits the type or amount of work one can do." This is the main disability question available in most public datasets and commonly used in most of the previous works on disability.

HRS has an advantage over other datasets as it allows researchers to determine the severity of the respondent's disability based on a wealth of health information instead of relying on subjective measures of severity (e.g., health condition limits work "somewhat" or "a lot"). As a benchmark, I use a measure of severity proposed by Brault (2008, 2012) and Taylor (2018) such that individuals are considered "severely disabled" if they are both disabled and satisfy one or more of the following seven criteria.

1. Deaf, blind, or unable to see, hear, or have speech understood
2. Unable to perform the following functional activities: walking, using stairs, lifting/carrying, grasping small objects
3. Need to use a wheelchair, cane, crutches, or walker

4. Need assistance of another person to perform the following ADLs or IADLs: getting around inside the home, getting in or out of bed or a chair, bathing, dressing, eating, or toileting (ADLs), going outside the home, managing money and bills, preparing meals, doing light housework, taking prescription medicines, using the telephone (IADLs)
5. Has Alzheimer's disease, dementia, or senility
6. Has an intellectual or developmental disability (e.g., autism, cerebral palsy)
7. Had one or more selected symptoms that interfered with everyday activities: was frequently depressed or anxious, had trouble getting along with others, had trouble concentrating, had trouble coping with stress

Those who report being disabled but do not fall under any of the seven criteria listed above are classified as "moderately disabled." Respondents who do not report being disabled are considered "healthy." Note that under this definition, a "severely disabled" individual may not necessarily have any difficulty in performing an ADL or IADL. For example, a deaf individual will be categorized as "severely disabled" since deafness can limit the amount or type of work one can do (criterion #1) but they may not have any difficulties in performing basic daily activities.

2.1.3 Background on SSDI

SSDI is designed to replace a worker's income in the event of a work-preventing illness or disability. In 2014, 11 million beneficiaries (9 million working-age beneficiaries and 2 million dependents) received a total of 120 billion dollars in benefit payments. Under SSDI, "disability" is defined as the "inability to engage in substantial gainful activity (SGA) by reason of a medically determinable physical or mental impairment expected to result in death or last at least 12 months." The program is administered by the Social Security Administration (SSA) and individuals must file an application to a local SSA field office.

The disability determination process consists of multiple stages and benefits are awarded based on either medical or vocational considerations. If an applicant meets the SSA's listing of qualifying medical conditions (or provides evidence that the applicant's medical condition is "equal" to that in the SSA's medical listing), they are awarded benefits based on medical considerations. Applicants who are not accepted at this stage are then considered whether their residual functional capacity allows them to work in either their past jobs or any type of work in the national economy based on vocational guidelines (e.g., age, work experience, education). SSDI awards based on these vocational considerations have grown rapidly over the years such that they account for roughly half of all SSDI awards (Morton, 2015).

Once awarded, SSDI beneficiaries receive a monthly benefit in which the amount is based on their past average monthly earnings. The benefit amount does not depend on the severity of the disability since SSDI is designed for workers whose impairments are "severe enough."[8] The formula for SSDI benefits is almost identical to that for Social Security Retirement benefits where replacement rates are lower for beneficiaries with higher past earnings. Unlike Retirement benefits, however, SSDI benefits are not reduced for receiving benefits earlier than the full retirement age. On average, the replacement rate is about 50% and in 2015, the average monthly SSDI payment was $1,166 for disabled workers. SSDI benefits automatically convert to Retirement benefits when beneficiaries reach full retirement age.

It is worth noting that the Supplemental Security Income (SSI) program is another program available for disabled individuals under full retirement age. Despite having the same disability determination process as SSDI, SSI differs from SSDI as it is a means-tested program with strict financial eligibility criteria and its average monthly payment amount is considerably lower ($541 in 2015). This paper focuses on SSDI due to several reasons. First, married individuals are significantly more likely to receive SSDI when they become disabled as they have higher past earnings (making SSDI payments higher than SSI payments) and they are less likely to meet SSI's strict asset and income eligibility criteria. Second, SSI payments are deducted $1 to $1 by SSDI payments. Lastly, SSI's financial eligibility criteria pose additional modeling challenges (as described in footnote 26). In Section 3, I describe how my dynamic programming model tractably accounts for means-tested benefits (including SSI) while explicitly incorporating key features of SSDI.

2.1.4 Summary Statistics

Table 1 provides summary statistics of married men in the HRS by their health status. First, about 20% of husbands are disabled with nearly 10% of husbands categorized as severely disabled. While employment rates drop significantly with disability severity, about 18% of severely disabled husbands still report being employed. Also, disabled husbands are less educated and have less wealth on average. A sizable fraction of disabled husbands receive SSDI benefits, roughly 21% and 46% for the moderately and severely disabled, respectively.

The second panel of Table 1 reports heterogeneity in the primary health condition associated with the disability. For both moderate and severely disabled husbands, musculoskeletal

[8] This does not imply that SSA can perfectly screen out non-meritorious claims. Since disability status is private information, sizable errors may arise in the screening process. For example, Nagi (1969) finds that 19% of initial allowances were undeserving and 48% of denied applicants were truly disabled. Using the HRS data, Benitez-Silva et al. (2004) conclude that over 40% of SSDI recipients are not truly work-limited.

Table 1: Summary Statistics of Married Men by Disability Severity

	Healthy	Moderate	Severe
Age (mean)	57.7	58.7	58.3
	[3.64]	[3.65]	[3.60]
Years of education (mean)	13.7	12.7	12.0
	[2.96]	[2.87]	[3.32]
Household wealth (median, in $1,000)	287.66	181.05	91.70
	[1,517]	[836.6]	[686.2]
Employed (in %)	85.64	43.75	18.40
Receives SSDI (in %)	0.28	20.75	45.98
Associated primary health condition (top 3, in %)†			
1) Musculoskeletal system	-	58.26	43.43
2) Heart, circulatory and blood conditions	-	18.52	15.98
3) Neurological and sensory conditions	-	1.30	14.87
4) Respiratory system conditions	-	6.68	4.48
Number of ADLs difficult to perform (mean)§	-	-	1.19
			[1.34]
Number of IADLs difficult to perform (mean)§	-	-	1.00
			[1.31]
Stayed overnight in hospital (last 2 years, in %)	13.03	31.18	43.28
Number of hospital nights (last 2 years, mean)‡	4.82	8.07	14.83
	[8.68]	[13.35]	[25.89]
Made any doctor visit (last 2 years, in %)	88.73	95.03	96.53
Number of doctor visits (last 2 years, mean)*	6.20	12.89	21.02
	[8.64]	[22.66]	[33.71]
Person-year observations	22,728	3,320	2,860
(%)	78.62	11.48	9.89

Notes: Results are based on a sample of married men aged 50 to 64 in the HRS Core survey (1992-2014). All summary statistics are weighted by HRS sample weights as the HRS oversamples Blacks and Hispanics. Standard deviations are in brackets. Dollar values are in 2015 dollars.

† The three most common health condition groups for moderately (1, 2, and 4) and severely disabled husbands (1, 2, and 3) are reported.

‡ This is conditional on having any overnight hospital stay in the last two years.

* This is conditional on making at least one doctor visit in the last two years.

§ This is out of a total of six Activities of Daily Living (ADLs; walking across a room, dressing, bathing or showering, eating, getting in and out of bed, and using the toilet) and five Instrumental Activities of Daily Living (IADLs; preparing hot meals, shopping for groceries, making phone calls, taking medications, and managing money).

conditions (e.g., arthritis, back/neck/spine problems) and heart, circulatory, and blood conditions (e.g., heart attack, stroke, high blood pressure) are the top two health conditions primarily associated with their disabilities. However, moderately disabled husbands are more likely to have musculoskeletal conditions than severely disabled husbands.

The third panel of Table 1 shows that on average, severely disabled husbands have difficulty performing 1.2 ADLs and one IADL. Furthermore, compared to moderately disabled husbands, those who are severely disabled are 40% more likely to stay overnight in a hospital, and once they do, they are hospitalized for a significantly longer period. While both moderately and severely disabled husbands are equally likely to make a doctor visit within a two-year period, severely disabled husbands frequent doctors more often than moderately disabled husbands do (13 vs. 21 visits in two years). All of these facts suggest that individuals with severe disabilities require a higher level of assistance from another person to perform basic daily activities as well as to treat and manage their medical conditions.

Table 2 indicates that both the fraction of husbands receiving care from their wives and the number of hours they receive increase with disability severity. Here, I utilize both the Core and CAMS data where the Core survey measures spousal care as helping a spouse perform ADLs or IADLs while the CAMS measures spousal care as treating or managing a spouse's medical condition.[9] About 56% of severely disabled husbands receive their wives' help in performing ADLs or IADLs with 14% of severely disabled husbands receiving help for more than 25 hours per week. Even for moderately disabled husbands, 20% report receiving help from their wives to treat or manage their medical conditions. This indicates that wives spend a sizable amount of time in caregiving once their husbands become disabled.

Finally, Table 3 reveals substantial differences in caregiver utilization between single and married men. Table 3 focuses on a subsample that consists of severely disabled men aged 50 to 64 who receive help from someone else to perform at least one ADL or IADL. The most striking difference between single and married men comes from who provides the care that they receive. For married men, 97.5% receive care from their wives. Only 5.3% receive care from non-relative caregivers such as caregivers from organizations or institutions, paid helpers, and professional helpers. Also, while 17% of married men have Medicaid coverage, only 1.6% of married men utilize caregivers covered by Medicaid. In contrast,

[9]Note that if a disabled husband receives help in performing one or more ADLs or IADLs, then by definition, he is classified as severely disabled (due to the fourth criterion described in Section 2.1.2). Therefore, caregiving hours are zero for wives of moderately disabled husbands when using the spousal care measure in the Core survey. In contrast, wives' caregiving hours using the CAMS data can be defined for both moderately disabled and severely disabled husbands.

Table 2: Share of Wives Providing Care (by Husbands' Disability Severity, %)

	Help husbands perform at least one ADL/IADL (Core)†		Help treat/manage husbands' medical condition(s) (CAMS)	
	Moderate	Severe	Moderate	Severe
$(0, 25]$ hours/week	-	41.76	18.53	35.75
>25 hours/week	-	14.40	1.53	5.46
Person-year obs.	-	1,750	364	271

Notes: Results are based on a sample of wives in the HRS whose husbands are of the ages 50 to 64 (Core: 2000-2014, CAMS: 2007-2015). All summary statistics are weighted by HRS sample weights.
† If a disabled husband receives help with an ADL or IADL, then by definition, he is "severely disabled" due to the fourth criterion in Section 2.1.2. Therefore, this information is not available for moderately disabled husbands.

Table 3: Summary Statistics of Severely Disabled Men Receiving Care

	Single*	Married
Number of caregivers (in %):		
One	60.43	72.90
Two	24.85	16.84
Three or more	14.72	10.26
Caregivers' relationship with respondents‡ (in %)		
Wives	-	97.51
Daughters	18.60	10.01
Sons	8.60	10.21
Other relatives¶	43.45	11.59
Non-relatives†	52.86	5.25
Covered by Medicaid (in %)	44.15	16.64
Receive care from Medicaid-covered caregiver(s) (in %)	17.23	1.55
Person-year observations	444	1,005

Notes: Results are based on a sample of severely disabled men aged 50 to 64 in the HRS Core who report receiving help from someone else in performing at least one ADL or IADL (2002-2014). All summary statistics are weighted by HRS sample weights.
∗ "Singles" include men who are either divorced, separated, widowed or never married.
¶ Includes stepsons, stepdaughters, son-in-laws, daughter-in-laws, grandchildren, fathers, father-in-laws, mothers, mother-in-laws, brothers, brother-in-laws, sisters, sister-in-laws, and individuals that are coded as "other relatives" in the HRS. Among these types of relatives, single men mostly receive care from "other relatives" (13% of single men in this table), sisters (11%), brothers (7.5%), and mothers (6.4%). In contrast, married men tend to receive care from grandchildren (2.8% of married men in this table), "other relatives" (2.0%), stepdaughters (1.8%), and daughter-in-laws (1.5%).
† Includes caregivers from organizations or institutions, paid helpers, and professional helpers.
‡ Since respondents may have multiple caregivers, the sum is greater than 100%.

more than half of single men receive care from non-relative caregivers and 40% of men with Medicaid coverage receive care from caregivers paid by Medicaid. This implies that for married households, spouses are the primary caregivers despite the existence of alternative market options and coverage through Medicaid.

2.2 Event Study Framework and Results

In this section, I use an event study framework to report changes in wives' labor supply and caregiving hours following their husbands' job displacement or disability. Job displacements are defined as job separations due to either a business closure or being laid off or let go. All other separation reasons (e.g., quits, health, family, new job, retirement) and separations from a self-employed job are not categorized as job displacements. The estimation sample is restricted to households where both spouses are under age 65.

For a married household i at time t, the estimation model is

$$y_{it} = \alpha_i + \gamma_t + X'_{it}\beta + \sum_{k=-4}^{5} \delta_k \cdot I_{itk} + \epsilon_{it} \tag{1}$$

where y_{it} denotes the dependent variable of interest (namely, weekly working hours of husbands and wives, and wives' weekly caregiving hours), γ_t are year dummies, and X_{it} is a vector of control variables. The variable I_{itk} denotes an indicator for being k years since the onset of the event (either disability or job displacement). The onset year is based on the first year that the event is observed for each respondent. I control for 4 years prior and 5 years after the onset. Therefore, δ_k measures the change in the dependent variable at k years of onset relative to 5 or more years before the onset. This approach is similar to that of Meyer and Mok (2019), who in turn build upon the approach of Jacobson et al. (1993), Stephens (2001), and Charles (2003).

The vector X_{it} includes a quartic in both spouses' ages, census division dummies, household size, and the length of the current marriage (in years). X_{it} also includes dummy variables for each spouse indicating whether their age is 62 or above to account for the fact that the early eligibility of Social Security retirement benefits is age 62. Wives' disability severity is also included in X_{it} when the dependent variable corresponds to wives' outcomes.

While X_{it} includes a number of control variables, the event study coefficients (δ_k's) are largely unaffected by the inclusion or exclusion of most of these variables. For example, Figure A.11 reports the event study coefficients based on a minimal set of controls (age

and age squared of both spouses) and Table A.3 reports the event study results based on a matched sample when the full set of controls is used and when a smaller set of controls (a quadratic in both spouses' ages and the wife's disability status) is used. These results are similar to the main results that are described below.

Figure 1 plots the event study coefficients (δ_k's) and Table A.1 reports the point estimates and standard errors. Figure 1a shows that for both job displacements and disability shocks, husbands significantly reduce working hours at the onset of the shock and this persists even five years after the shock. This implies that disability shocks as well as job displacements are associated with a persistent drop in husbands' earnings. In Appendix A, I also show that event study regressions of earnings produce similar results (Figures A.1a and A.1b).

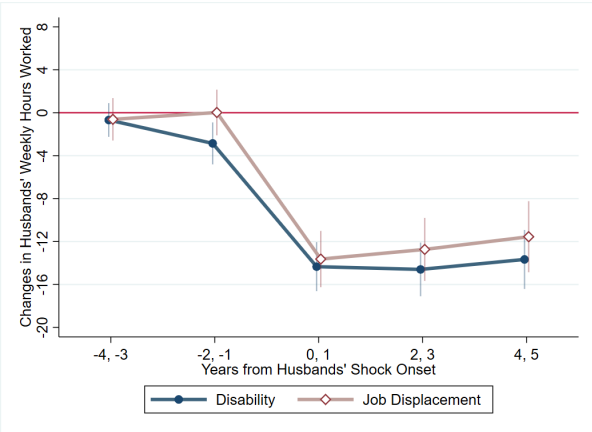
Figure 1b documents how wives adjust their working hours in response to their husbands' wage shocks. First, wives increase their weekly working hours by 3 hours on average following their husbands' job displacement and these estimates are statistically significant. Since the average weekly working hours prior to their husbands' job displacement is about 25 hours, this is equivalent to a 12% increase in working hours. This is comparable to the findings by Stephens (2002) who used a sample of working-age married women in the Panel Study of Income Dynamics (PSID) and found an 11% increase in annual hours of work after their husbands' job displacement. Also, the increase in wives' working hours starts from one to two years before their husbands' job displacement. This pattern is consistent with prior works that found that households have private information regarding their likelihood of a future job loss and that these types of subjective expectations are predictive of realized job losses (Stephens, 2004; Hendren, 2017).

In contrast, wives with disabled husbands do not increase their labor supply. Point estimates indicate that wives reduce working hours by 1 hour compared to 5 or more years before their husbands' disability onset and all of the estimates are statistically insignificant. These results are consistent with several previous studies that have also found small added worker effects in response to husbands' health shocks (Charles, 1999; Coile, 2004; Gallipoli and Turner, 2011; Fadlon and Nielsen, 2021).

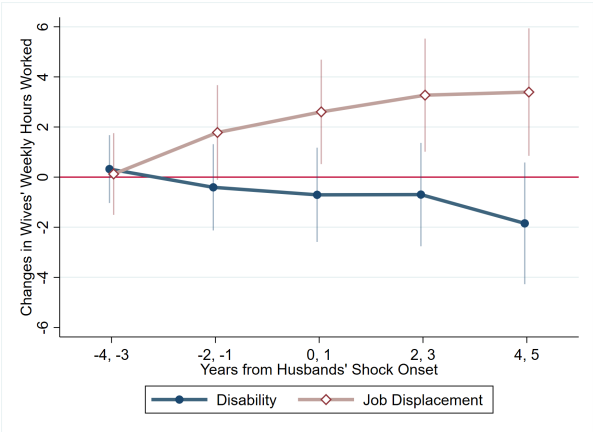
Finally, Figure 1c reports changes in wives' weekly caregiving hours using the HRS Core survey. As robustness, column (4) of Table A.1 reports the event study results using the spousal care hours in the HRS CAMS. Results from both data sources are quantitatively similar where wives spend on average 2 to 3 hours more per week on spousal care. This is comparable to the magnitude of the added worker effect observed in the event of husbands' job displacement (2 to 3 hours per week as shown in Figure 1b).

Figure 1: Changes in Household Outcomes by Husbands' Onset Years

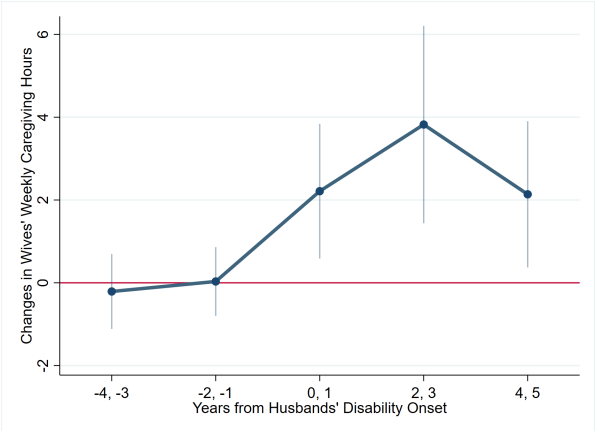
(a) Husbands' Weekly Hours Worked



(b) Wives's Weekly Hours Worked



(c) Wives' Caregiving Hours



Notes: Results are based on a sample of married households in the HRS Core survey (subfigures (a) and (b): 1992-2014, subfigure (c): 2000-2014) where both spouses are under age 65. All event study regressions control for a quartic in both spouses' ages, dummies for each spouse indicating whether their age is 62 or above, household size, length of current marriage, census division, and year and household fixed effects. Subfigures (b) and (c) additionally control for wives' disability status. The vertical lines through each dot indicate 95% confidence intervals.

2.2.1 Robustness and Supplemental Analyses

While Figure 1 shows that added worker effects in the event of husbands' disability are small and statistically insignificant, there may be several confounding factors. First, these results may be driven by households receiving SSDI benefits. Second, households may have different expectations for different types of disabilities such that it is not surprising to observe small added worker effects if the disability is highly expected. Third, households that experience a disability shock may not be similar to those that do not experience one. Fourth, spousal labor supply responses may be attenuated due to correlated health shocks between the two spouses. Finally, spousal labor supply and caregiving responses to husbands' disability might be driven by wives with weak labor force attachment. These concerns are addressed in Appendix B where I show that 1) spousal labor supply responses to husbands' disability are small even when the first four concerns are accounted for, and 2) the sizable increase in caregiving hours and the small labor supply responses are observed regardless of wives' labor force attachment.

Lastly, Appendix A reports results from supplemental event study analyses where I examine the impact of husbands' disability on earnings and the likelihood of SSDI applications and awards for both spouses.

3 Dynamic Model of Married Households

This section describes a dynamic programming model that is estimated and used for the welfare analysis of various counterfactual SSDI policies. The dynamic nature of the model allows it to account for the intertemporal labor supply decisions of both spouses, wives' caregiving choices, household savings, and SSDI application decisions pre- and post-husbands' disability. As a result, the model can be used to compute the ex-ante insurance value of SSDI prior to the disability onset. Additionally, the model incorporates SSDI, unemployment insurance, and means-tested government transfers since differences in policy parameters across various social welfare programs affect household responses to husbands' earnings shocks. Finally, the model allows the household to hire paid caregivers from the market.

All households enter the model as married consisting of a husband and a wife denoted as $j \in \{h, w\}$. I assume unitary households where households are single decision-making units.[10] I denote t as the husband's age and set the wife's age as $t - 3$ since this is the

[10]Since the main objective of this paper is to develop and estimate a household model with time allocation to leisure and spousal care and to use this model for the welfare analysis of SSDI at the household level,

average age difference between the two spouses in the HRS data.[11] The model period starts at $t_1 = 50$ and households die with certainty at $t_T = 90$. A period is a year. Households dissolve through (exogenous) death or divorce, and I assume that there is no remarriage.

Sources of uncertainty – The following exogenous shocks are realized at the beginning of each period t:

1. Mortality and divorce shocks: Spouse $j \in \{h, w\}$ dies with probability $\delta^j_{m,t}(s^j_{t-1}, e^j)$, which depends on their age, health status (s^j_{t-1}), and education type (e^j). Education type is exogenously given and its values are discretized into 0 (without a bachelor's degree) and 1 (bachelor's degree or higher). The household can also dissolve through divorce with probability $\delta_d(s^h_{t-1}, s^j_{t-1})$, which depends on the health status of both spouses.[12]

Conditional on the household's survival, the following shocks are realized.

2. Disability shocks: The husband's health status $s^h_t \in \{0, 1, 2\}$ (healthy, moderate, and severe) and the wife's health status $s^w_t \in \{0, 1\}$ (healthy, disabled) are realized.[13] The household health status $s_t = (s^h_t, s^w_t)$ evolves each period according to a Markov process and I allow for correlation between the two spouses' health status by assuming that the transition probability jointly depends on the age, previous period's health status, and education type of both spouses.

3. Displacement shocks and job arrivals: Husbands who were working in the previous period receive a job displacement shock with probability $\delta_{jd}(s^h_{t-1}, e^h)$, which depends on his health status and education type. Jobs arrive at a rate of λ.

4. Wage shocks: Each spouse's wage offer depends on their age, health status, and education type. In addition, both spouses receive idiosyncratic wage shocks each period.

I focus on the unitary framework and abstract from endogenous marriage and separation over the life-cycle. Although a non-unitary framework allows researchers to explore a different set of questions (e.g., how disability shocks affect the household bargaining process, the intra-household allocation of resources, and marital stability), this introduces additional complications under a dynamic setup regarding modeling divorce as a threat point and issues in the commitment of future resources. This type of extension is beyond the purpose of this paper and is left for future research.

[11] This improves computational tractability as additionally including the wife's age as a state variable substantially increases the state space.

[12] Divorce rates do not depend on education type since based on my data sample, education type is not statistically significant when predicting the likelihood of divorce once health status is controlled for.

[13] Since the paper primarily focuses on analyzing household responses to the husband's health shock, the wife's health status is assumed to be binary to maintain computational tractability.

Preferences – The household period utility is specified as

$$u(c, l^h, l^w, tc, fc, App; s) = \theta(s^h) \cdot \frac{c^{1-\gamma} - 1}{1-\gamma} + \psi_h \cdot \frac{(l^h)^{1-\gamma_h} - 1}{1-\gamma_h} + \psi_w \cdot \frac{(l^w)^{1-\gamma_w} - 1}{1-\gamma_w} + \eta_t(s^h) \cdot \ln \kappa(tc, fc; s^h) - \iota(s^h) \cdot App. \tag{2}$$

The household receives utility from household consumption c, leisure of each spouse l^h and l^w, and the domestic good $\kappa(tc, fc; s^h)$, which is produced using time inputs tc and fc (described in further detail below). Leisure time l^h and l^w depend on health status as described in equations (6) and (7). The household incurs a disutility $\iota(s^h) \geq 0$ (e.g., "hassle" or "stigma") when applying for SSDI benefits where $App \in \{0, 1\}$ indicates whether the household is applying for SSDI benefits in the given period.[14]

The term $\theta(s^h)$ is included as a tractable way of accounting for health state dependence in consumption utility. Normalizing $\theta(0) = 1$, if $\theta(s^h)$ is greater (less) than 1 in the disabled states, this implies positive (negative) health state dependence since the marginal utility of consumption is multiplied by $\theta(s^h)$. For example, expenditures on vacations would drop when one becomes disabled, which implies that $\theta(s^h)$ is less than one for expenditures on vacations. On the other hand, it is likely that demand for prepared meals, transportation services, and household services would increase in the disabled state such that $\theta(s^h)$ is greater than one for those consumption goods. Notice that $\theta(s^h)$ in the model is a catch-all measure that averages over all types of consumption goods at the household level. I do not make any a priori assumption on the direction of the health state dependence in consumption utility.

The household produces a domestic good κ using two time inputs: time input from the wife's caregiving (tc) and time input from paid caregivers (fc).[15] One possible interpretation

[14]Some papers model the stigma costs of receiving welfare benefits (e.g., lack of self-esteem, reputation costs due to neighbors learning about the benefit receipt) with Currie (2006) and Ko and Moffitt (2022) providing an excellent summary of the literature on welfare take-up. Note that in this paper, $\iota(s^h)$ (which includes the stigma costs of application) and the stigma costs of SSDI receipt are not separately identified. This is partly due to the model's assumption that SSDI receipt is an absorbing state and therefore, there is no endogenous choice to leave this state (refer to the subsection 'Disability Insurance' and footnote 22 for further modeling details). Currie (2006) suggests that costs associated with learning about and applying for programs (which $\iota(s^h)$ can reflect) are likely more important than stigma costs.

[15]I do not consider informal care provided by adult children since in my sample, the wife is the primary caregiver (see Table 3) and I don't find evidence of the wife's care depending on the number of adult children that the couple has. It is worth noting that my data sample consists of relatively younger couples in the HRS (i.e., husbands and wives younger than age 65) so family care arrangements may be different for older couples in the HRS. Indeed, when I examine married couples in the HRS Assets and Health Dynamics Among the Oldest Old (AHEAD) data (where the average age of respondents is 81), the probability that wives provide care to their husbands decreases with the number of adult children that couples have. This data pattern observed in the HRS AHEAD is consistent with previous works such as Byrne et al. (2009) that find that

for the domestic good κ is that it represents the husband's well-being from receiving informal and/or formal care (although other interpretations are possible). The domestic good κ is assumed to be produced according to

$$\kappa(tc, fc; s^h) = \begin{cases} 1 & \text{if } s^h = 0 \text{ or } (tc, fc) = (0,0) \\ (\alpha_\kappa tc^{\gamma_\kappa} + (1-\alpha_\kappa) fc^{\gamma_\kappa})^{\frac{1}{\gamma_\kappa}} & \text{otherwise.} \end{cases} \tag{3}$$

Guided by the data patterns in the HRS, (tc, fc) is discretized into six choices: (0,0), (part-time,0), (0, part-time), (full-time,0), (0,full-time), and (full-time,full-time).[16]

Conditional on his disability status s^h, $\eta_t(s^h)$ denotes the husband's care needs. Since the period-utility from the domestic good is proportional to $\eta_t(s^h)$ (see equation (2)), the household will allocate more time inputs (informal and/or formal care hours) when the husband has a higher degree of care needs. Care needs differ across households and time such that η evolves according to

$$\eta_t(s^h) = \begin{cases} 0 & \text{if } s^h = 0 \\ \mu_\eta(s^h) + \epsilon_t & \text{if } s^h \in \{1,2\} \end{cases} \tag{4}$$

$$\epsilon_t = \rho_\eta(s^h) \cdot \epsilon_{t-1} + \xi_t, \quad \xi_t \sim N(0, \sigma^2_{\xi,s^h}) \quad \text{if } s^h \in \{1,2\}. \tag{5}$$

Equations (4) and (5) indicate that disability status s^h requires care needs of $\mu_\eta(s^h)$ on average but husbands face an additional idiosyncratic shock ϵ_t that follows a standard AR(1) process. I assume that healthy individuals do not have any care needs by setting $\eta_t(0) = 0$. The term ϵ_t allows for (unobservable) heterogeneity in care needs even conditional on disability status s^h. For example, variation in associated health conditions may lead to differences in care needs.[17] Also, conditional on disability state s^h, some husbands may use equipment such as wheelchairs and walkers instead of receiving care from their wives.[18] Disability may also worsen or multiple conditions may develop over time. Equations (4) and

spousal care arrangements vary by the characteristics of adult children.

[16] In particular, (part-time,part-time), (full-time,part-time), and (part-time,full-time) are not included in the set of available choices. With the exception of husbands receiving both full-time spousal care and full-time formal care, I find that when a severely disabled husband receives care from both his spouse and a paid-helper, either the spouse or the paid-helper's time input accounts for 90% of the total amount of care time.

[17] Among severely disabled husbands in the HRS, 58% of those with neurological and sensory conditions (e.g., blind, deaf, multiple sclerosis) report having difficulty in any ADL/IADLs compared to 80% of those with musculoskeletal conditions and 83% of those with heart, circulatory, and blood conditions.

[18] About 60% of severely disabled husbands in the HRS who do not receive spousal care report using equipment or devices including railings, canes, walkers, wheelchairs, or lifts to perform ADLs.

(5) incorporate these types of heterogeneity in a tractable way since $\rho_\eta(s^h)$ can capture the persistence in care needs stemming from the nature of the health condition and ξ_t captures any idiosyncratic changes in care needs including the use of equipment or the development of multiple health conditions over time.

Next, l^h, l^w, and tc are chosen subject to the time constraints

$$l^h = \bar{L} - h^h - \phi^h(s^h) - \left(\phi^h_{emp}(s^h) + \phi^h_{emp,\eta}(s^h) \cdot g(\eta, s^h)\right) \cdot \mathbf{1}(h^h > 0) - \phi^h_w(s^w) \quad (6)$$

$$l^w = \bar{L} - h^w - tc - \phi^w(s^w) - \phi^w_{emp}(s^w) \cdot \mathbf{1}(h^w > 0) \quad (7)$$

where $\bar{L}$ denotes the time endowment available for each spouse in each period and h^h and h^w denote the husband and wife's labor market hours, respectively. Labor market hours h^h and h^w are discretized into three choices: not working, working part-time, and working full-time.

Equation (6) indicates that husbands allocate their time to leisure and market hours but incur a time cost of $\phi^h(s^h)$ and a fixed time cost of working, $\phi^h_{emp}(s^h)+\phi^h_{emp,\eta}(s^h)\cdot g(\eta, s^h)$. The term $\phi^h(s^h)$ can be thought of as "sick time" that burns some of the husband's leisure time (e.g. experiencing pain, being bedridden, visiting doctors), although other interpretations are possible. The fixed time cost of working depends on health status and the degree of care needs where $g(\eta, s^h)$ is a monotonically increasing function of η. In practice, I set $g(\eta, s^h)$ to take values 0, 1, and 2 when $\eta(s^h)$ falls under the first, second, and third tertile of the stationary distribution of $\eta(s^h)$. In other words, conditional on disability status s^h, husbands in the top tertile of the care needs distribution incur an additional fixed cost of working $\phi^h_{emp,\eta}(s^h)$ compared to the husbands in the middle tertile. These time costs allow the model to replicate the data pattern in which even conditional on disability status, husbands who receive full-time care exhibit considerably lower employment rates compared to those who receive part-time care or no care. I assume that healthy husbands do not incur additional time costs such that $\phi^h(0) = \phi^h_{emp}(0) = \phi^h_{emp,\eta}(0) = 0$.

Finally, husbands incur a time cost $\phi^h_w(s^w)$ depending on their wives' health status. This can be thought of as a tractable way to account for the husband's time spent in caregiving when his wife becomes disabled. I assume $\phi^h_w(0) = 0$ when wives are healthy.

Wives allocate their time to leisure l_w, market work h_w, and spousal care tc. Similar to husbands, wives incur a time loss $\phi^w(s^w)$ and a fixed time cost of working, $\phi^w_{emp}(s^w)$ when they are disabled. These time costs are assumed to be zero when wives are healthy ($\phi^w(0) = \phi^w_{emp}(0) = 0$). Due to $\phi^w(s^w)$, the wife's marginal disutility of providing care for her husband will be higher when she is disabled compared to when she is healthy.

Disability Insurance – Key features of the Social Security Disability Insurance (SSDI) are modeled to incorporate the complexities of the program. First, whether the husband applies for SSDI is an endogenous choice ($App_t \in \{0, 1\}$). Application is costly since the household incurs a disutility $\iota(s^h)$ and the husband cannot work ($h_t^h = 0$) or receive wage offers during the application period.[19] Conditional on applying, SSDI is awarded with probability $Pr(DI_{t+1} = 1|s_t^h, t, App_t)$, which depends on the husband's health status and age. This reflects the fact that SSA cannot perfectly observe the true disability status of the applicant. The probability of receiving SSDI benefits for healthy husbands is assumed to be zero ($Pr(DI_{t+1} = 1|s_t^h = 0, t, App_t = 1) = 0$).[20]

Successful applicants who applied in period t receive benefits from period $t+1$. Husbands are not allowed to work while receiving disability benefits.[21] Benefit amount is calculated in the same manner as Social Security Retirement benefits, which is a monotonic function of average lifetime earnings at age t, y_t (see Appendix C for further details). Receiving SSDI is an absorbing state where husbands continue receiving SSDI benefits each period and do not return to work. This is a standard assumption in the literature, partly motivated by the small fraction of SSDI awards that are terminated due to recipients returning to work.[22] Lastly, although SSDI application choices are explicitly modeled for the husband only, I take into account that the wife may also receive SSDI by including the wife's SSDI income as one source of household non-labor income in the budget constraint (see equation (12)).

Offered Hourly Wages, Labor Market Frictions, and Unemployment Insurance – Employed husbands face the risk of being displaced with probability $\delta_{jd}(s_t^h, e^h)$. Non-employed hus-

[19] This mimics the first step of SSA's disability determination process where applicants earning more than the substantial gainful activity (SGA) limit ($1,070 per month in 2014) are automatically denied benefits. Average application processing time is roughly 4∼6 months for initial determinations but becomes significantly longer for appeals.

[20] In my HRS sample, less than 0.5% of healthy husbands report ever applying for SSDI. Also, conditional on being a healthy applicant, the probability of being awarded benefits is similar to that observed for moderately disabled applicants. This is suggestive of "healthy" husbands being only marginally healthy and being more closer to moderately disabled husbands in other dimensions that are unobservable to the researcher. Given the very small fraction of healthy applicants in the data and the fact that the model cannot account for unobservable dimensions that distinguish marginally healthy individuals from moderately disabled individuals, I assume that the probability of a healthy applicant receiving SSDI benefits in the next period is zero.

[21] This reflects the SSDI program rule that earnings above the substantial gainful activity (SGA) threshold will lead to the termination of disability benefits.

[22] In 2012, only 5% of SSDI terminations were due to beneficiaries working above the SGA threshold. In contrast, 55% of terminations were due to SSDI benefits rolling over to Retirement benefits once beneficiaries reached full retirement age and 35% were due to the death of the recipient (Morton, 2014).

bands who are neither applying nor receiving SSDI benefits receive wage offers with probability λ. Displaced husbands receive a one-period unemployment insurance (UI) benefit equal to 23% of the previous period's earnings.[23]

Each household i receives wage offers and makes labor supply decisions once wages are revealed. The wage offer process evolves according to

$$\log w_{it}^h = \alpha_0^h + \alpha_1^h \cdot t + \alpha_2^h \cdot t^2 + \alpha_3 \cdot e_i^h + \sum_{s=1}^{2} \varphi_s^h \cdot \mathbf{1}(s_{it}^h = s) + \zeta_{it}^h + \epsilon_{it}^h \tag{8}$$

$$\log w_{it}^w = \alpha_0^w + \alpha_1^w \cdot (t-3) + \alpha_2^w \cdot (t-3)^2 + \tilde{\alpha}_3 \cdot e_i^w + \varphi^w \cdot \mathbf{1}(s_{it}^w = 1) + \zeta_{it}^w + \epsilon_{it}^w \tag{9}$$

$$\zeta_{it}^j = \zeta_{i,t-1}^j + \nu_{it}^j, \quad \begin{pmatrix} \nu_{it}^h \\ \nu_{it}^w \end{pmatrix} \overset{iid}{\sim} N\left[0, \begin{pmatrix} \sigma_{\nu,h}^2 & \sigma_{\nu_{h,w}} \\ \sigma_{\nu_{h,w}} & \sigma_{\nu,w}^2 \end{pmatrix}\right], \quad j \in \{h, w\} \tag{10}$$

$$\begin{pmatrix} \epsilon_{it}^h \\ \epsilon_{it}^w \end{pmatrix} \overset{iid}{\sim} N\left[0, \begin{pmatrix} \sigma_{\epsilon,h}^2 & \sigma_{\epsilon_{h,w}} \\ \sigma_{\epsilon_{h,w}} & \sigma_{\epsilon,w}^2 \end{pmatrix}\right] \tag{11}$$

where w_{it}^j denotes the hourly wage of spouse $j \in \{h, w\}$. For both spouses, log hourly wages depend on their own age, education type, and health status.[24] Each spouse receives a permanent wage shock ν_{it}^j and a transitory shock ϵ_{it}^j and these two shocks are assumed to be independent.[25] The permanent (transitory) wage shocks of the two spouses are assumed to be contemporaneously correlated with covariance $\sigma_{\nu_{h,w}}$ ($\sigma_{\epsilon_{h,w}}$).

Retirement – Husbands can "retire" (defined in the model as completely exiting the labor force and receiving Social Security Retirement benefits until death) starting from age 62. I assume that all husbands retire by age 65. If husbands retire before age 65, their Social Security Retirement benefits are reduced permanently according to Social Security rules (6.7% reduction for each retirement year before age 65). Since the model assumes that wives

[23] Average UI replacement rates were about 46% between 2011 to 2017. Since UI benefits are provided for (a maximum of) 26 weeks and my model period is a year (52 weeks), I set the UI replacement rate as 23%.

[24] To maintain tractability, offered log hourly wages do not depend on the individual's previous employment status. Therefore, certain opportunity costs of spousal care (e.g., human capital depreciation due to being out of the labor force to provide care (Skira, 2015)) are not considered and the opportunity costs of caregiving in this model should be considered as a lower bound. These types of dynamic opportunity costs of caregiving can potentially be more important for younger households.

[25] In practice, it is difficult to distinguish transitory wage shocks from measurement error in wages. Since ignoring the variance of measurement error may affect the estimates of the wage parameters, I follow previous studies such as Meghir and Pistaferri (2004) and Blundell et al. (2016) and assume that a predetermined fraction of the variance of (residual) log hourly wage growth is due to measurement error. Based on estimates from Bound et al. (1994), I set this value as 0.304.

are three years younger than their husbands and since all husbands retire by the age of 65, wives are assumed to retire at age 62.

When both spouses are retired ($t = 65$ and onward), household consumption and savings are the only choices made during this period. Also, the household receives Social Security Retirement benefits, defined as the sum of the husband's benefit and the wife's spousal benefits (see Appendix C for further details and discussion). Following program rules, SSDI benefits are automatically converted to Retirement benefits once the husband turns age 65.

Budget Constraint – In each period, the household faces the budget constraint

$$\begin{aligned} A_{t+1} =& (1+r)A_t + \sum_{j\in\{h,w\}} w_t^j h_t^j + UI_t + b_t + I_t + T_t \\ & - c_t - \tau_t - m_t - p_{fc} \cdot fc_t \end{aligned} \tag{12}$$

where the household receives asset income rA_t, labor income $w_t^h h_t^h + w_t^w h_t^w$, unemployment benefits UI_t, Social Security benefits b_t, all other sources of non-labor income I_t, and government transfers T_t. The household consumes c_t and also incurs payroll and federal taxes τ_t, out-of-pocket medical expenses m_t, and formal care expenses $p_{fc} \cdot fc_t$.

Unemployment benefits UI_t are available for one period when the husband is displaced. Household Social Security benefits b_t (either Disability or Retirement) are assumed to be a function of age t, the husband's average lifetime earnings y_t, whether the husband receives disability benefits ($DI_t = 1$), and whether the husband chose early retirement ($ER_t = 1$). Note that b_t reflects the sum of both spouses' retirement benefits when both are retired.

All other sources of household non-labor income include pensions, annuities, veteran benefits, and other lump sum income of both spouses as well as the wife's SSDI and unemployment benefits. Instead of explicitly modeling the wife's SSDI application behavior and job displacement process, the wife's income from SSDI and UI are incorporated in the form of household non-labor income, I_t. I assume that I_t is a function of age, education type, and health status of both spouses.

Payroll and federal income taxes τ_t are computed according to Appendix D. The couple's out-of-pocket medical expenses $m_t = m(t, s_t^h, s_t^w, e^h, e^w)$ are assumed to be exogenous and depend on age, health status, and education type of both spouses. Lastly, $p_{fc} \cdot fc_t$ denotes household expenditures on formal care where p_{fc} is the hourly market price of formal care and fc_t is the annual hours of formal care that the household purchases.

For low-income households, government transfers T_t provide a minimum consumption

level $\underline{c}_g$ that satisfies

$$T_t = \max\Big\{0,\ \underline{c}_g - \big((1+r)A_t + \sum_{j\in\{h,w\}} w_t^j h_t^j + UI_t + b_t + I_t \\ - \tau_t - m_t - p_{fc}\cdot fc_t\big)\Big\} \tag{13}$$

$$\underline{c}_g \quad = \quad \begin{cases} \underline{c}_{agg} & \text{if } fc_t = 0 \\ \underline{c}_{fc} & \text{if } fc_t > 0. \end{cases} \tag{14}$$

Equations (13) and (14) are a tractable of way of incorporating the minimum standard of living guaranteed by means-tested programs such as the Supplemental Security Income (SSI), the Supplemental Nutrition Assistance Program (SNAP), Medicaid, and Section 8 housing assistance vouchers. This is an aggregate approximation of all available means-tested programs following the influential work of Hubbard et al. (1995).[26]

The consumption floor takes on two values ($\underline{c}_{agg}$ and $\underline{c}_{fc}$) to reflect the fact that a) some Medicaid programs (e.g., Home and Community Based Services (HCBS) Medicaid Waivers and certain state Medicaid programs) cover the cost of formal care for eligible individuals, and b) these programs may have different financial eligibility requirements from other means-tested programs.

Finally, households are not allowed to borrow such that $A_t \geq 0$ holds for each period. This is partly due to the fact that it is infeasible to borrow against future Social Security retirement and disability benefits as well as means-tested program benefits.

Terminal Utility Upon Household Dissolution – Individual behavior after the dissolution of a married household (due to divorce or the death of one or both spouses) is not explicitly

[26] Although the disability determination process is the same for both SSDI and SSI, SSI requires married applicants to hold less than $3,000 in assets to be eligible for benefits. However, many forms of assets are excluded from this $3,000 limit including an individual's home and adjacent land, and one car (Morton, 2014). This makes it difficult to precisely model SSI since it requires modeling different types of assets and imposing assumptions regarding how these different types of assets are consumed. Also, SSI provides a flat monthly amount that is deducted by both unearned (including SSDI benefits, which are deducted $1 to $1) and earned income (including own and spouse's earnings). Given that the purpose of SSI is to provide households a minimum standard of living and thus benefits are deducted accordingly if the household has additional resources through unearned and earned income, equation (13) reflects the nature of SSI while maintaining tractability.

modeled.[27] Instead, the surviving spouse j receives a terminal utility $v(W_t^j)$ specified as

$$v(W_t^j) \quad = \quad \psi_v \, \frac{\left(W_t^j + k_v\right)^{1-\gamma}}{1-\gamma}, \quad j \in \{h, w\} \tag{15}$$

where $W_t^j = W_t^j(a_t^j, y_t)$ denotes the sum of spouse j's wealth (a_t^j) and the present discounted value of the stream of (future) retirement benefits based on y_t (the husband's average lifetime earnings at t).[28] The term $k_v \geq 0$ is a shifter that affects the curvature of $v(W_t^j)$ and governs the degree to which households are risk-averse over consumption and W_t^j.[29] This allows households to be less risk-averse over W_t^j than consumption (for instance, due to potential government transfers that spouse j can receive when they become single). The functional form of equation (15) is commonly used in the literature that models bequest motives as its parameters are easy to interpret and can support various interpretations of bequest motives (De Nardi et al., 2010, 2021; French and Jones, 2011; Lockwood, 2018; Lee and Tan, 2023).

The value of a_t^j depends on whether spouse j is a widow/er or divorcee. Widow/ers are assumed to receive all of the household's assets ($a_t^j = A_t$) while divorcees split the household's assets equally ($a_t^h = a_t^w = \frac{1}{2}A_t$). Retirement benefits for single men are computed based on their own average lifetime earnings y_t. For single females, retirement benefits are computed based on the Social Security spousal benefit formula where widows receive 100% of their deceased husband's Primary Insured Amount (PIA) while divorcees receive 50% of their ex-husbands' PIA (see Appendix C for further details and discussion).

Model Solution – Define the vector of state variables at period t as $\boldsymbol{X}_t = \{A_t, s_t^h, s_t^w, y_t, \vartheta_t, DI_t, ER_t, e^h, e^w, \zeta_t^h, \zeta_t^w, \epsilon_t\}$, which consists of household assets (A_t), the health status of the two spouses (s_t^h, s_t^w), the husband's average lifetime earnings at age t (y_t), whether the husband is displaced ($\vartheta_t \in \{0, 1\}$), whether the husband is receiving SSDI benefits ($DI_t \in \{0, 1\}$), whether the husband retired before age 65 ($ER_t \in \{0, 1\}$), the education type of both spouses ($e^h, e^w \in \{0, 1\}$), idiosyncratic wage shocks of both spouses (ζ_t^h, ζ_t^w), and the idiosyncratic

[27] This is because the primary goal of this project is to understand the behavior of married couples who have an additional source of insurance provided by their spouses.

[28] Refer to Appendix C for further details and discussion on using the husband's average lifetime earnings y_t to calculate the wife's retirement benefits.

[29] Assuming perfect certainty and no health-state dependence, $v'(0) = u_c(\psi_v^{-\frac{1}{\gamma}} \cdot k_v)$ holds. Under these conditions, $\psi_v^{-\frac{1}{\gamma}} \cdot k_v$ can be interpreted as a consumption threshold where households would not leave wealth when consumption is lower than $\psi_v^{-\frac{1}{\gamma}} \cdot k_v$. The higher k_v is, the more W_t^j is a luxury good such that households are more risk-averse over consumption than W_t^j.

shock to care needs (ϵ_t). For each period t, households solve

$$
\begin{aligned}
V_t(\boldsymbol{X}_t) = \max_{\substack{c_t, h_t^h, h_t^w, \\ tc_t, fc_t, App_t}} \; & u(c_t, l_t^h, l_t^w, tc_t, fc_t, App_t; s_t) \\
& + \beta \Big\{ \big(1 - \delta_{m,t}^h(s_t^h, e^h)\big)\big(1 - \delta_{m,t}^w(s_t^w, e^w)\big)\big(1 - \delta_d(s_t^h, s_t^w)\big) E_t\big[V_{t+1}(\boldsymbol{X}_{t+1}|\boldsymbol{X}_t)\big] \\
& + \big(1 - \delta_{m,t}^h(s_t^h, e^h)\big)\big(1 - \delta_{m,t}^w(s_t^w, e^w)\big) \; \delta_d(s_t^h, s_t^w)\big(\sum_{j \in \{h,w\}} v(W_{t+1}^j)\big) \\
& + \big(1 - \delta_{m,t}^h(s_t^h, e^h)\big) \cdot \delta_{m,t}^w(s_t^w, e^w) \cdot v(W_{t+1}^h) \\
& + \delta_{m,t}^h(s_t^h, e^h) \cdot \big(1 - \delta_{m,t}^w(s_t^w, e^w)\big) \cdot v(W_{t+1}^w) \; \Big\}
\end{aligned}
\tag{16}
$$

subject to time and budget constraints (6), (7), (12), (13), and (14).

The model does not have an analytical solution and therefore, is solved numerically. This is done by solving the value functions at the terminal period t_T and iterating backward such that I solve for the value functions and the decision rules for each period.

4 Estimation of the Dynamic Model

To estimate the parameters of the model, I employ a two-step estimation method similar to the one used by Gourinchas and Parker (2002), De Nardi et al. (2010), and French and Jones (2011). In the first step, I estimate or calibrate certain parameters that are identified without explicitly using the model. Given the first step parameters, the remaining 40 parameters are estimated by indirect inference (Smith, 1993; Gourieroux et al., 1993). First, I numerically solve the model for a given initial guess of the parameter values and simulate forward to generate simulated moments. Based on the fit between the simulated moments and the data moments, I update the parameter guess and repeat this process until I find the parameter values that generate the closest fit between the simulated moments and the data moments.

Formally, denote the vector of model parameters that are estimated in the first stage as $\boldsymbol{\theta_f}$ and those that are estimated in the second stage as $\boldsymbol{\theta_s}$. Then, the estimate $\hat{\boldsymbol{\theta}}_{\boldsymbol{s}}$ is chosen such that it minimizes the weighted distance between the vector of data moments $\boldsymbol{m_d}$ and the vector of simulated moments $\boldsymbol{m_s}(\hat{\boldsymbol{\theta}}_{\boldsymbol{f}}, \boldsymbol{\theta_s})$ where the weight is specified by the matrix $\hat{W}$. Mathematically, this is expressed as

$$
\hat{\boldsymbol{\theta}}_{\boldsymbol{s}} \;=\; \arg\min_{\boldsymbol{\theta_s}} \big(\boldsymbol{m_d} - \boldsymbol{m_s}(\hat{\boldsymbol{\theta}}_{\boldsymbol{f}}, \boldsymbol{\theta_s})\big)' \; \hat{W} \; \big(\boldsymbol{m_d} - \boldsymbol{m_s}(\hat{\boldsymbol{\theta}}_{\boldsymbol{f}}, \boldsymbol{\theta_s})\big). \tag{17}
$$

Following Pischke (1995), I use a diagonal weighting matrix $\hat{W}$, which is the inverse of the variance-covariance matrix of the data along the diagonal and zero elsewhere.

4.1 Estimation Sample

When simulating households, I use the first observation of each married household in the HRS sample as the state vector and simulate forward. Table 4 provides a summary of this initial distribution. I make additional sample restrictions such that both spouses are white. This is because 1) the HRS mostly consists of white respondents, and 2) I do not find evidence of significant racial differences in spousal responses to husbands' disability in my sample. Appendix E provides further discussions regarding the estimation sample being restricted to whites.

Table 4: Summary Statistics of the Initial Distribution by Husbands' Health Status

	Husbands' Health Status		
	Healthy	Moderate	Severe
Husbands' characteristics			
Age (mean)	56.26	57.27	57.23
Average lifetime earnings (mean, in $)	30,747	26,965	22,229
Hourly wages (mean, in $)†	27.38	22.58	19.14
Has a bachelor's degree (or higher) (in %)	26.68	15.80	8.09
Wives' characteristics			
Age (mean)	53.09	53.75	53.57
Hourly wages (mean, in $)†	15.31	14.24	12.64
Disabled (in %)	14.87	22.99	28.72
Has a bachelor's degree (or higher) (in %)	17.86	11.49	9.92
Household characteristics			
Assets (median, in $1,000)	253.91	189.73	100.33
Observations	3,040	348	383
	(80.6%)	(9.2%)	(10.2%)

Notes: This table reports summary statistics of the initial sample used in the simulation. The initial sample consists of the first year of observation for each married couple in the HRS. Additionally, the sample is restricted to couples in which both spouses are white and younger than 65. All dollar values are in 2015 dollars.

† For respondents who were not working in their first year of observation, I use their wage in their previous job as a proxy.

4.2 First Stage Parameters

Table 5 reports the baseline values of the first-stage parameters. Appendix F provides further details on how certain parameters were estimated from the HRS.

Table 5: First Stage Parameters

Parameter	Value
Time endowment, $\bar{L}$	5,840 (=16 hours × 365 days)
Labor market hours, h_t^h, h_t^w	Full-time: 2,000 (40 hours × 50 weeks) Part-time: 1,000 (20 hours × 50 weeks)
Caregiving hours, tc_t	Full-time: 2,000 Part-time: 350 hours (7 hours × 50 weeks, based on the average value in my sample)
Hourly price of formal care, p_{fc}	\$22 (U.S. median in 2016, (Genworth, 2022))
Coefficient of relative risk aversion, γ	1.5
Curvature of leisure utility function, γ_h, γ_w	1
Real interest rate, r	0.03
Discount factor, β	$\frac{1}{1.03}$
Job displacement rates, $\delta_{jd}(s^h, e^h)$	Table A.9 (using the HRS)
Job arrival rate, λ	0.99
Divorce rates, $\delta_d(s^h, s^w)$	Table A.10 (using the HRS)
Mortality rates, $\delta_{m,t}^j(s_{t-1}^j, e^j)$	Figure A.2 (using the HRS)
Health transition probabilities	Figures A.3 and A.4 (using the HRS)
SSDI award probabilities	Table A.11 (using the HRS)
Household medical expenses, m_t	Table A.12 (using the HRS)
Household non-labor income, I_t	Table A.13 (using the HRS)
Husbands' time cost when wives are disabled, $\phi_w^h(1)$	220.48 hours (average value in my sample)
Disutility of SSDI application when severely disabled, $\iota(2)$	0

Notes: This table reports the baseline values of the first-stage parameters. Refer to Appendix F for further details on how some of the parameters were estimated using the HRS.

Parameters γ, r, and β are set to values that are commonly assumed in the literature (Gourinchas and Parker, 2002; Cagetti, 2003; Brown and Finkelstein, 2008; Gallipoli and Turner, 2011; Low and Pistaferri, 2015; Autor et al., 2019). The job arrival rate is set to $\lambda = 0.99$, which is similar to job arrival rates estimated in previous works when converted to an annual basis.[30] In Section 5.2.1, I show that given the calibrated values of $\gamma_h = 1$ and $\gamma_w = 1$, the model generates labor supply elasticities within the range reported by previous studies. Section 5.2.1 also discusses the model's ability to replicate the SSDI application rate among severely disabled husbands given the calibrated value of $\iota(2) = 0$.

4.3 Second Stage Parameters

Given the first stage parameters, the remaining model parameters are estimated using indirect inference. There are a total of 40 parameters including the health state dependence in consumption utility ($\theta(s^h), s^h \in \{1, 2\}$), the husband and wife's weight on leisure utility ($\psi_j,\ j \in \{h, w\}$), the husband and wife's time costs by disability status ($\phi^j(s^j), \phi^j_{emp}(s^j)$, $\phi^h_{emp,\eta}(s^h), j \in \{h, w\}, s^h \in \{1, 2\}, s^w = 1$), the terminal utility parameters (ψ_v, k_v), the parameters that govern the husband's care needs ($\mu_\eta(s^h), \rho_\eta(s^h), \sigma_{\xi,s^h}, s^h \in \{1, 2\}$), the parameters that govern the production function of the domestic good ($\alpha_\kappa, \gamma_\kappa$), the minimum consumption levels provided by government transfers ($\underline{c}_{agg}, \underline{c}_{fc}$), the disutility of applying for SSDI when moderately disabled ($\iota(1)$), and the parameters that govern the wage offer functions of the two spouses (a total of 15 parameters).

4.3.1 Identification

To verify whether the second stage parameters are identified, I perform a visual inspection where for each parameter, I plot the criterion function (equation (17)) around the converged parameter value while keeping the remaining parameters fixed. If the plot has a flat region, one might be concerned that the criterion function does not have a unique minimum and thus the parameter is not identified. The criterion function plots for all 40 parameters are included in Figures A.5 and A.6 in the Appendix. Reassuringly, none of the plots have a noticeable flat region.

[30] Low et al. (2010) estimate a quarterly job arrival rate of 0.76–0.82 from the PSID. Merkurieva (2019) reports an average monthly job arrival rate of 0.23 based on the CPS data.

Table 6: List of Targeted Moments

Moment Type	# of Moments	Model Fit and Moment Indices
Wives' labor supply responses to their husbands' disability (FE regressions)	4	Panel A of Table 8
Husbands' employment and part-time rates by their health and wives' care choices	15	Panels A, C, and D of Table A.15
Wives' employment and part-time rates by their health	3	Panel B of Table A.15
Median and 25th percentile of household assets by husbands' age and health	15	Panel B of Table 8, Panel A of Table A.17
Care choices (formal and informal) by husbands' health	11	Panels C and D of Table 8, Panel C of Table A.17
SSDI application rate	1	Panel B of Table A.17
Regression coefficients of log hourly wage	9	Panel A of Table A.16
Other wage moments (Appendix H)	6	Panel B of Table A.16

Notes: This table summarizes the 64 targeted moments into eight types. The last column lists the relevant tables that report the model fit and moment indices (#1 to #64) for each moment.

4.3.2 Targeted Moments and the Sensitivity of Parameters

Table 6 summarizes the 64 targeted moments used in the estimation. For wives' labor supply responses, I run fixed effect regressions of wives' employment and weekly hours on a quadratic in both spouses' ages, dummies for husbands' disability severity, a dummy for wives' disability status, and household fixed effects. I use the coefficients of the dummies for husbands' disability severity as targeted moments. For care choices, I generate moments using the Core survey for severely disabled husbands and the CAMS data for moderately disabled husbands (see footnote 9 for further details).

While the second stage parameters are estimated by jointly targeting all 64 moments, it is helpful to understand which moments are primarily informative of pinning down each parameter. To confirm this, I compute the sensitivity of each parameter using the method proposed by Andrews et al. (2017). I scale the sensitivity measures such that they reflect the absolute local change in parameter value to a one standard deviation change in each moment. Due to the large number of model parameters and targeted moments, I only report

the sensitivity measures of four parameters $\theta(1)$, $\theta(2)$, α_κ, and γ_κ in Figures 2 and 3. For the remaining parameters, I generate heat maps such that for each parameter, the moments with a darker shade indicate those with higher sensitivity values (Figures A.7 to A.10 with further details in Appendix G.2). I also index each moment from #1 to #64 and label the moment indices in Tables 8, A.15, A.16, and A.17. These moment indices are also used in Figures 2, 3, and A.7 to A.10.

Figures 2, 3, and A.7 to A.10 corroborate that the sensitivity measures align with heuristic arguments regarding which moments primarily govern which parameters. First, Figure 2 indicates that the health state dependence in consumption utility $\theta(s^h)$ is pinned down by matching wives' labor supply responses to their husbands' disability (moment #1 for $\theta(1)$ and moments #2 and #4 for $\theta(2)$) as well as median household assets by disability severity (moments #15 and #16 for $\theta(1)$ and moments #17 to #19 for $\theta(2)$). Intuitively, changes in spousal labor supply responses across husbands' health states are informative of $\theta(s^h)$ since conditional on the realization of each health state s^h, wives' working hours are chosen such that they reveal how much consumption is valued in the form of spousal earnings.[31]

For the parameters of the domestic good $(\alpha_\kappa, \gamma_\kappa)$, Figure 3 indicates that moments regarding formal care usage (moments #47 to #49) are particularly informative. For example, since α_κ governs the weight between spousal care and formal care, the fraction of severely disabled husbands who hire paid helpers (moment #47) has the highest sensitivity value. Similarly, the fraction of severely disabled husbands who receive care from both their wives and paid helpers (moment #48) is informative of γ_κ since it governs the degree of complementarity between spousal care and paid formal care.

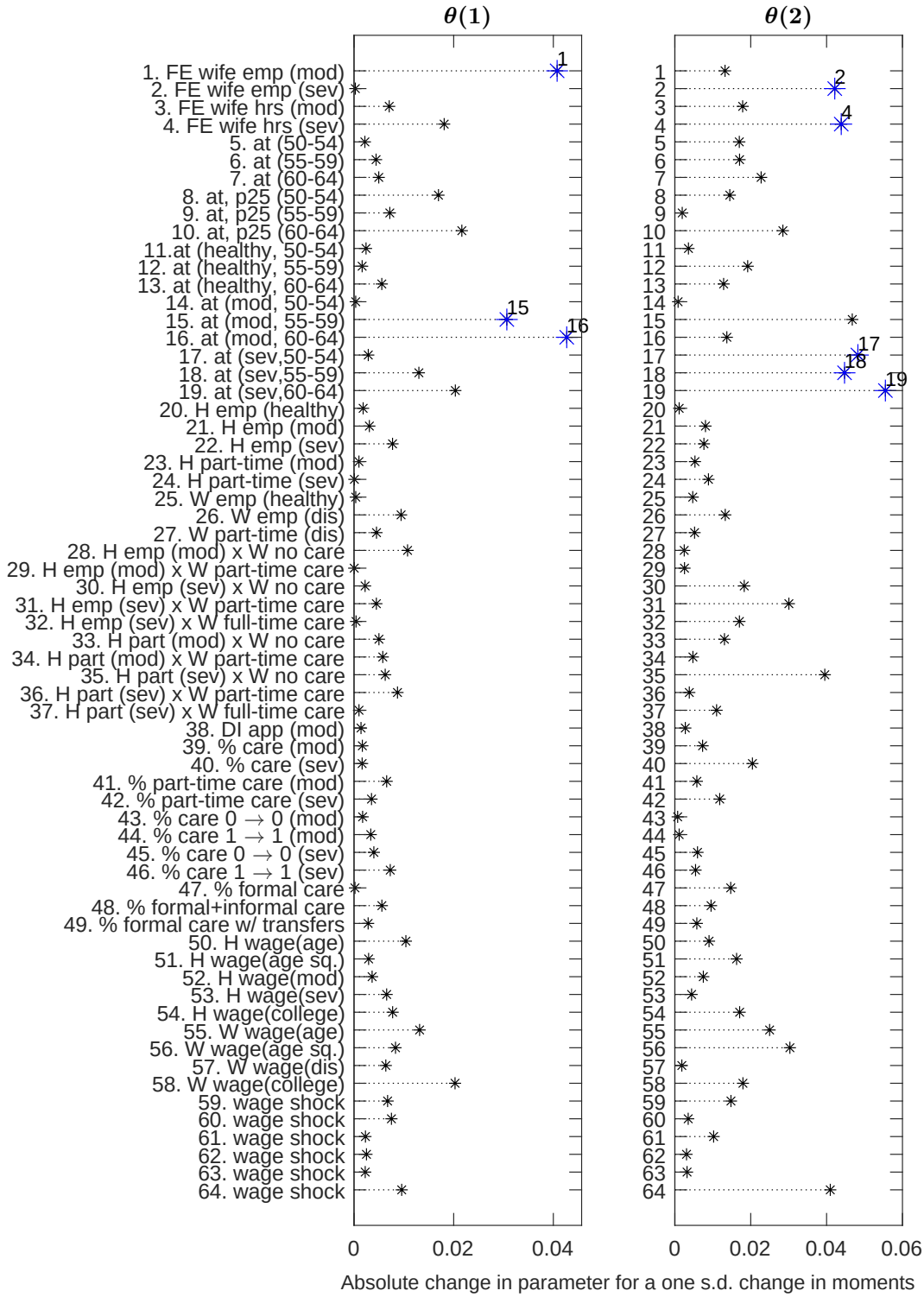
The husband's weight on leisure utility (ψ_h) and his time costs in the disabled states $(\phi^h(s^h), \phi^h_{emp}(s^h), \phi^h_{emp,\eta}(s^h), s^h \in \{1, 2\})$ are pinned down by matching moments regarding husbands' average employment rates and part-time employment rates (moments #20 to #37 of Figure A.7). Intuitively, an increase in either $\phi(s^h)$ or $\phi^h_{emp}(s^h)$ lowers the probability of husbands working. However, conditional on working, husbands are more likely to work part-

[31]For the purpose of illustration, consider a static environment where the period utility is specified as equation (2). Assuming interior solutions and using equation (7), the first order conditions indicate that

$$\theta(s^h) \cdot c^{-\gamma} = \frac{\psi_w \cdot (\bar{L} - h_w - tc)^{-\gamma_w}}{w_w}, \qquad \forall s^h$$

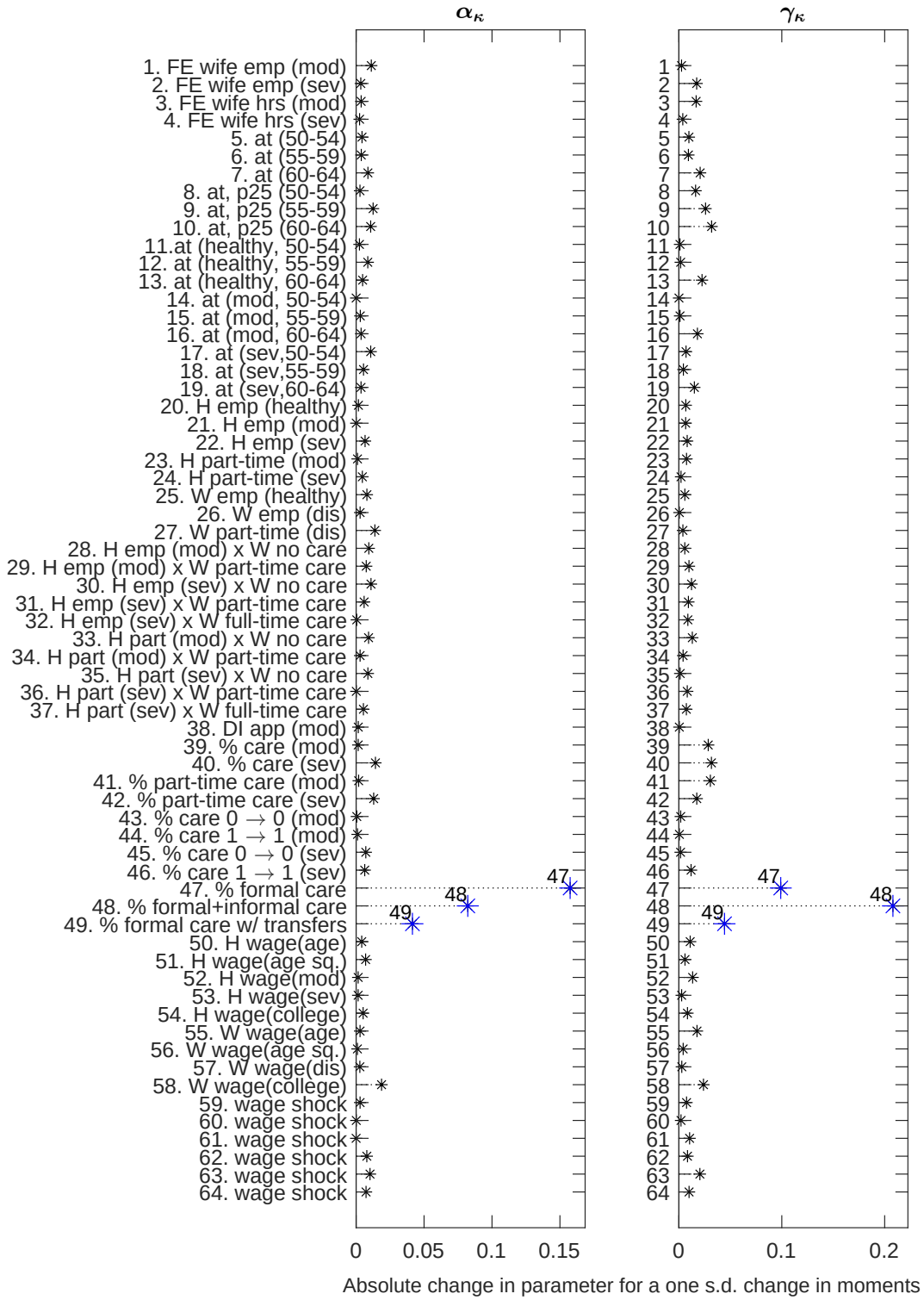
holds (assuming $\phi^w(s^w) = \phi^w_{emp}(s^w) = 0$ for the simplicity of exposition). Conditional on tc, this equation provides a direct link between household consumption and wives' market hours. This argument is also illustrated by Fadlon and Nielsen (2019) who propose using spousal labor supply responses across different states as sufficient statistics to infer welfare gains from social insurance programs.

Figure 2: Sensitivity of $\theta(1)$ and $\theta(2)$



Notes: The moment indices #1 to #64 correspond to those in Tables 8, A.15, A.16, and A.17.

Figure 3: Sensitivity of α_κ and γ_κ



Notes: The moment indices #1 to #64 correspond to those in Tables 8, A.15, A.16, and A.17.

time when $\phi(s^h)$ increases whereas a higher $\phi^h_{emp}(s^h)$ increases the probability of full-time work. Therefore, jointly matching employment and part-time employment rates is helpful for recovering $\phi(s^h)$ and $\phi^h_{emp}(s^h)$. Husbands' employment rates by their health status and wives' caregiving choices are informative of $\phi^h_{emp,\eta}(s^h)$ since husbands with greater care needs are more likely to receive their wives' care while being less likely to work.

The wife's weight on leisure utility (ψ_w) and time costs ($\phi^w(s^w), \phi^w_{emp}(s^w), s^w = 1$) are recovered by matching wives' employment rates and part-time employment rates by health status (moments #25 to #27 of Figures A.7 and A.8). The disutility of applying for benefits when moderately disabled, $\iota(1)$, is inferred by matching the SSDI application rate among moderately disabled husbands (moment #38 of Figure A.9).

Median and 25th percentile household asset profiles are informative of the terminal utility parameters ψ_v and k_v and the minimum household consumption floor $\underline{c}_{agg}$ as these parameters govern the household's wealth holdings over the life-cycle (moments #5 to #19 of Figures A.8 and A.9). Some of the employment moments of severely disabled husbands are also informative of k_v since the lower k_v is, husbands with low average lifetime earnings (y_t) will be more incentivized to work and increase their y_t as household assets and y_t both affect the surviving spouse j's wealth upon household dissolution ($W^j_t = W^j_t(a^j_t, y_t)$).

Parameters related to the husband's care needs ($\mu_\eta(s^h), \rho_\eta(s^h), \sigma_{\xi,s^h}$) are pinned down by matching data moments regarding wives' caregiving choices (moments #39 to #46 of Figure A.8). Specifically, the fraction of husbands receiving spousal care (moments #39 and #40) are informative of the average care need $\mu_\eta(s^h)$ while moments regarding the persistence in wives' caregiving choices (moments #43 to #46) are informative of $\rho(s^h)$. For households with severely disabled husbands, σ_{ξ,s^h} affects the fraction of part- and full-time caregivers since wives will more likely choose full-time caregiving when their husbands receive a higher idiosyncratic shock in care needs (moment #42 of Figure A.8).

Since $\underline{c}_{fc}$ is the consumption floor for households who receive government transfers while incurring formal care expenses, this parameter is recovered by matching the fraction of severely disabled husbands who hire Medicaid-covered paid helpers in the data (moment #49 of Figure A.9). The wage parameters governing equations (8) and (9) are primarily recovered by matching the fixed effect regression coefficients of log hourly wages for each spouse (moments #50 to #58 of Figures A.9 and A.10). For parameters that govern the variance and covariance of the permanent and transitory wage shocks (equations (10) and (11)), the wage moments specified in Appendix H (moments #59 to #64 of Figure A.10) have the highest sensitivity values.

5 Results

5.1 Parameter Estimates: Baseline vs. "No-care" Model

In addition to the baseline model specified in Section 3, I re-estimate the model where husbands' care needs $\eta_t(s^h)$ are set to zero in all health states (referred as the "no-care" model). Under the "no-care" specification, not only does the household never purchase paid helpers, the wife never provides care and only allocates her time between leisure and market hours. The goal of this exercise is to highlight how the estimates of key preference parameters differ when we do not take into account that disability shocks additionally entail care needs and increase the household's demand for spousal and/or market-purchased care. The corresponding parameter estimates are reported in Tables 7 and A.14. When I estimate the "no-care" model, I use the same moments as described in Section 4.3 except for the moments that involve wives' caregiving choices and households' formal care choices.

One of the key preference parameters that has significant implications for evaluating the welfare benefits of SSDI is the health state dependence in household consumption utility, $\theta(s^h)$. This is because ideally, transfers should be made from the healthy state (in the form of taxes) to the disabled state (in the form of disability benefits) such that the marginal utilities of consumption in both states are equal. For the moderately disabled state, both the baseline and "no-care" model estimates indicate that the marginal utility of consumption is slightly higher (8–10%) than in the healthy state. However, $\theta(2)$ is significantly lower under the "no-care" model as the baseline model suggests that the marginal utility of consumption in the severely disabled state is 46% higher than in the healthy state whereas the "no-care" model indicates that it is only 9% higher.

The sizable difference in $\theta(2)$ between the two models aligns with the sensitivity analysis in Section 4.3 that spousal labor supply responses to husbands' disability are highly informative of $\theta(s^h)$. By omitting the fact that wives of severely disabled husbands spend a significant amount of time in caregiving, the "no-care" model incorrectly interprets the small spousal labor supply responses as households' valuation of consumption in the severely disabled states being lower than it actually is.[32] Furthermore, the estimates of $\theta(1)$ do not differ significantly between the two models as caregiving hours for moderately disabled husbands are modest compared to the amount of care provided to severely disabled husbands.

[32] Based on the first order conditions described in footnote 31, the equation $\theta(s^h) \cdot c^{-\gamma} = \frac{\psi_w \cdot (\bar{L} - h_w - tc)^{-\gamma_w}}{w_w}$ indicates that $tc > 0$ reduces the time endowment that can be allocated to leisure and therefore, increases the marginal disutility of h_w in the disabled states. This implies that for a given level of h_w, $\theta(2)$ has to be lower under the "no-care" model ($tc = 0$) for the equation to hold.

Table 7: Second Stage Estimates of the Model Parameters I

	(a) Baseline	(b) "No-care"†
Health state dependence in consumption utility		
$\theta(1)$	1.083 (0.028)	1.099 (0.075)
$\theta(2)$	1.461 (0.066)	1.093 (0.058)
Production function of the domestic good		
α_κ Weight on wives' time	0.561 (0.034)	-
γ_κ Substitution parameter	0.418 (0.013)	-
Husbands' wage offer function		
Moderate disability	-0.115 (0.024)	-0.116 (0.023)
Severe disability	-0.225 (0.030)	-0.216 (0.044)
Wives' wage offer function		
Disabled	-0.075 (0.023)	-0.073 (0.021)
Minimum consumption floor ($2015)		
$\underline{c}_{agg}$	32,208 (1,711)	33,459 (1,327)
$\underline{c}_{fc}$	26,555 (2,597)	-
Husbands' leisure time costs (in hours), [as a fraction of $\bar{L} = 5,840$]		
$\phi^h(1)$, $\phi^h(2)$	2220, 2265 [0.38, 0.39] (136.4), (152.5)	2366, 2266 [0.41, 0.39] (234.6), (109.6)
$\phi^h_{emp}(1)$, $\phi^h_{emp}(2)$	175.4, 450.0 [0.03, 0.08] (62.33), (72.67)	178.0, 450.0 [0.03, 0.08] (64.26), (87.01)
$\phi^h_{emp,\eta}(1)$, $\phi^h_{emp,\eta}(2)$	70.8, 164.2 [0.01, 0.03] (32.10), (33.10)	-
Wives' leisure time costs (in hours), [as a fraction of $\bar{L} = 5,840$]		
$\phi^w(1)$	2,622 [0.45] (121.9)	2,698 [0.46] (104.5)
$\phi^w_{emp}(1)$	212.8 [0.04] (80.38)	196.7 [0.03] (43.35)
Remaining parameters	Table A.14	

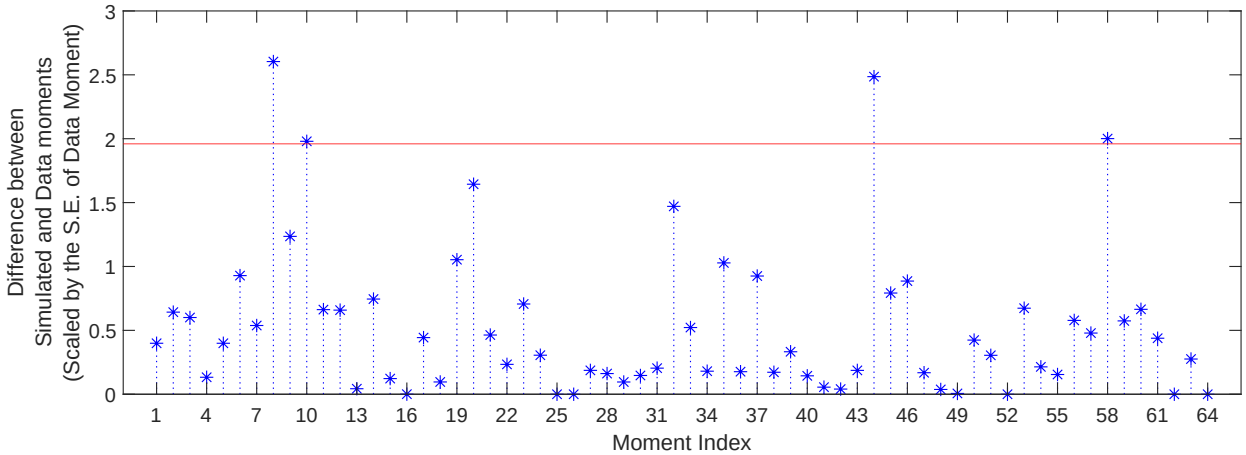
Notes: Standard errors are in parentheses. Refer to Appendix G.3 on how standard errors are computed.
† Parameter estimates when the model abstracts from husbands' care needs (i.e., $\eta_t(s^h)$ is always zero such that time inputs to care (both in the form of wives' time and paid helpers) are always zero and wives allocate their time to leisure and market work only).

Based on the parameter estimates of the production function of the domestic good, spousal care and formal care are substitutes ($0 < \gamma_\kappa < 1$). This is in line with findings from previous works such as Van Houtven and Norton (2004), Charles and Sevak (2005), and Coe et al. (2015). Under the baseline model, husbands' offered hourly wages are reduced by 11.5% and 22.5% when they are moderately and severely disabled, respectively. These magnitudes are somewhat larger than those estimated by Low and Pistaferri (2015) (5.7% and 17.7% for moderately and severely disabled men) who use a sample of men aged 23 to 62 in the PSID. Disability reduces wives' offered hourly wage by 7.5% under the baseline, which is smaller in magnitude than that of husbands. Lastly, a brief discussion of some of the remaining parameters can be found in Appendix G.4.

5.2 Model Fit

Table 8 reports the model fit of select targeted moments while the model fit of remaining targeted moments are reported in Tables A.15 to A.17. Figure 4 summarizes the model fit by reporting the absolute difference between the simulated and data moments, scaled by the standard error of each data moment. Overall, the model generates a good fit as most of the simulated moments are within one standard error of the data moments.

Figure 4: Summary of Model Fit



Notes: This figure reports the absolute difference between simulated and data moments, scaled by the standard error of each data moment. The moment indices #1 to #64 correspond to those in Tables 8, A.15, A.16, and A.17. The red line goes through 1.96.

Table 8: Model Fit of Select Targeted Moments

	Model	Data	Model	Data
Panel A: Changes in Wives' Labor Supply by Husbands' Disability†				
	Wives' Employment Rate		Wive's Weekly Hours (in hours)	
Moderate	-0.010	-0.015 [#1] (0.013)	-0.264	0.025 [#3] (0.481)
Severe	-0.005	-0.017 [#2] (0.019)	-0.356	-0.268 [#4] (0.662)
Panel B: Median Household Assets (by husbands' age and health, in $1,000)				
	All		Healthy	
Ages 50 - 54	233.36	237.70 [#5] (10.88)	254.47	261.52 [#11] (10.65)
Ages 55 - 59	281.45	289.05 [#6] (8.184)	313.33	320.38 [#12] (10.71)
Ages 60 - 64	330.39	325.52 [#7] (9.052)	371.43	370.94 [#13] (11.35)
	Moderate		Severe	
Ages 50 - 54	190.90	173.43 [#14] (23.45)	109.97	100.33 [#17] (21.74)
Ages 55 - 59	213.12	210.80 [#15] (18.94)	117.19	119.19 [#18] (20.81)
Ages 60 - 64	241.11	241.10 [#16] (15.04)	153.82	137.02 [#19] (15.95)
Panel C: Fraction of Wives Providing Care (by husbands' health)				
	Moderate		Severe	
All	0.191	0.203 [#39] (0.036)	0.542	0.538 [#40] (0.028)
Part-time	0.191	0.189 [#41] (0.036)	0.423	0.422 [#42] (0.025)
Panel D: Formal Care Usage Among Severely Disabled Husbands (in %)				
Use formal care			0.214	0.264 [#47] (0.297)
Use both spousal and formal care			0.119	0.109 [#48] (0.266)
Use formal care covered by Medicaid			0.042	0.041 [#49] (0.160)

Notes: Standard errors are in parentheses. The numbers in brackets are moment indices that correspond to Figures 2, 3, and A.7 to A.10. All moments are conditional on both spouses being younger than 65. Dollar values are in 2015 dollars. The remaining moments are in Tables A.15 to A.17.
† Based on fixed effect regressions of labor supply variables on indicators of husbands' disability severity, a quadratic in both spouses' ages, a dummy for wives' disability, and household fixed effects. The reported moments are the regression coefficients for the indicators of husbands' disability severity.

5.2.1 Robustness: Untargeted Moments

As robustness, I verify whether the baseline model can generate data patterns that were not targeted in the estimation procedure. First, I simulate median asset profiles by husbands' education and health status using the baseline model and report the model fit in Table A.18. Although these moments were not matched in the estimation procedure, Table A.18 shows that the model can produce a reasonable fit.

Next, Figure A.11 confirms that the baseline model can reproduce the event study results in Figure 1. The only exception is the increase in wives' labor supply responses one or two years before their husbands' job displacement. As described in Section 2.2, this increase is likely due to households' private information on the likelihood of a future job loss. Since this feature is not present in the dynamic model, the simulated data cannot match this pattern.

In addition, I compare the model fit of household consumption responses to husbands' disability and show the results in Figure A.12. Data moments are generated by running fixed effect event study regressions using household expenditure data in the HRS CAMS. While the HRS CAMS contains comprehensive information on household expenditures, the confidence intervals on the estimates from the HRS CAMS are unfortunately wide due to the sample size being substantially smaller than the Core survey. Despite these limitations, the point estimates indicate that the simulated data and the HRS CAMS follow similar patterns.

Given that γ_h and γ_w are calibrated parameters, I also examine the labor supply elasticities that the model generates. Assuming certainty and interior conditions, γ_h and γ_w govern the Frisch labor supply elasticities of the husband and wife. However, in the model, labor market hours are discretized into three choices (not working, working part-time, and working full-time) so interior conditions do not always hold. Therefore, I measure labor supply elasticities for husbands and wives respectively by introducing a 20% increase in simulated wages at the beginning of the simulation period and computing the change in total hours worked in that period. This labor supply elasticity will be smaller than the Frisch labor supply elasticity due to wealth effects. The resulting labor supply elasticities are 0.11 (husbands) and 0.27 (wives), which is within the range labor supply elasticities reported by previous studies (Keane, 2011; Chetty et al., 2011; Chetty, 2012; Blundell et al., 2016).

Finally, I examine whether the model can replicate the SSDI application rates among severely disabled husbands given that $\iota(2)$ is calibrated to zero. The model generates a rate of 12.2%, which is slightly lower than the value observed in the data (14.3%).

Table 9: Simulated Added-Worker Effects Using Baseline Model Estimates

Changes in Wives' Weekly Hours Worked [as percentage of pre-onset mean]	(1) Baseline care needs	(2) No care needs† ($\eta_t(s^h) = 0$)
Panel A: Husbands' Disability Onset		
Post × Severe	0.118 [0.47%]	1.546 [5.89%]
Post × Non-severe	0.012 [0.05%]	0.167 [0.64%]
Pre-onset mean (hours)	25.25	26.24
Panel B: Husbands' Job Displacement Onset		
Post	2.21 [9.06%]	2.30 [9.02%]
Pre-onset mean (hours)	24.39	25.49

Notes: This table reports results from fixed effect regressions of wives' weekly working hours using model simulated data. "Post" is an indicator for whether it is within two years after the onset of the husband's event. "Severe" indicates whether the husband's disability is severe or not. Changes in wives' weekly working hours as a percentage of the pre-onset mean are reported in brackets. All regressions control for a quadratic in both spouses' ages, a dummy for the wife's disability status, and household fixed effects.
† Column (2) reports simulated added-worker effects using baseline model estimates but when care needs $\eta_t(s^h)$ are always zero such that the household never allocates resources towards husbands' care (both spousal care and formal care).

5.3 Simulated Added-Worker-Effects When Spousal Care Needs Are Removed

Building on parameter estimates that generate good model fit, I use the model to quantify the extent to which spousal labor supply responses to husbands' disability shocks are attenuated due to husbands' care needs. To do so, I estimate simulated added-worker effects using the baseline model estimates (column (a) of Tables 7 and A.14) while assuming that $\eta_t(s^h)$ is always zero. Under this scenario, the need for spousal care or formal care is completely removed such that households never allocate resources to their husbands' care. I measure simulated added-worker effects by running fixed effect regressions of wives' weekly working hours on an indicator for whether it is within two years after the onset of their husbands' event ("Post"). All regressions control for a quadratic in both spouses' ages, a dummy for the wife's disability status, and household fixed effects.

The results are reported in Table 9. As a benchmark, column (1) reports simulated added-worker effects under baseline care needs and corroborates that spousal labor supply responses to husbands' disability are small when wives spend time in caregiving. In contrast, column

(2) shows that removing spousal care needs increases added-worker effects when husbands become severely disabled. Specifically, wives of severely disabled husbands increase their weekly working hours by 1.5 hours, which is equivalent to a 5.9% increase. This magnitude is comparable to wives' labor supply responses to their husbands' death reported by Fadlon and Nielsen (2021) where the authors found that women increased their labor force participation by 7.6% and annual earnings by 6.8% after their husbands' death. These findings imply that husbands' care needs play a sizable role in attenuating wives' labor supply responses.

Panel B of Table 9 reports simulated added-worker effects in response to the husband's job displacement. Columns (1) and (2) indicate that wives increase their weekly working hours by 9% under both scenarios and therefore, removing husbands' care needs has little impact on spousal labor supply responses to husbands' job displacement.

5.4 Evaluating the Welfare Benefits of SSDI Policies

In this section, I use the estimated model to analyze the welfare benefits of current and counterfactual SSDI policies relative to their costs. One caveat when interpreting the results in this section is that these counterfactual exercises are partial equilibrium analyses. Therefore, neither general equilibrium effects nor potential costs or benefits that occur during the earlier periods of the life cycle are accounted for.

First, the ex-ante insurance value of SSDI is calculated using a compensating variation measure, x. I define x as the lump sum amount of asset that needs to be given at the start (i.e., age 50) under the counterfactual economy where SSDI does not exist such that the expected utilities under the baseline world with SSDI and the counterfactual world with no SSDI are equal. Therefore, x is the monetary value that each household places on the insurance value of SSDI. This can be formally expressed as

$$V_{50}(A_t, \mathbf{\Theta}_t|\text{economy with SSDI}) = V_{50}(A_t + x, \mathbf{\Theta}_t|\text{economy with no SSDI}) \tag{18}$$

where $\mathbf{\Theta}_t$ denotes the vector of state variables excluding assets (A_t).

I calculate x for each simulated household of ages 50 to 54 in my initial sample and divide the average compensating variation by the average present discounted value of SSDI benefits to get a measure of how much a dollar of SSDI benefits is valued ex-ante. This exercise is done using the baseline model as well as the "no-care" model that sets husbands' care needs to zero (using corresponding parameter estimates reported in column (b) of Tables 7 and A.14). The goal of this exercise is to quantify the difference in the ex-ante insurance value

of SSDI that each model predicts. These results are reported in Table 10.

Row (2) of Table 10 reports that under the baseline model, households value each dollar of SSDI benefits as $1.04. This implies that given the degree of moral hazard in the model, the welfare benefits (i.e., ex-ante insurance value) of SSDI are higher than its costs under the baseline model. In contrast, the "no-care" model predicts the insurance value of SSDI as 99 cents per each dollar of SSDI benefit payments. This implies that SSDI benefits for married households need to be higher when we take into account that the insurance role of spousal labor supply is reduced due to time spent in caregiving. In terms of magnitudes, SSDI benefits need to be 4.7% higher in order to equate the insurance value of SSDI to the value predicted by the "no-care" model (row (3) of Table 10). Note that an increase in benefits will decrease the insurance value of SSDI relative to its costs as it increases work disincentives for both husbands and wives.

Table 10: Ex-ante Insurance Value of SSDI for Married Households

	Model	
	Baseline	"No-care"*
Health state dependence estimates $(\theta(1), \theta(2))$	(1.08, 1.46)	(1.10, 1.09)
(1) Ex-ante insurance value of SSDI (in $)†		
Mean	5,244	4,991
Median	3,833	3,613
25th percentile	2,107	1,938
75th percentile	6,897	6,600
(2) Ex-ante insurance value of SSDI per dollar of SSDI benefits (in $)‡	1.04	0.99
Difference from "no-care" model	0.05 (0.009)	-
(3) Required % change in SSDI benefits such that (2) equals 0.99	+4.7%	-

Notes: This table reports the ex-ante insurance value of SSDI for married households first observed between ages 50 to 54. Nominal dollar amounts are in 2015 dollars. Bootstrap standard errors are in parentheses.
* An alternative model specification that ignores husbands' care needs (i.e, $\eta_t(s^h)$ is always zero) such that the household never allocates resources to wives' caregiving time or purchasing paid helpers. The corresponding parameter estimates reported in column (b) of Table 7 are used.
† For each simulated household, the ex-ante insurance value is measured as the lump sum amount of asset that should be given upon entering the counterfactual economy where SSDI does not exist such that the expected utilities at the beginning of the model under the economies with and without SSDI are equal. Refer to equation (18) for a formal definition.
‡ Computed as the average ex-ante insurance value over the average present discounted value of SSDI benefits.

Next, I consider two types of government-budget-neutral policy reforms that reduces SSDI benefits but provides additional transfers that subsidize care. The goal of this exercise is to analyze whether these types of policy reforms can improve utilitarian social welfare and to quantify their magnitude in doing so. The first type of reform provides a flat amount of annual caregiving benefits b_{care} to eligible SSDI beneficiaries while the second type provides SSDI beneficiaries with in-kind transfers that fully cover the cost of paid helpers up to full-time hours. Both of these types of transfers are common features of social disability insurance programs in many OECD countries but are not available under the current SSDI program.

For the first reform policy ("Policy (1)" from hereafter), I consider a hypothetical policy where SSDI beneficiaries receive an annual amount of b_{care} when their care needs $\eta_t(s^h)$ are greater than some threshold z and when they receive full-time care from their spouses.[33] In my data sample, about 5% of severely disabled men are completely unable to perform one or more ADLs. Since this subgroup would require a higher level of care and is more easily identifiable as being "severely disabled," I set z such that 5% of severely disabled husbands are eligible for this caregiving benefit. For the second type of policy reform, I consider two cases: "Policy (2-1)" in which in-kind transfers for formal care are available to SSDI beneficiaries who are in the top 5% of the care needs distribution (similar eligibility criterion as Policy (1)) and "Policy (2-2)" where in-kind transfers are provided to all SSDI beneficiaries regardless of their care needs. The results are shown in Table 11.

Table 11 shows that Policy (2-1), which reduces benefits by 14.57% for everyone but fully covers the cost of formal care for eligible beneficiaries, provides the largest increase in welfare while maintaining the same government budget as the baseline policy. On average, Policy (2-1) increases the welfare benefits of SSDI by 3.1% ($\frac{\$5,405}{\$5,244} \approx 1.031$) and the welfare gain is larger among low-income couples (a 12.4% increase for couples in the first (bottom) income quintile and a 8.6% increase for couples in the second income quintile).

Reducing benefits for everyone by 0.64% but providing annual caregiver benefits of $5,666 for eligible SSDI beneficiaries (Policy (1)) also improves utilitarian social welfare given the same government budget but the increase is extremely small. This finding can be explained by the fact that 1) Policy (1) requires wives to provide full-time spousal care to be eligible

[33] In reality, monitoring the spouse's caregiving hours may be challenging, and this could be one reason why many states have consumer-directed Medicaid programs that allow participants to hire their friends or relatives as paid caregivers but not their spouses. Despite these challenges, as of 2021, 19 states allow spouses to become paid caregivers through their state Medicaid programs and employ a variety of methods to monitor fraud and abuse (Teshale et al., 2021; American Council on Aging, 2022). When interpreting the counterfactual results, it must be noted that administration and monitoring costs are not included.

Table 11: Counterfactual Budget-Neutral Policy Reforms

- Baseline: Current SSDI policy
- Government budget-neutral reform that maximizes social welfare*

(1) Caregiver benefits: Reduce SSDI benefits by 0.64% but provide annual caregiver benefits of $5,666 to eligible SSDI beneficiaries†

(2-1) In-kind transfers: Reduce SSDI benefits by 14.57% but fully cover the cost of paid helpers for eligible SSDI beneficiaries‡

(2-2) In-kind transfers: Reduce SSDI benefits by 42.79% but fully cover the cost of paid helpers for all SSDI beneficiaries

	Ex-ante Insurance Value of SSDI Policy¶			
	Baseline	Policy (1)	Policy (2-1)	Policy (2-2)
Mean	$5,244	$5,252	$5,405	$3,326
By income quintiles§				
Q1 (bottom)	$2,895	$2,913	$3,253	$2,448
Q2	$4,269	$4,285	$4,634	$3,007
Q3	$5,384	$5,395	$5,638	$3,399
Q4	$6,991	$7,000	$7,117	$4,187
Q5 (top)	$7,902	$7,895	$7,779	$4,293

* A utilitarian social welfare function is assumed.

† For Policy (1), I assume that SSDI beneficiaries can receive supplemental caregiver benefits if a) husbands are in the top 5% of the distribution of care needs and b) their wives provide full-time spousal care.

‡ Similar to Policy (1), I assume that SSDI beneficiaries are eligible for the in-kind transfer if the husband is within the top 5% of the care needs distribution.

¶ For each simulated household, the ex-ante insurance value is measured as the lump sum amount of asset that should be given upon entering the counterfactual economy where SSDI does not exist such that the expected utilities at the beginning of the model under the economies with and without SSDI are equal (refer to equation (18) for a formal definition). Each cell reports simple averages within each group.

§ Income quintiles are based on husbands' average lifetime earnings at age 50 (measured using their Social Security earnings histories).

for caregiver benefits (and therefore, wives will have to forgo earnings), and 2) given the baseline model estimates, spousal care and formal care are substitutes ($\gamma_\kappa = 0.418$) and the weight on formal care hours ($1 - \alpha_\kappa = 0.439$) for the production function of the domestic good is non-negligible.

Finally, providing in-kind transfers that fully cover formal care costs for all beneficiaries requires SSDI benefits to be reduced by 42.79% in order to maintain budget neutrality (Policy (2-2)). Although providing in-kind transfers for formal care expenses would increase wives' labor supply responses to their husbands' disability, this reform lowers welfare compared to the baseline policy due to its large reduction in benefits.

While the dynamic model does not incorporate Medicare benefits provided to SSDI beneficiaries, I perform a "back-of-the-envelope" counterfactual exercise as a robustness check for the welfare analyses described above. I do this by assuming that SSDI beneficiaries are immediately eligible for an annual Medicare benefit of $13,098 (Cubanski et al., 2016) and re-do the counterfactual exercises shown in Tables 10 and 11. Note that this exercise does not account for the the two-year waiting period for Medicare benefits.

With additional Medicare benefits, the average ex-ante insurance value of SSDI under the baseline model is $7,745 whereas it is $7,349 under the "no-care" model. This is a 5.4% difference ($\frac{\$7,745}{\$7,349} \approx 1.054$), which is similar to the difference reported in Table 10 ($\frac{\$5,244}{\$4,991} \approx 1.051$). Furthermore, the baseline model with Medicare benefits also predicts that given the same government budget, providing in-kind transfers for formal care expenses to eligible beneficiaries generates larger welfare gains while the welfare gains from providing caregiver benefits for eligible beneficiaries is small.

Tables 10 and 11 point toward a couple of important conclusions. First, Table 10 shows that the consumption smoothing benefits of SSDI relative to the government expenditures on benefits increase to a sizable extent when we take into account that the insurance role of wives' labor supply is reduced due to time allocated to spousal care. Furthermore, Tables 10 and 11 imply that utilitarian social welfare can be improved given the same government budget level by targeting resources to disabled beneficiaries with greater care needs (particularly in the form of in-kind transfers that cover the cost of hiring paid caregivers).

6 Conclusion

This paper provides empirical evidence that spousal care plays an important role in understanding married women's labor supply responses to their husbands' disability and evaluating

the welfare benefits of current and counterfactual SSDI policies. The key results of this paper can be summarized as follows. First, while spousal labor supply responses to husbands' disability are small, there is a significant increase in wives' time spent in spousal care. Second, the insurance value of SSDI relative to its costs is underestimated when we do not consider the fact that caregiving needs substantially reduce the insurance role of spousal labor supply. Lastly, counterfactual policy experiments indicate that for the same government budget level, it is possible to improve utilitarian social welfare by reducing overall SSDI benefit levels but subsidizing care for eligible SSDI beneficiaries, especially in the form of in-kind transfers that cover formal care expenses.

When interpreting these results, a couple of caveats should be noted. First, this paper's findings are based on the analysis of married households and the disability shock of the husband. Although this paper's findings still apply to a large fraction of the population that SSDI covers, they may not be generalizable to disabled singles since singles cannot rely on spousal earnings or spousal care and this may affect the welfare benefits of SSDI for single households. In addition, spousal responses (in terms of labor supply, caregiving, and marital stability) and their implications for the welfare analysis of SSDI policies may differ in the event of wives' disability. Finally, this paper is based on a sample of relatively older households (mostly focusing on respondents aged 50 to 64). Although this is the primary age group of SSDI beneficiaries, the results from this paper may differ when considering younger households. For example, younger couples may face a higher probability of divorce in the event of a disability and the time out of the labor force due to caregiving can be more costly since human capital accumulation occurs at a faster rate during the earlier years of one's working life. Accounting for further heterogeneity in household structure and enriching this paper's model accordingly are important directions for future work.

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Appendix

A Supplementary Event Study Analyses

Table A.1 reports the point estimates and standard errors for Figure 1.

Table A.1: Changes in Household Outcomes by Husbands' Event Onset Years

	H's Disability				H's Job Displacement	
	(1) H's Weekly Hours Worked	(2) W's Weekly Hours Worked	(3) W's Weekly Care (Core)†	(4) W's Weekly Care (CAMS)‡	(5) H's Weekly Hours Worked	(6) W's Weekly Hours Worked
Year = -4, -3	-0.675	0.321	-0.210	-	-0.613	0.124
	(0.801)	(0.691)	(0.461)		(1.008)	(0.831)
Year = -2, -1	-2.856***	-0.407	0.032	0.845	0.024	1.781*
	(0.996)	(0.878)	(0.423)	(0.645)	(1.085)	(0.964)
Year = 0, 1	-14.34***	-0.706	2.213***	1.930**	-13.63***	2.604**
	(1.165)	(0.959)	(0.830)	(0.857)	(1.337)	(1.063)
Year = 2, 3	-14.60***	-0.697	3.823***	1.806**	-12.73***	3.271***
	(1.275)	(1.052)	(1.216)	(0.868)	(1.497)	(1.151)
Year = 4, 5	-13.67***	-1.845	2.138***	-	-11.55***	3.394***
	(1.402)	(1.238)	(0.901)		(1.689)	(1.297)
R-sq.	0.235	0.108	0.016	0.069	0.154	0.109
Observations	24,069	23,424	11,540	1,595	20,645	26,590

Notes: This table reports results from fixed effect event study regressions using a sample of married households in the HRS (1992-2014) where both spouses are under age 65. All specifications control for a quartic in both spouses' ages, dummies for each spouse indicating whether their age is 62 or above, household size, length of current marriage, census division, and year and household fixed effects. Columns (2) to (4) and column (6) additionally control for wives' disability severity. Standard errors are in parentheses, clustered at the household level. ***, **, * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

† Measure of spousal care in the HRS Core (2000-2014): time spent helping the husband perform (Instrumental) Activities of Daily Living (ADL/IADLs).

‡ Measure of spousal care in the HRS CAMS (2007-2015): time spent treating or managing the husband's medical condition(s). Since the CAMS data have a smaller sample size and shorter survey waves, column (4) reports changes in weekly caregiving hours up to 3 years post-onset relative to 3 or more years before the husband's disability.

Figures A.1a and A.1b report the percentage change in husbands' (wives') earnings by husbands' event onset years. To estimate the percentage change in earnings, I follow Meyer and Mok (2019) and estimate a Poisson fixed effect regression model specified as

$$y_{it} = \exp\Big(\alpha_i + \gamma_t + X'_{it}\beta + \sum_{k=-4}^{5} \delta_k \cdot I_{itk}\Big) + \epsilon_{it}. \tag{19}$$

Compared to using the log-linear specification (i.e., using $\log(y_{it})$ as the dependent variable), the Poisson specification allows the inclusion of observations with zero earnings. This is an attractive feature given that a sizable fraction of disabled individuals do not work. The estimated percentage change is computed as $\exp(\delta_k) - 1$. The data patterns reported in Figures A.1a and A.1b are similar to those in Figure 1. While husbands' disability and job displacement are associated with large and persistent decreases in earnings, wives only increases their earnings in response to their husbands' job displacement.

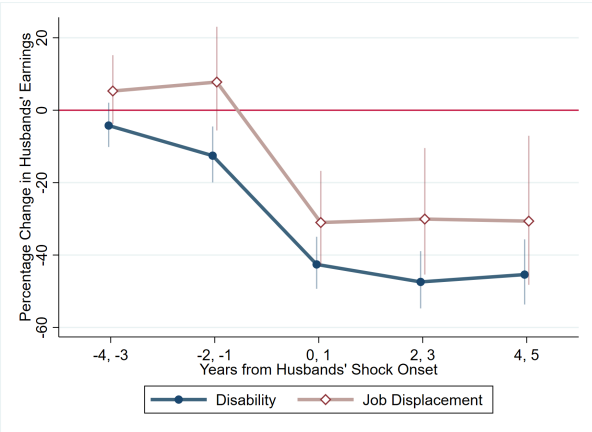
Figures A.1c and A.1d report the husband and wife's SSDI application and award by the husband's disability onset years. Both figures are based on estimating the fixed effect event study specification shown in equation (1). For Figure A.1c, the dependent variable is an indicator for whether the husband (wife) filed an SSDI application in year t. Similarly, the dependent variable in Figure A.1d is an indicator for whether the husband (wife) was awarded SSDI benefits in year t. To construct the dependent variables, I use administrative Social Security data (Form 831 Disability Records) with detailed information on the year and month of the respondent's SSDI application, whether SSDI benefits were awarded or not, and the year and month the benefit was awarded.[34]

Figure A.1c indicates that the husband's SSDI application occurs within three years of his disability onset. Application rates increase by 11.4 p.p. within one year of onset, 3.3 p.p. in the second and third year of onset, and falls to zero by the fourth and fifth year of onset. Furthermore, the wife's SSDI application is not correlated with her husband's SSDI application. Similar patterns are observed for SSDI awards (Figure A.1d) where the husband's probability of a SSDI award increases by 7.1 p.p. within one year of onset and by 4.0 p.p. in the second and third year of onset. Again, the timing of the wife's SSDI award is not correlated with the timing of her husband's SSDI award.

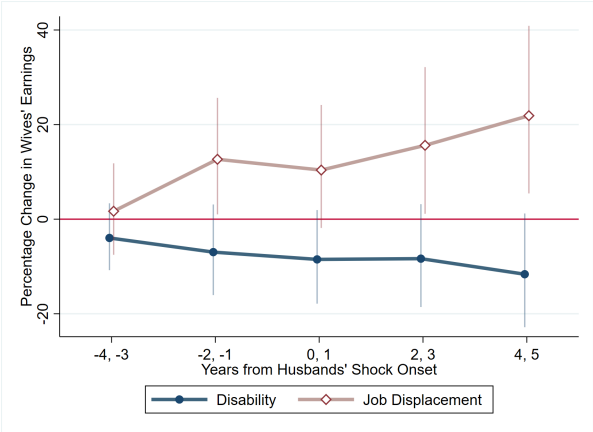
[34] Another benefit of using administrative Social Security data is that I can identify whether the SSDI benefit is based on the respondent's own earnings history or whether it is a spousal benefit based on the spouse's earnings history. This feature is especially relevant when examining the wife's SSDI receipt since females are more likely to receive spousal benefits. For Figure A.1d, the dependent variable is equal to one only when the SSDI award is based on the respondent's own earnings history.

Figure A.1: Changes in Household Outcomes by Husbands' Onset Years II

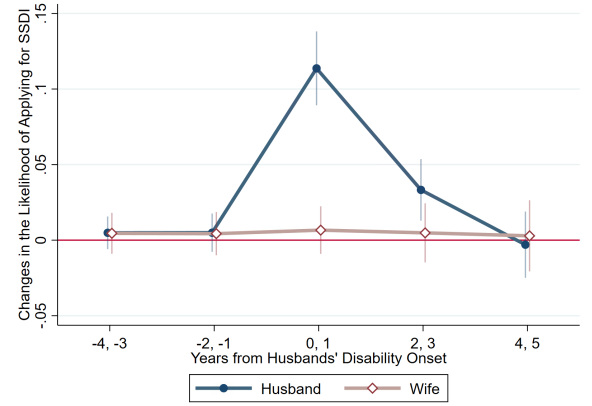
(a) Husbands' Earnings



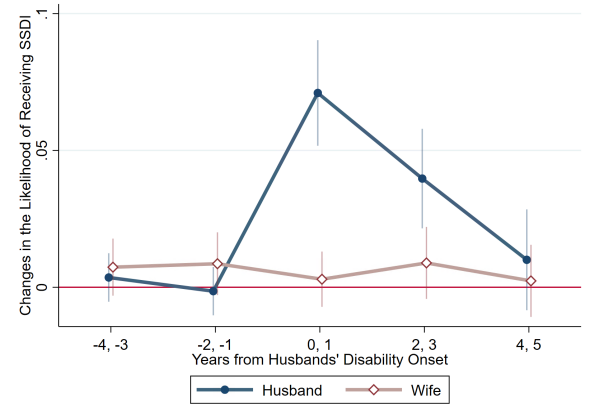
(b) Wives's Earnings



(c) SSDI Applications



(d) SSDI Awards



Notes: Results are based on a sample of married households in the HRS Core survey (1992-2014) where both spouses are under age 65. All event study regressions control for a quartic in both spouses' ages, dummies for each spouse indicating whether their age is 62 or above, household size, length of current marriage, census division, and year and household fixed effects. Subfigure (b) additionally controls for wives' disability status. The vertical lines through each dot indicate 95% confidence intervals.

B Robustness of Spousal Responses to Husbands' Disability and Job Displacement

This section provides additional analyses regarding wives' labor supply and caregiving responses to their husbands' disability or job displacement. Table A.2 reports the effect of husbands' disability onset on their wives' weekly working hours where all event study regressions are based on equation (1) but with additional control variables. Column (1) reports the baseline result that is documented in Figure 1b for comparison.

SSDI or SSI receipt – Column (2) additionally controls for whether a household is receiving SSDI benefits or Supplemental Security Income (SSI). The coefficients in column (2) imply that indeed wives with husbands who receive disability benefits are more likely to reduce working hours but the estimates are statistically insignificant. Moreover, spousal labor supply responses are still small and statistically insignificant even after controlling for disability benefit receipt. Therefore, the small spousal labor supply responses shown in Figure 1b do not seem to be driven by households whose husbands are receiving SSDI or SSI benefits.

Disabilities due to accidents versus non-accidents – Another concern is that highly expected disabilities would not elicit substantial spousal responses and these disabilities may be the reason why added worker effects in response to disability shocks are small. I explore this issue by distinguishing whether a disability is a result of an accident or not as disabilities caused by accidents are more likely to be regarded as an unexpected shock. Formally, the estimation model is

$$y_{it} = \alpha_i + \gamma_t + X'_{it}\beta + \sum_g \left(\sum_{k=-4}^{5} \delta_k^g \cdot I_{itk}^g \right) + \epsilon_{it} \tag{20}$$

where g indicates the disability group (whether the disability is due to an accident or not). Column (3) reports δ_k^g for both disability groups. Again, added worker effects are not observed for both groups. Although there exists heterogeneity in the degree in which disabilities are expected, this does not seem to be the main driving force given that households cannot perfectly predict the timing of disabilities.

Correlated health shocks between the two spouses – I also investigate the potential concern that the small spousal labor supply responses to husbands' disability may be driven by

Table A.2: The Effect of Husbands' Disability Onset on Wives' Weekly Hours Worked

	(1)	(2)	(3)		(4)
			Cause of disability		
			Non-Accident	Accident	
Year = -4, -3	0.321	0.332	0.601	-0.717	0.322
	(0.691)	(0.690)	(0.785)	(1.384)	(0.746)
Year = -2, -1	-0.407	-0.370	0.106	-2.001	-0.187
	(0.878)	(0.877)	(0.974)	(1.844)	(0.952)
Year = 0, 1	-0.706	-0.565	-0.640	-0.611	-0.559
	(0.959)	(0.957)	(1.057)	(1.940)	(1.017)
Year = 2, 3	-0.697	-0.440	-0.230	-1.279	0.0925
	(1.052)	(1.068)	(1.183)	(1.966)	(1.117)
Year = 4, 5	-1.845	-1.526	-1.309	-2.370	-1.424
	(1.238)	(1.267)	(1.372)	(2.380)	(1.330)
Receiving SSDI	-	-1.625	-1.644		-
		(1.479)	(1.485)		
Receiving SSI	-	-1.346	-1.390		-
		(2.630)	(2.639)		
Includes (Onset × Wives' disability)†	No	No	No		Yes
Observations	23,424	23,424	23,424		23,424
R-sq	0.108	0.108	0.109		0.109

Notes: This table reports results from fixed effect regressions of wives' weekly working hours on husbands' disability onset years. The estimation sample is restricted to married households where both spouses are under age 65 in the HRS Core survey (1992-2014). All event study regressions control for a quartic in both spouses' ages, dummies for each spouse indicating whether their age is 62 or above, wives' disability status, household size, length of current marriage, census division, and year and household fixed effects. Standard errors are in parentheses, clustered at the household level.

† This specification additionally includes interactions of the husband's disability onset dummies and the wife's disability status.

disability shocks being correlated between the two spouses. First, I perform an event study regression using a simpler version of equation (1) where the dependent variable is an indicator for whether it is the wife's disability onset year and X_{it} only includes a quadratic in both spouses' ages to account for life cycle effects. The point estimates of the onset year dummies are close to zero and all statistically insignificant. Combined with the findings shown in Figures A.1c and A.1d, these results indicate that there is little evidence of the timing of the disability shocks between the two spouses being correlated.

Second, I estimate the impact of the husband's disability onset on the wife's weekly working hours using the estimation model

$$y_{it} = \alpha_i + \gamma_t + X'_{it}\beta + \left(\sum_{k=-4}^{5} \delta_k \cdot I_{itk} + \sum_{k=-4}^{5} \delta_k^d \cdot I_{itk} \cdot I_{itk}^d \right) + \epsilon_{it} \tag{21}$$

where I_{itk}^d is an indicator for whether the wife is disabled at t and X_{it} is the full set of controls (including a dummy for the wife's disability status) as described in Section 2.2. The interaction terms $I_{itk} \cdot I_{itk}^d$ are added to account for potential heterogeneity in spousal labor supply responses due to correlated health shocks. Column (4) of Table A.2 reports the δ_k's (i.e., the main effects) and indicates that added worker effects are still non-existent.

Matching "treated" and "control" households – In addition, I address the concern that households that experience a disability or job displacement ("treated households") might be significantly different from those that do not experience the event ("control households"). To do so, I create a matched sample where I match "treated households" to "control households" based on their first survey year, initial (i.e., first survey year) household assets, and both spouses' ages and educational attainment. I restrict matched households to be within 3 percentiles of initial household assets and within 5 years of age. For educational attainment, I create an indicator for whether a spouse has a bachelor's degree or higher and require an exact match. I match without replacements and allow a "treated household" to be matched to a maximum of three "control households" for the disability sample and eight "control households" for the job displacement sample.[35]

Table A.3 shows the event study regression results using the matched samples. I also report results from an alternative specification that controls for a smaller number of variables (namely, a quadratic in both spouses' ages and year and household fixed effects). Reassur-

[35]The matching ratio of three and eight are based on the ratio of "treated" and "control" households in my sample.

ingly, the estimated spousal responses to husbands' disability or job displacement are similar to those reported in Section 2.2. Furthermore, the estimated coefficients are largely unaffected by whether I use the full set of control variables or not.

Caregiving responses by wives' labor force attachment – Finally, one might be concerned that the increase in wives' time spent in spousal care and their small labor supply response to their husbands' disability is driven by those with weaker labor force attachment (and hence are less capable of increasing their working hours in response to their husbands' earnings shock). The results shown in Table A.4 address this concern by dividing households into two groups based on wives' labor force attachment and estimating equation (1) separately for each group. I proxy for wives' labor force attachment by computing their average lifetime earnings at age 45 based on their Social Security earnings history.

Columns (1) and (1') indicate that spousal labor supply responses to husbands' disability are small and statistically insignificant for both groups. Point estimates indicate that wives of with high labor force attachment decrease their working hours in response to their husbands' disability, although all of the estimates lack statistical significance. Columns (2), (3), (2'), and (3') confirm that sizable increases in time spent in spousal care are observed for both groups.

Table A.3: Wives' Labor Supply and Caregiving Responses to their Husbands' Event Onset (Matched Sample)

	Husbands' Disability				Husbands' Job Displacement	
	(1) Weekly working hours	(1') Weekly working hours	(2) Weekly hours of care	(2') Weekly hours of care	(3) Weekly working hours	(3') Weekly working hours
Year = -4, -3	0.844	0.821	-0.524	-0.547	0.068	0.207
	(0.860)	(0.861)	(0.766)	(0.763)	(0.957)	(0.954)
Year = -2, -1	-0.215	-0.203	-0.163	-0.253	1.887*	2.244**
	(1.041)	(1.041)	(0.646)	(0.628)	(1.082)	(1.097)
Year = 0, 1	-0.137	-0.174	2.231**	2.162*	2.514**	2.879**
	(1.114)	(1.107)	(1.134)	(1.135)	(1.211)	(1.230)
Year = 2, 3	-0.441	-0.445	3.642**	3.450**	2.325*	2.806**
	(1.261)	(1.257)	(1.622)	(1.624)	(1.304)	(1.325)
Year = 4, 5	-1.158	-1.325	2.485*	2.358*	3.007**	3.563**
	(1.477)	(1.476)	(1.266)	(1.240)	(1.494)	(1.512)
Full set of controls†	Yes	No	Yes	No	Yes	No
Observations	15,782	15,861	6,529	6,589	18,700	18,801
R-sq	0.045	0.039	0.021	0.011	0.052	0.042

Notes: This table reports results from event study regressions of wives' caregiving and weekly working hours on husbands' event onset years (either disability or job displacement) using the HRS Core survey (1992-2014). The estimation sample is created by matching households that experience the husband's event to those that don't. I match households based on their first survey year, household assets in their first survey year, and both spouses' ages and education. Refer to the main text in Appendix B for further details on the matching process. Caregiving is defined as the amount of time spent helping a spouse in performing ADL/IADLs. Following Abadie and Spiess (2022), standard errors are clustered at the level of the matched sets and are reported in parentheses. The asterisks * and ** indicate statistical significance at the 10 and 5 percent level, respectively.

† The full set of controls include a quartic in both spouses' ages, dummies for each spouse indicating whether their age is 62 or above, wives' disability status, household size, length of current marriage, census division, and year and household fixed effects. Columns (1'), (2'), and (3') are based on a smaller set of controls consisting of a quadratic in both spouses' ages and year and household fixed effects.

Table A.4: Wives' Labor Supply and Caregiving Responses to their Husbands' Disability, by Wives' Labor Force Attachment

	Wives' labor force attachment†					
	High			Low		
	(1) Weekly working hours	(2) Provides care (0/1)	(3) Weekly hours of care	(1') Weekly working hours	(2') Provides care (0/1)	(3') Weekly hours of care
Year = -4, -3	0.866	0.0112	0.091	0.490	0.002	-0.734
	(1.045)	(0.014)	(0.105)	(1.093)	(0.018)	(1.544)
Year = -2, -1	-0.750	0.005	0.090	0.727	0.034	0.520
	(1.373)	(0.020)	(0.222)	(1.387)	(0.025)	(1.321)
Year = 0, 1	-0.504	0.093***	1.028***	0.261	0.128***	2.569
	(1.450)	(0.033)	(0.349)	(1.508)	(0.035)	(2.509)
Year = 2, 3	-0.988	0.110***	1.606**	0.709	0.136***	7.263**
	(1.551)	(0.036)	(0.707)	(1.691)	(0.044)	(3.041)
Year = 4, 5	-2.435	0.097***	1.689**	-0.878	0.176***	1.315
	(1.825)	(0.037)	(0.787)	(2.126)	(0.058)	(2.714)
Observations	9,716	4,898	4,898	7,182	2,657	2,657
R-sq	0.140	0.037	0.047	0.096	0.044	0.090

Notes: This table reports results from fixed effect regressions of wives' caregiving and weekly working hours on husbands' disability onset years. The estimation sample is restricted to married households where both spouses are under age 65 in the HRS Core survey (2000-2014). Caregiving is defined as the amount of time spent in helping a spouse in performing ADL/IADLs. All event study regressions control for a quartic in both spouses' ages, dummies for each spouse indicating whether their age is 62 or above, wives' disability status, household size, length of current marriage, census division, and year and household fixed effects. Standard errors are in parentheses, clustered at the household level. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent level, respectively.

† As a proxy for wives' labor force attachment, households are divided into two groups based on wives' average lifetime earnings at age 45. The fixed effect regressions are run separately for each group. For each group, the average lifetime earnings at age 45 (in 2015 dollars) is $14,460 (high) and $2,256 (low). The total quarters of Social Security covered earnings at age 45 are 76.94 (high) and 23.27 (low).

C Social Security Benefit Computation

This section discusses how SSDI and Retirement benefits are computed in the dynamic programming model. Note that in reality, SSDI benefit calculation differs slightly from that of Retirement benefits as it allows up to five years of the lowest earnings (including zero earnings) to be excluded from the calculation of benefits. I abstract from modeling this

element since a) it requires tracking the five lowest earnings and thus greatly increases the state space, and b) the Retirement benefit formula provides a reasonable approximation of the SSDI benefit amount.

In the model, household retirement benefits are computed as the sum of both spouses' retirement benefits based on the husband's average lifetime earnings. In practice, wives can receive retirement benefits based on their own earnings records (primary benefit) as well as spousal benefits based on their (former) husbands' earnings (secondary benefit). This occurs when entitled spousal benefits are greater than primary benefits since secondary benefits are deducted \$1 to \$1 by primary benefits. For example, a widow may be entitled to \$700 in primary benefits but \$1,000 in spousal benefits based on her deceased husband's earnings. Then she can receive a total of \$1,000 (\$700 as primary benefits and \$300 as secondary benefits) as retirement benefits. Since husbands are the main earners in most married households in my data (roughly 85% in the HRS), wives' entitled spousal benefits are generally greater than their primary benefits. Modeling the wife's retirement benefits to be equivalent to entitled spousal benefits based on her husband's earnings history is a way to keep the model tractable while capturing the main features of the data that the Social Security benefit system generates.

To compute Social Security benefits (either SSDI or Retirement), I first approximate average lifetime earnings at age t_b as

$$y_{t_b} = \frac{\sum_{t=t_0}^{t_b} e_t^*}{35} \tag{22}$$

where t_b denotes the age that the husband first receives Social Security benefits and t_0 denotes the first year of earnings. e_t^* denotes period earnings subject to the maximum taxable earnings e^{max} and is expressed as

$$e_t^* = \min\{w_t^h h_t^h, e^{max}\}. \tag{23}$$

I set $e^{max} = \$118,500$ based on the Social Security maximum taxable earnings in 2015.

The husband's Average Indexed Monthly Earnings (AIME) is computed as

$$AIME(y_{t_b}) = \frac{y_{t_b}}{12} \tag{24}$$

where y_{t_b} denotes his average lifetime earnings (measured at age t_b). In reality, indexed nominal earnings are used when computing the AIME so that benefits reflect the general rise

in the standard of living that occurred during the worker's working lifetime. Since all dollar values in the model are in 2015 dollars, equation (24) provides a reasonable approximation of the AIME without the need to introduce a wage index for each calendar year.

Next, the Primary Insurance Amount (PIA) is computed using the AIME according to

$$\begin{aligned} PIA(y_{t_b}) &= 0.90 \times \min\{AIME(y_{t_b}), b_1\} \\ &\quad + 0.32 \times \min\Big\{\max\{AIME(y_{t_b}) - b_1, 0\}, b_2 - b_1\Big\} \\ &\quad + 0.15 \times \max\{AIME(y_{t_b}) - b_2, 0\} \end{aligned} \tag{25}$$

where b_1 and b_2 denote bend points that reflect the three progressive replacement factors (90%, 32%, and 15%) applied to the three brackets of AIME. I use $b_1 = \$826$ and $b_2 = \$4{,}980$ based on the policy parameters in 2015.

Since the model period is annual, disability benefits are computed as

$$b_t(y_{t_b}, DI_t = 1) = 12 \times PIA(y_{t_b}). \tag{26}$$

For retirement benefits, I use the fact that wives are eligible for 50% of their husbands' PIA and calculate annual household retirement benefits as

$$b_t(y_{t_b}, DI_t = 0) = 12 \times (1.5 \times PIA(y_{t_b})). \tag{27}$$

D Taxes

Household taxes $\tau_t = \tau(A_t, w_t^h h_t^h, w_t^w h_t^w, UI_t, b_t, I_t)$ are computed as the sum of payroll taxes of both spouses and federal income tax ($\tau_t = \tau_{P,t}^h + \tau_{P,t}^w + \tau_{F,t}$). State income taxes are not modeled due to wide variation in state tax codes.

Payroll tax – Payroll tax consists of Social Security and Medicare tax. Social Security tax is 6.2% of earnings capped at the maximum taxable earnings while the Medicare tax rate is 1.45% and earnings are uncapped. Therefore, each spouse's payroll tax $\tau_{P,t}^j$ is specified as

$$\tau_{P,t}^j = 0.062 \times \min\{w_t^j h_t^j, e^{max}\} + 0.0145 \times w_t^j h_t^j, \quad j \in \{h, w\}. \tag{28}$$

Federal income tax – Federal income tax is a progressive tax on labor and non-labor income. First, define taxable household income (TI_t) as the sum of asset income, earnings, unem-

Table A.5: Taxable Social Security Benefits for Married Taxpayers (in $)

Provisional Income†	Taxable Social Security Benefits
(A) Less than $32,000	None
(B) $32,000 to $44,000	Lesser of 50% of benefits or 50% of provisional income above $32,000 (max $6,000)
(C) Greater than $44,000	Lesser of 85% of benefits or 85% of provisional income above $44,000 plus the amount from line (B)

Source: Table 1 from Congressional Research Service, *Social Security: Taxation of Benefits* (CRS Report RL32552), June 12, 2020.
† Provisional income is defined as the sum of asset income, earnings, all other sources of non-labor income excluding Social Security benefits, and 50% of Social Security benefits.

ployment benefits, taxable Social Security benefits (tb_t), and all other non-labor income, subtracted by the standard household deduction (d).

$$TI_t = \max\{rA_t + w_t^h h_t^h + w_t^w h_t^w + UI_t + tb_t + I_t - d, 0\} \tag{29}$$

I set d as $d = \$12{,}600$ based on the standard deduction for married households filing jointly in 2015. Taxable Social Security benefits are computed according to Table A.5.

Similar to the PIA computation formula, the federal income tax has seven progressive tax rates that are applied to seven taxable income brackets. Table A.6 reports the amount of federal income tax $\tau_{F,t}$ that the household pays based on taxable household income TI_t. I use the 2015 income tax brackets for married households filing jointly.

Table A.6: Federal Income Tax by Taxable Household Income Brackets (in $)

Taxable Household Income (TI_t)	Federal Income Tax ($\tau_{F,t}$)
0 - 18,450	$0.1 \times TI_t$
18,451 - 74,900	$1,845 + 0.15 \times (TI_t - 18,450)$
74,901 - 151,200	$10,312.5 + 0.25 \times (TI_t - 74,900)$
151,201 - 234,500	$29,387.5 + 0.28 \times (TI_t - 151,200)$
234,501 - 411,500	$51,577.5 + 0.33 \times (TI_t - 234,500)$
411,501 - 464,850	$111,324 + 0.35 \times (TI_t - 411,500)$
464,851+	$129,996.5 + 0.396 \times (TI_t - 464,850)$

Note: All values are in 2015 dollars.

E Estimation Sample of the Dynamic Model

This section provides further discussion regarding the estimation sample of the dynamic model being restricted to white couples. First, Table A.7 reports the racial composition of married couples in the HRS. About 82% of married couples are those in which both spouses are white and therefore, my estimation sample covers the majority of the HRS sample.

Second, I verify whether spousal responses to husbands' disability differ between whites and non-whites. To do so, I perform event study regressions using the equation

$$\begin{aligned} y_{it} &= \alpha_i + \gamma_t + X'_{it}\beta + \sum_{k=-4}^{-1} \left(\delta_k \cdot I_{itk} + \delta_k^{nw} \cdot I_{itk} \cdot I_i^{nw} \right) \\ &\quad + \sum_{k=0}^{5} \left(\delta_k^s \cdot I_{itk}^s + \delta_k^{s,nw} \cdot I_{itk}^s \cdot I_i^{nw} \right) + \sum_{k=0}^{5} \left(\delta_k^s \cdot I_{itk}^{ns} + \delta_k^{ns,nw} \cdot I_{itk}^{ns} \cdot I_i^{nw} \right) + \epsilon_{it} \quad (30) \end{aligned}$$

where I_i^{nw} is an indicator for whether the husband of household i is non-white, I_{itk}^s is an indicator for being k years since disability onset and the disability being severe, and I_{itk}^{ns} is an indicator for being k years since disability onset and the disability being non-severe. I allow for separate post-onset dummies by husbands' disability severity (I_{itk}^s and I_{itk}^{ns}) to control for potential racial differences in husbands' disability severity. The definition of the remaining variables are the same as those described in Section 2.2. The dependent variable is either the wife's weekly working hours or caregiving hours. Given this specification, δ_k^{nw}, $\delta_k^{ns,nw}$, and $\delta_k^{s,nw}$ reflect the difference in spousal responses to husbands' disability between couples with non-white husbands and those with white husbands (conditional on husbands' disability severity).

Table A.8 reports the estimates of δ_k^{nw}, $\delta_k^{ns,nw}$, and $\delta_k^{s,nw}$. Columns (1) and (3) are based

Table A.7: Racial Composition of Married Couples in the HRS (in %)

	Wife		
Husband	White	Black	Other
White	81.8	0.3	2.8
Black	0.4	7.0	0.4
Other	3.2	0.2	3.9

Notes: This table reports the race of both spouses for all married couples in the HRS (1992-2014). All values are in percentages and weighted by HRS sample weights.

Table A.8: Racial Differences in Wives' Labor Supply and Caregiving Responses to their Husbands' Disability

	Weekly working hours		Weekly hours of care	
	(1)	(2)	(3)	(4)
Year = -4, -3 × Non-white	1.367	0.493	0.164	0.566
	(1.561)	(1.718)	(0.686)	(0.986)
Year = -2, -1 × Non-white	2.476	0.145	1.189	0.899
	(2.496)	(2.199)	(2.606)	(1.689)
Year = 0, 1 × Non-white				
× Not severe	0.935	0.760	-0.684	-0.0794
	(2.244)	(2.761)	(1.329)	(2.199)
× Severe	0.682	-2.751	-1.242	2.553
	(2.516)	(2.792)	(6.058)	(8.284)
Year = 2, 3 × Non-white				
× Not severe	1.382	-0.652	-1.370	0.159
	(2.265)	(2.658)	(1.744)	(2.869)
× Severe	-1.790	-0.329	1.461	0.650
	(3.355)	(4.463)	(5.483)	(6.532)
Year = 4, 5 × Non-white				
× Not severe	0.486	-0.364	-0.216	0.839
	(2.608)	(3.133)	(1.739)	(2.831)
× Severe	-0.280	0.336	1.590	0.652
	(2.917)	(3.638)	(4.469)	(5.299)
Full sample†	Yes	No	Yes	No
Observations	23,376	21,368	11,497	10,131
R-sq	0.104	0.105	0.055	0.060

Notes: This table reports results from event study regressions of wives' weekly working hours and caregiving hours on husbands' disability onset years using the HRS Core survey (1992-2014). All regressions control for onset year dummies, a quartic in both spouses' ages, dummies for each spouse indicating whether their age is 62 or above, wives' disability status, household size, length of current marriage, census division, and year and household fixed effects. Given that onset year dummies are already controlled for, the results above reflect differences in spousal responses between households with white husbands and households with non-white husbands. Standard errors are in parentheses, clustered at the household level.
† The full sample includes couples of all races in the HRS (white, black, and other). Columns (2) and (4) are based on additional sample restrictions where a) both spouses are of the same race, and b) only white couples and black couples are included.

on couples of all races (white, black, or other). Columns (2) and (4) are based on additional sample restrictions where a) both spouses are of the same race, and b) only white couples and black couples are included. For both the spousal labor supply responses and caregiving responses, most of the point estimates are close to zero and all of the point estimates are statistically insignificant. This indicates that there is no conclusive evidence of significant differences in spousal responses to husbands' disability between white and non-white couples.

F First Stage Parameters

This section provides further details on the first stage parameters used in the dynamic programming model.

Job displacement rates – Annual job displacement rates $\delta_{jd}(s_t^h, e^h)$ are calculated from the HRS by measuring the fraction of workers that become displaced in the next 12 months, conditional on current disability status and education type. These values are reported in Table A.9. I use self-reported dates on when respondents left their previous employer due to either a business closure or being laid off or let go.

Divorce rates – Biennial divorce rates $\tilde{\delta}_d(s_t^h, s_t^w)$ are computed as the fraction of married couples in the HRS that divorced in the next survey wave, conditional on both spouses' health status. To approximate annual divorce rates $\delta_d(s_t^h, s_t^w)$ from the biennial rates $\tilde{\delta}_d(s_t^h, s_t^w)$, I assume that annual divorce rates between the survey waves are equal and use the relationship $1 - \tilde{\delta}_d(s_t^h, s_t^w) = \big(1 - \delta_d(s_t^h, s_t^w)\big)^2$. The resulting parameter values are reported in Table A.10.

SSDI award probabilities – Using administrative data on respondents' disability benefit claims, I compute the annual SSDI award probabilities for husbands who apply for benefits. Table A.11 reports the annual SSDI award probability conditional on the husband's age and disability status at the year of application. Age 55 is used as a cutoff since the vocational criteria for SSDI eligibility become more lenient for applicants of ages 55 and over.[36] Indeed, Table A.11 reports that while moderately disabled applicants younger than age 55 are significantly less likely to be awarded compared to their severely disabled counterparts,

[36] Chen and van der Klaauw (2008) use this institutional feature to estimate the work disincentive effects of SSDI in a regression discontinuity framework.

Table A.9: Husbands' Annual Job Destruction Rates

	Husbands' Education type†	
Husbands' Disability	Low ($e^h = 0$)	High ($e^h = 1$)
Healthy ($s^h = 0$)	.053	.041
Moderate ($s^h = 1$)	.041	.094
Severe ($s^h = 2$)	.085	.024

Notes: Results are based on a sample of married households in the HRS Core survey (1992-2014) where the both spouses are white and under age 65. Job destruction is defined as job separations due to a business closure or being laid off or let go.
† "High" and "low" education are defined by whether the husband has a bachelor's degree (or higher) or not.

Table A.10: Annual Divorce Rates by Health Status

	Wives' Disability	
Husbands' Disability	Healthy ($s^w = 0$)	Disabled ($s^w = 1$)
Healthy ($s^h = 0$)	.0046	.0072
Moderate ($s^h = 1$)	.0049	.0054
Severe ($s^h = 2$)	.0075	.0127

Notes: Results are based on a sample of married households in the HRS Core survey (1992-2014) where the both spouses are white and under age 65.

Table A.11: Annual SSDI Award Rates by Husbands' Age and Disability

	Husbands' Age	
Husbands' Disability	Age < 55	$55 \leq$ Age ≤ 64
Moderate ($s = 1$)	.426	.620
Severe ($s = 2$)	.631	.640

Notes: This table reports the probability that husbands who applied for SSDI in year t would be awarded with benefits in year $t + 1$. Results are based on a sample of husbands in the HRS Core survey (1992-2014) who are white and under age 65.

this pattern does not hold for applicants aged 55 and over such that the award probabilities are similar for both moderately and severely disabled applicants.

Annual household medical expenses – Household medical expenses are defined as the sum of out-of-pocket medical expenses of the husband and the wife. While earlier waves of the HRS collected information on medical expenses in the past 12 months, the reference period for later waves is the past 2 years. Therefore, medical expenses are annualized by dividing them by the appropriate reference period. $m_t = m(t, s_t^h, s_t^w, e^h, e^w)$ is estimated by performing a linear regression of log household medical expenses on age, education type, and health status of both spouses, interactions of age and health status of both spouses, and dummy variables for whether each spouse is above age 65 (i.e., Medicare eligibility). Table A.12 reports the estimated coefficients.

Annual household non-labor income – I estimate $I_t = I(t, s_t^h, s_t^w, e^h, e^w)$ by running a linear regression of log non-labor income on the following controls for both spouses: a quadratic in age, education type, health status, interactions of age and education type, indicators for being above age 55/62/65,[37] interactions of being above 55 with age, and interactions of being above age 62/65 and health status. I use the sum of household pension income, household annuity income, household veteran benefits, the wife's SSDI income, the wife's unemployment benefits, and other household income such as lump sum income as my measure of household non-labor income. Table A.13 reports the estimated coefficients.

Mortality rates – Annual mortality rates are estimated from a logit regression model using reported death dates in the HRS data. I estimate logit regressions for men and women, separately. Covariates include a quadratic in age, indicators for disability status, and indicators for education type. Figure A.2 documents the fitted mortality rates by gender, age, and health status.

Health transition probabilities – Instead of estimating the health transition probabilities of each spouse separately, I define the household health status as $s_t = (s_t^h, s_t^w)$ (taking on six values, (0,0), (0,1), (1,0), (1,1), (2,0), and (2,1)) and estimate the biennial transition probabilities of s_t from the HRS data using a multinomial logit regression model. This allows

[37] I use these age milestones since depending on the pension plan, individuals can liquidate pension wealth as early as age 55, and ages 62 and 65 are the earliest ages for early and full Social Security retirement benefits.

Table A.12: Annual Household Medical Expenses (OLS Estimates)

Dependent variable: log(household out-of-pocket medical expenses)†	
Controls	Coefficients
Husbands' characteristics	
Moderate disability ($s^h = 1$)	0.520***
	(0.188)
Severe disability ($s^h = 2$)	1.046***
	(0.219)
Age	0.008***
	(0.003)
Age × Moderate disability	-0.005*
	(0.003)
Age × Severe disability	-0.012***
	(0.003)
Age 65+	0.011
	(0.025)
Bachelor's degree or higher	0.141***
	(0.026)
Wives' characteristics	
Disabled ($s^w = 1$)	0.976***
	(0.142)
Age	0.009***
	(0.003)
Age × Disabled	-0.010***
	(0.002)
Age 65+	-0.044
	(0.027)
Bachelor's degree or higher	0.142***
	(0.030)
Observations	46,590

Notes: Results are based on a sample of married couples in the HRS (1992-2014) where both spouses are white and are younger than age 90. Standard errors are in parentheses with ***, **, * indicating statistical significance at the 1, 5, and 10 percent levels, respectively.

† Household out-of-pocket medical expenses are the sum of both spouses' out-of-pocket medical expenses.

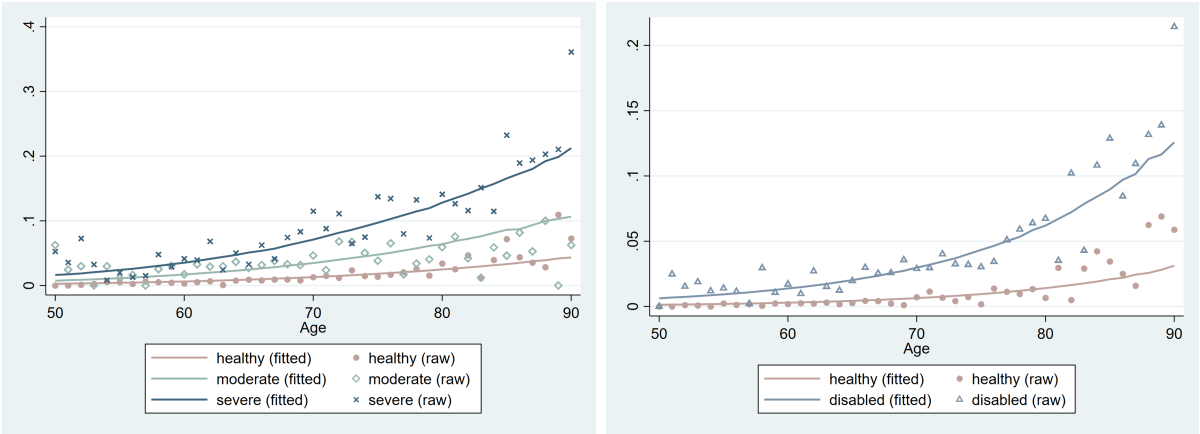
Table A.13: Annual Household Non-labor Income (OLS Estimates)

Dependent variable: log(household non-labor income)†		
Controls	Coefficients	Std. Err.
Husbands' characteristics		
Age	0.298***	0.039
$(\text{Age}/10)^2$	-0.252***	0.033
Moderate disability	0.457***	0.067
Severe disability	0.557***	0.084
Bachelor's degree or higher	-1.086***	0.270
Age × Bachelor's degree or higher	0.023***	0.004
Age 55+	-3.681***	1.127
(Age 55+) × Age	0.069***	0.021
Age 62+	0.236***	0.054
(Age 62+) × Moderate disability	-0.129	0.108
(Age 62+) × Severe disability	-0.273**	0.127
Age 65+	0.360***	0.070
(Age 65+) × Moderate disability	-0.212***	0.080
(Age 65+) × Severe disability	-0.578***	0.095
Wives' characteristics		
Age	0.074*	0.038
$(\text{Age}/10)^2$	-0.073**	0.036
Disabled	0.271***	0.049
Bachelor's degree or higher	-1.058***	0.282
Age × Bachelor's degree or higher	0.021***	0.004
Age 55+	-1.786**	0.883
(Age 55+) × Age	0.034**	0.016
Age 62+	0.067	0.054
(Age 62+) × Disabled	-0.188**	0.083
Age 65+	-0.023	0.070
(Age 65+) × Disabled	-0.325***	0.065
Observations	46,114	

Notes: Results are based on a sample of married couples in the HRS (1992-2014) where both spouses are white and are younger than age 90. ***, **, * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

† Household non-labor income is defined as the sum of household pension income, household annuity income, household veteran benefits, the wife's SSDI income, the wife's unemployment benefits, and other household income such as lump sum income.

Figure A.2: Fitted Annual Mortality Rates by Health Status



(a) Men **(b)** Women

Notes: Annual death probabilities are based on logit regressions of a quadratic in age, indicators for disability status, and education type. Solid lines indicate fitted mortality rates while each scattered marker indicates the average death probability in the data by age.

the possibility of one spouse's current health status to be correlated with the other spouse's health status in the following period. Covariates include current household health status, quadratic in age and education type for each spouse, interactions of age and age squared with household health status, and interactions of age and age squared with dummies for the education type for each spouse. Therefore, conditional on age and education type of both spouses, I obtain a six by six matrix of annual transition probabilities Π_a from the matrix of biennial transition probabilities Π_b using the relationship $\Pi_a^2 = \Pi_b$. Figures A.3 and A.4 report fitted biennial health transition probabilities for husbands and wives, respectively.

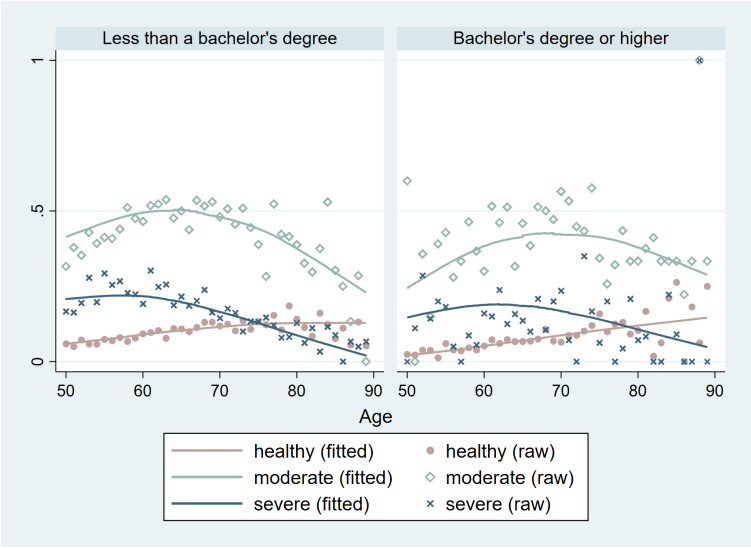
G Second Stage Parameters

G.1 Criterion Function Values

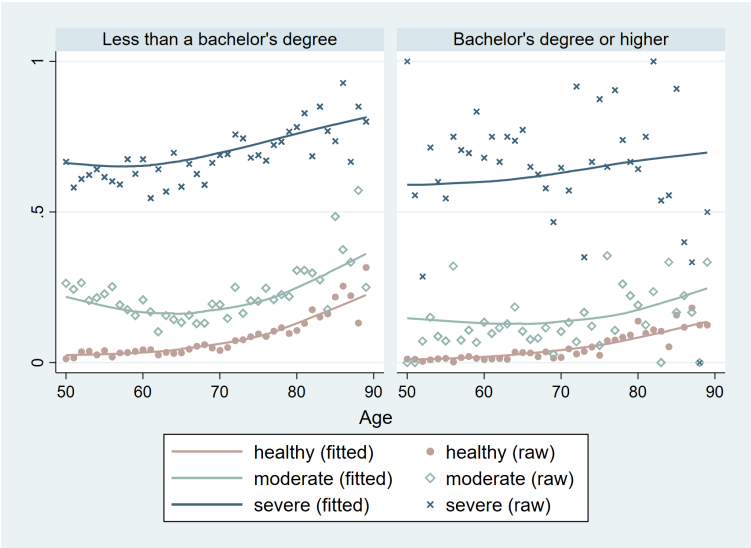
Figures A.5 and A.6 plot the criterion function around the converged parameter values for each second stage parameter (keeping other parameters fixed).

Figure A.3: Predicted Biennial Health Transition Probabilities for Husbands

(a) Husbands: Probability of Moderate Disability in $t+2$



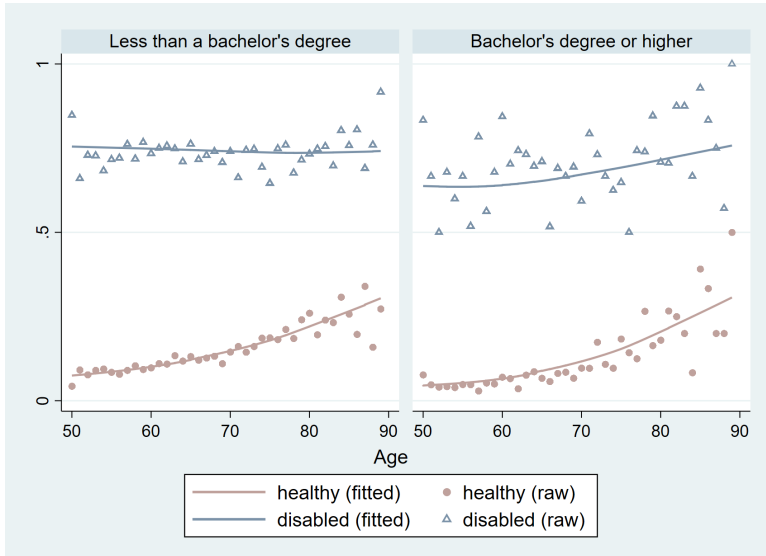
(b) Husbands: Probability of Severe Disability in $t+2$



Notes: These figures are based on a multinomial logit regression of biennial transition probabilities of household health status, $s_t = (s_t^h, s_t^w)$ (taking on six values, (0,0), (0,1), (1,0), (1,1), (2,0), and (2,1)). Covariates include current household health status, a quadratic in age and dummies for the education type for each spouse, interactions of age and age squared with household health status, and interactions of age and age squared with dummies for the education type for each spouse. Solid lines indicate predicted biennial transition rates while each scattered marker indicates the average biennial transition rate in the data.

Figure A.4: Predicted Biennial Health Transition Probabilities for Wives

(a) Wives: Probability of Disability in $t+2$

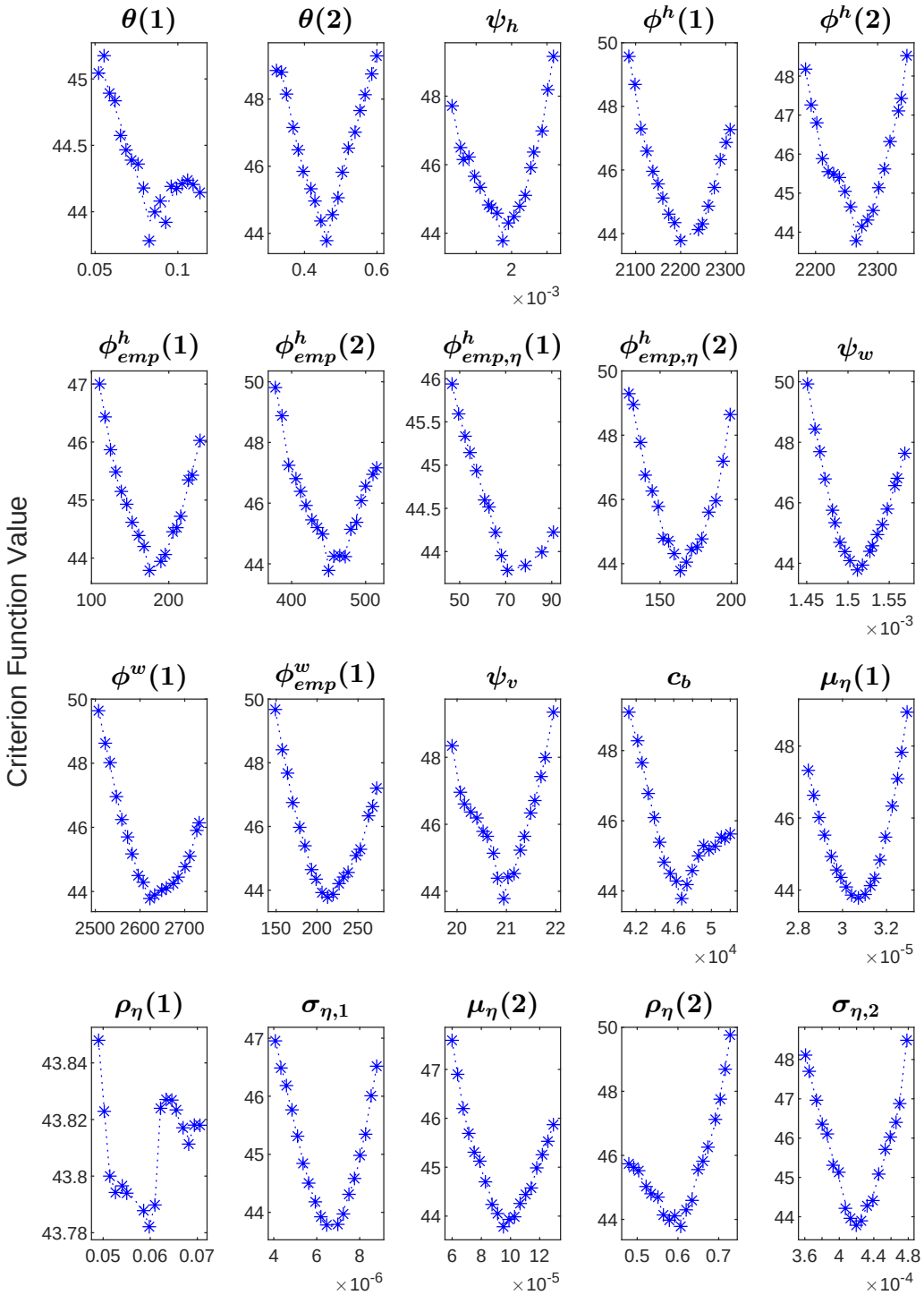


Notes: These figures are based on a multinomial logit regression of biennial transition probabilities of household health status, $s_t = (s_t^h, s_t^w)$ (taking on six values, (0,0), (0,1), (1,0), (1,1), (2,0), and (2,1)). Covariates include current household health status, a quadratic in age and dummies for the education type for each spouse, interactions of age and age squared with household health status, and interactions of age and age squared with dummies for the education type for each spouse. Solid lines indicate predicted biennial transition rates while each scattered marker indicates the average biennial transition rate in the data.

G.2 Sensitivity of Parameters

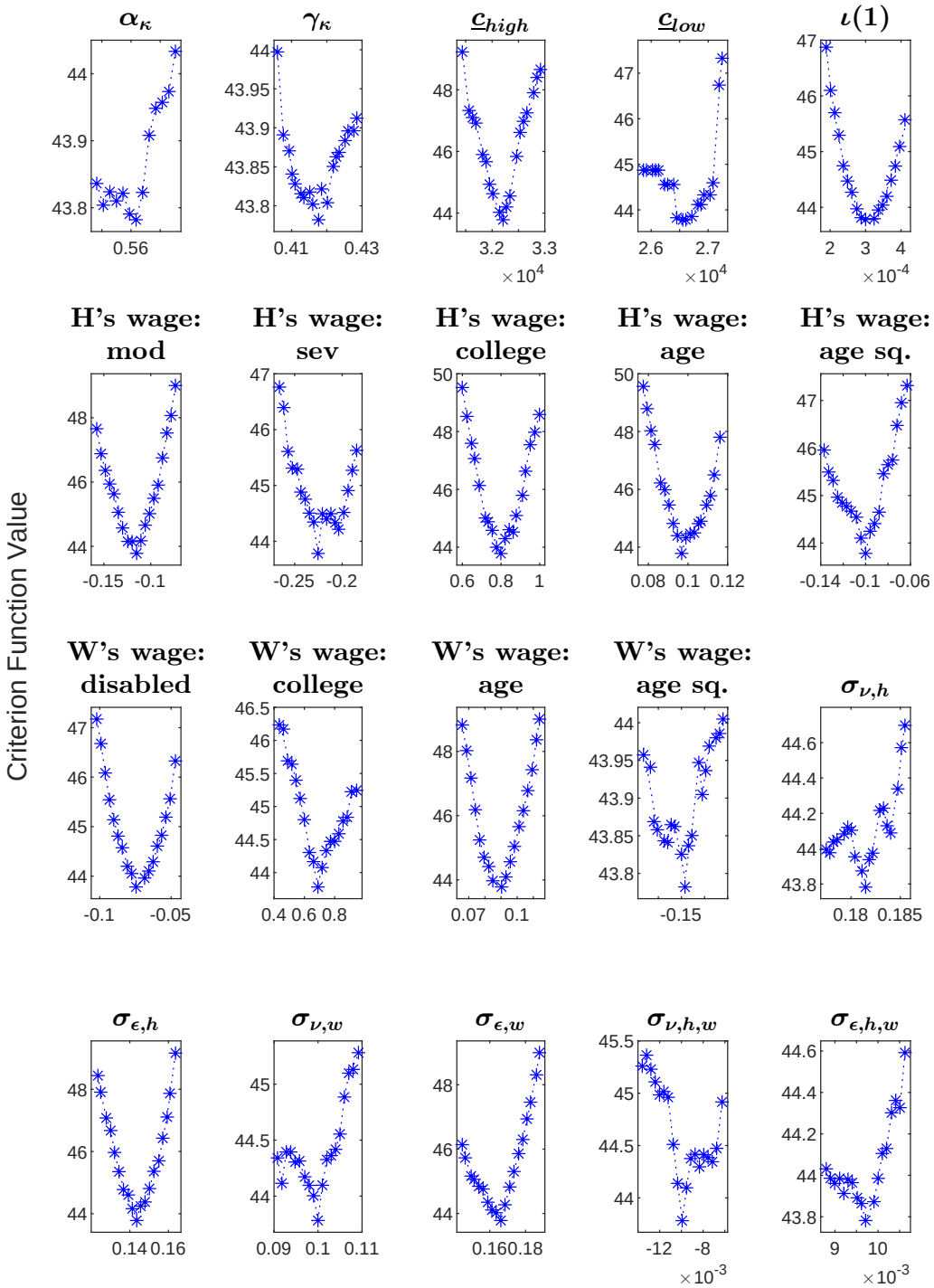
Following Andrews et al. (2017), I compute the sensitivity of second stage parameters such that they reflect the absolute local change in parameter value to a one standard deviation change in each moment. Due to the large number of parameters and moments, I re-scale the sensitivity measures such that they take values in the interval [0,1] and report them as heatmaps in Figures A.7 to A.10. For each parameter, the re-scaling is done such that the sensitivity measure is scaled by the highest value. For example, for parameter $\phi^h(1)$, the moment with the highest sensitivity value is moment #33 with a sensitivity value of 49.46. The moment with the second highest sensitivity is moment #23 with a sensitivity value of 49.04. Then, the re-scaled sensitivity value for moment #23 is $49.04/49.46 = 0.99$.

Figure A.5: Criterion Function Values for Second-Stage Model Parameters I



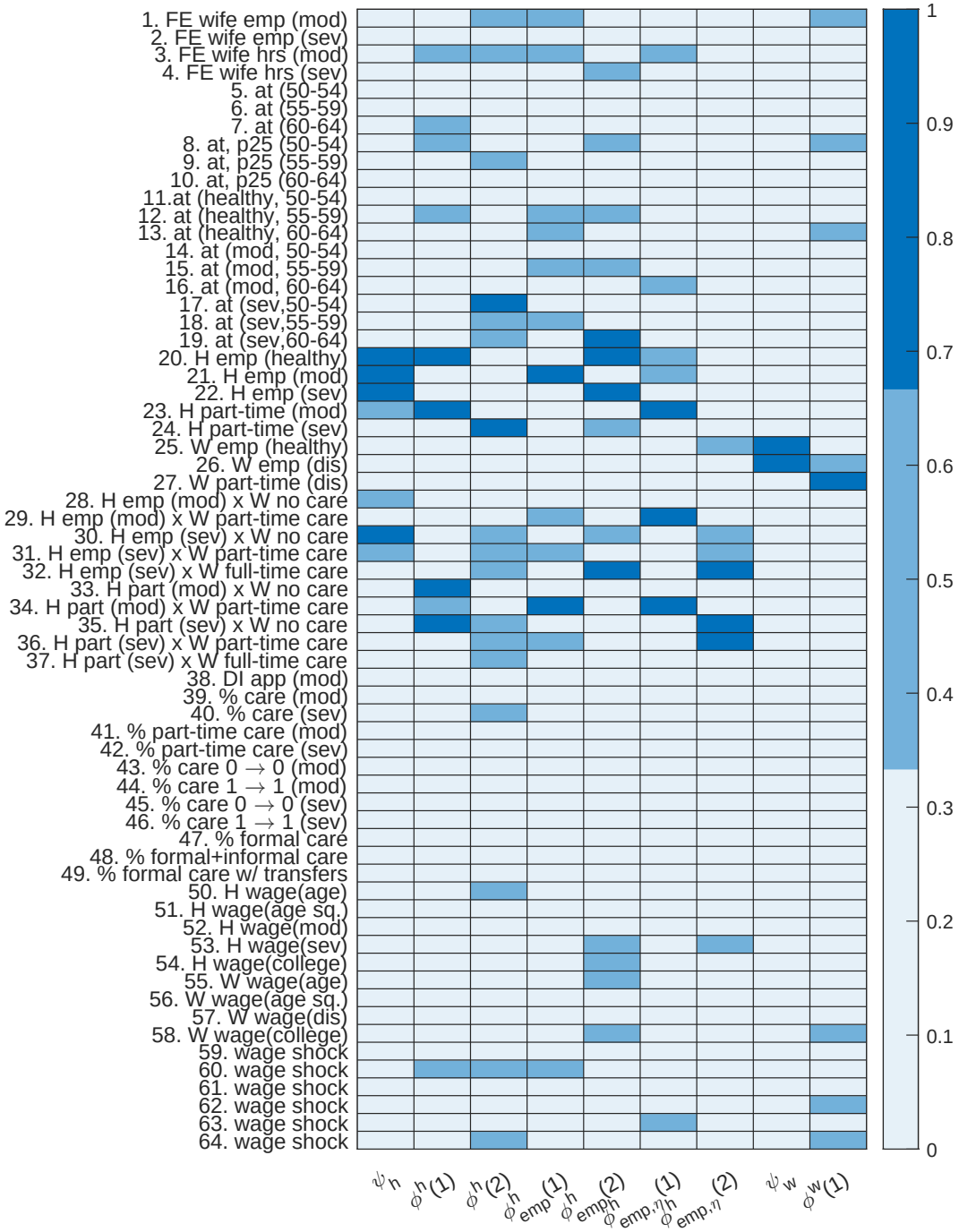
Notes: Each subfigure plots the criterion function value with respect to the corresponding model parameter (while keeping the remaining parameters fixed). All subfigures are centered around the converged parameter value. The asterisk markers indicate evaluated points and the dotted lines indicate fitted lines using linear interpolation.

Figure A.6: Criterion Function Values for Second-Stage Model Parameters II



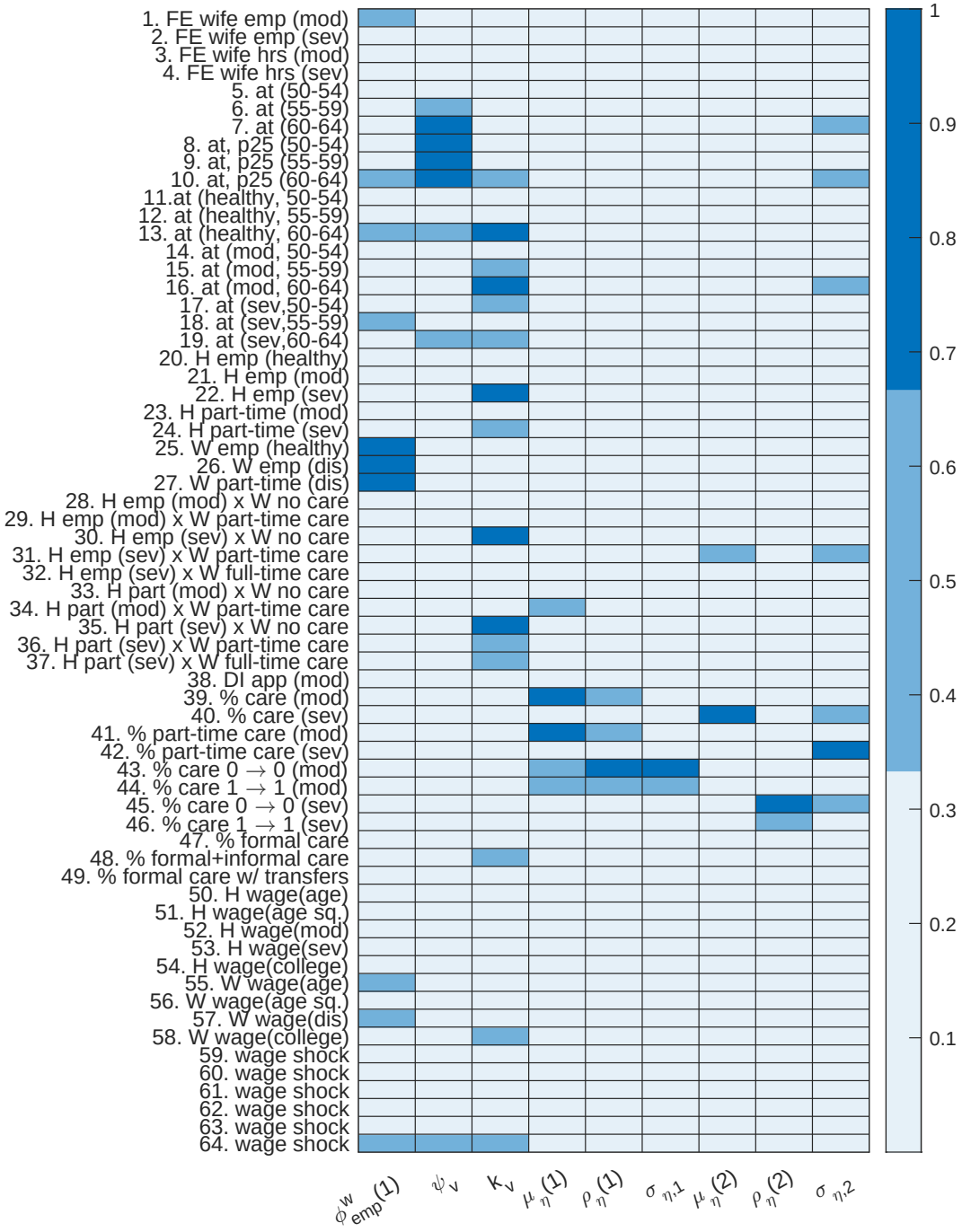
Notes: Each subfigure plots the criterion function value with respect to the corresponding model parameter (while keeping the remaining parameters fixed). All subfigures are centered around the converged parameter value. The asterisk markers indicate evaluated points and the dotted lines indicate fitted lines using linear interpolation.

Figure A.7: Sensitivity of Second Stage Parameters I



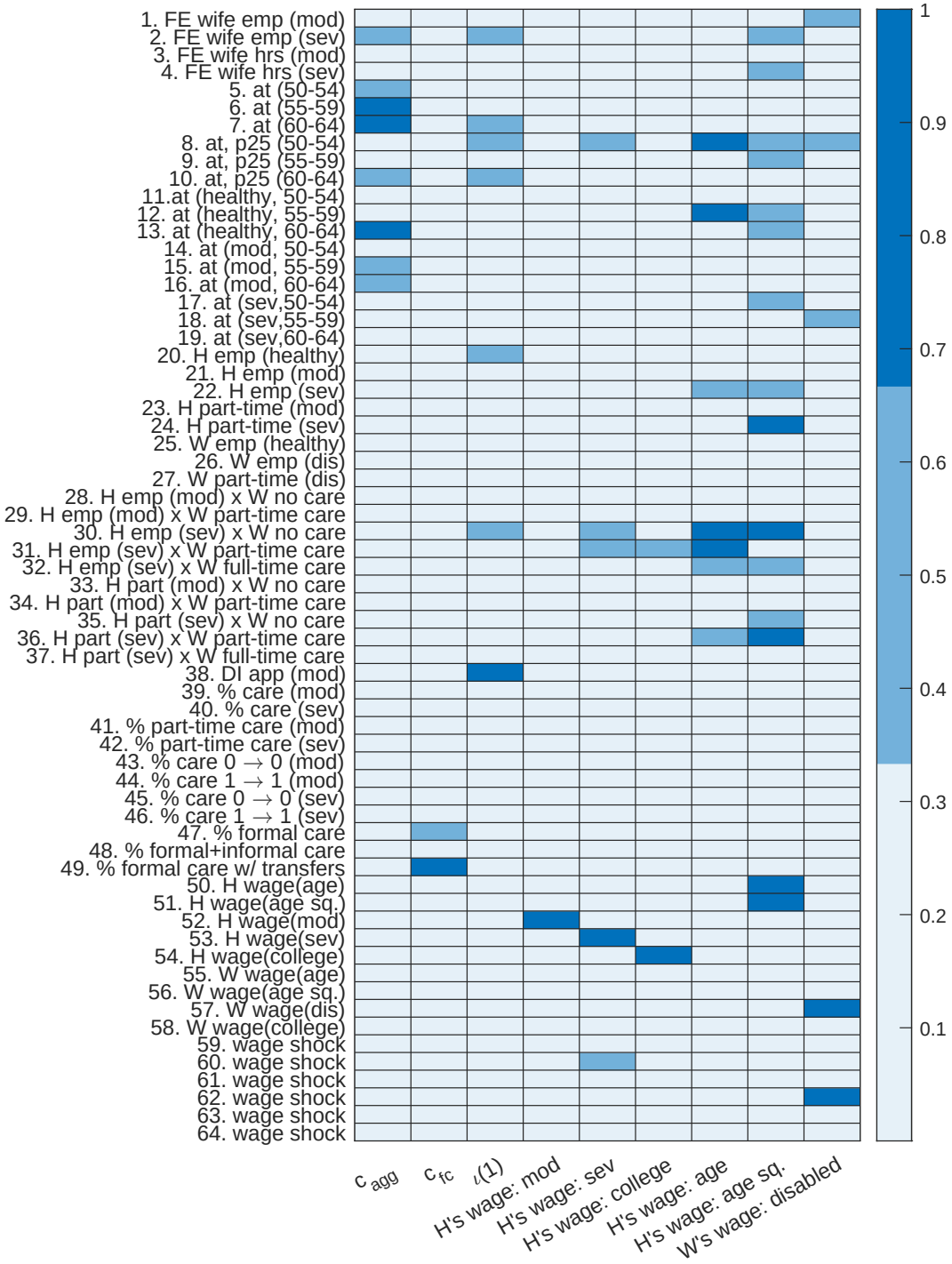
Notes: This heatmap presents the sensitivity of second stage parameters where the sensitivity measures have been rescaled to the interval [0,1]. The moment indices #1 to #64 correspond to those in Tables 8, A.15, A.16, and A.17. Refer to Section G.2 for further details.

Figure A.8: Sensitivity of Second Stage Parameters II



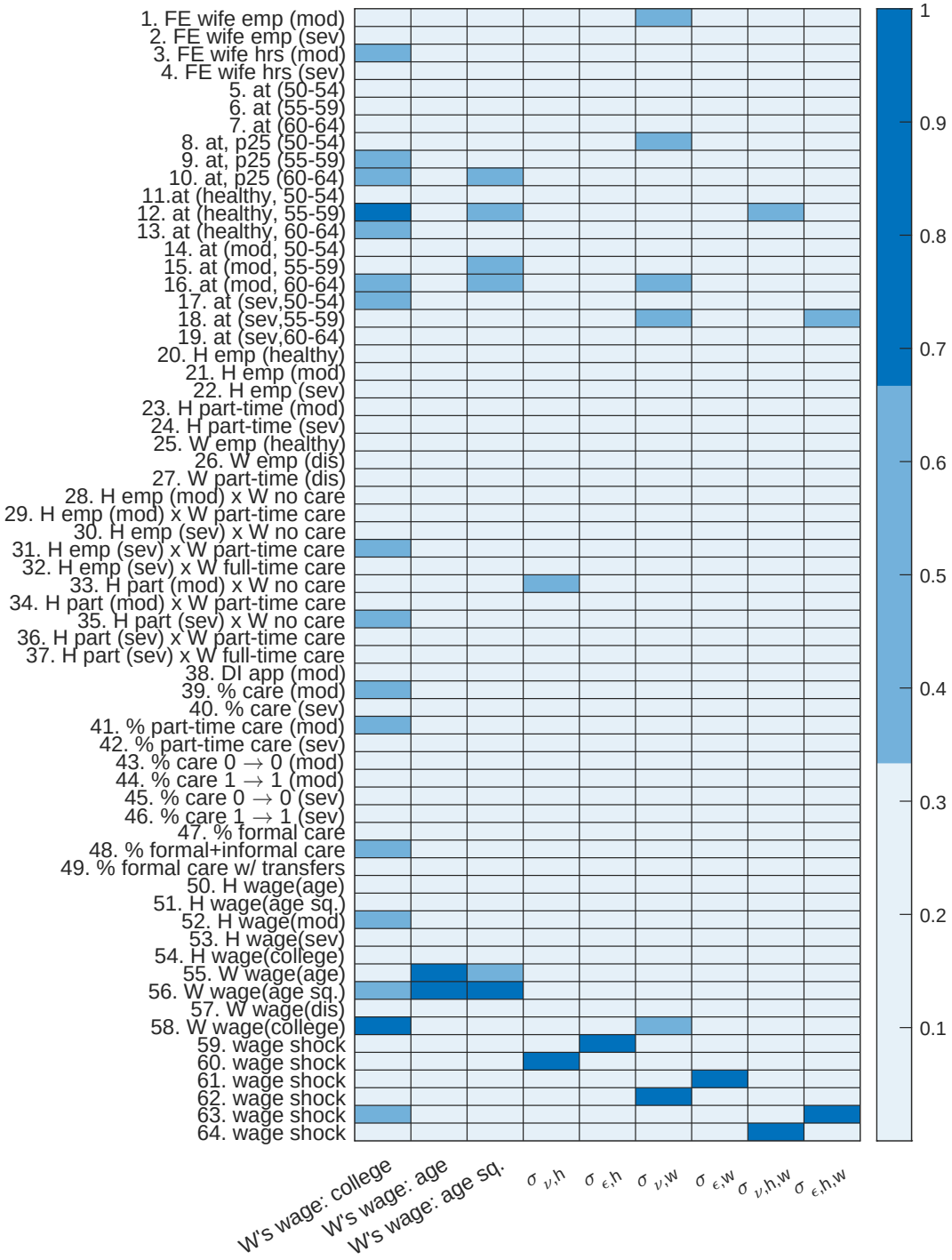
Notes: This heatmap presents the sensitivity of second stage parameters where the sensitivity measures have been rescaled to the interval [0,1]. The moment indices #1 to #64 correspond to those in Tables 8, A.15, A.16, and A.17. Refer to Section G.2 for further details.

Figure A.9: Sensitivity of Second Stage Parameters III



Notes: This heatmap presents the sensitivity of second stage parameters where the sensitivity measures have been rescaled to the interval [0,1]. The moment indices #1 to #64 correspond to those in Tables 8, A.15, A.16, and A.17. Refer to Section G.2 for further details.

Figure A.10: Sensitivity of Second Stage Parameters IV



Notes: This heatmap presents the sensitivity of second stage parameters where the sensitivity measures have been rescaled to the interval [0,1]. The moment indices #1 to #64 correspond to those in Tables 8, A.15, A.16, and A.17. Refer to Section G.2 for further details.

G.3 Computing Standard Errors of the Second Stage Model Parameters

Given the first stage parameter estimates ($\hat{\boldsymbol{\theta}}_{\boldsymbol{f}}$), the second stage estimates ($\hat{\boldsymbol{\theta}}_{\boldsymbol{s}}$) are chosen such that they minimize the weighted distance between the vector of data moments $\boldsymbol{m_d}$ and the vector of simulated moments $\boldsymbol{m_s}(\hat{\boldsymbol{\theta}}_{\boldsymbol{f}}, \hat{\boldsymbol{\theta}}_{\boldsymbol{s}})$ where the weight is specified by the matrix $\hat{W}$. Formally, this can be expressed as

$$\hat{\boldsymbol{\theta}}_{\boldsymbol{s}} = \underset{\boldsymbol{\theta_s}}{\arg\min} \left(\boldsymbol{m_d} - \boldsymbol{m_s}(\hat{\boldsymbol{\theta}}_{\boldsymbol{f}}, \boldsymbol{\theta_s})\right)' \hat{W} \left(\boldsymbol{m_d} - \boldsymbol{m_s}(\hat{\boldsymbol{\theta}}_{\boldsymbol{f}}, \boldsymbol{\theta_s})\right). \tag{31}$$

Following Gourieroux et al. (1993), standard errors of $\hat{\boldsymbol{\theta}}_{\boldsymbol{s}}$ are computed using the formula

$$var(\hat{\boldsymbol{\theta}}_{\boldsymbol{s}}) = \left(1 + \frac{1}{H}\right)(J'\hat{W}J)^{-1}(J'\hat{W}S\hat{W}J)(J'\hat{W}J)^{-1} \tag{32}$$

where H is the number of simulations, $J = \frac{\partial \boldsymbol{m_s}(\hat{\boldsymbol{\theta}}_{\boldsymbol{f}}, \boldsymbol{\theta_s})}{\partial \boldsymbol{\theta_s}}$, and S is the variance-covariance matrix of the data moments such that $S = var(\boldsymbol{m_d})$. I compute S via bootstrap. The matrix J is computed by first approximating the function $\boldsymbol{m_s}(\hat{\boldsymbol{\theta}}_{\boldsymbol{f}}, \boldsymbol{\theta_s})$ via curve fitting and then taking the derivative of the fitted curve to obtain $\frac{\partial \boldsymbol{m_s}(\hat{\boldsymbol{\theta}}_{\boldsymbol{f}}, \boldsymbol{\theta_s})}{\partial \boldsymbol{\theta_s}}$.

G.4 Estimated Second-Stage Parameter Values

Table A.14 reports the model parameter estimates that were not included in Table 7. The first panel of Table A.14 indicate that on average, care needs are higher and exhibit greater persistence for severely disabled husbands compared to moderately disabled husbands. As wives of severely disabled husbands are more likely to spend time in caregiving, this increases the marginal disutility of wives' market hours and discourages wives from working to make up for the loss in their husbands' earnings. The estimate of $\iota(1)$ is strictly positive in order to match SSDI application rates. Finally, estimates of the standard deviation and covariance of the permanent and transitory wage shocks are also within the range of estimates reported by Blundell et al. (2016).[38]

[38] Since Blundell et al. (2016) uses a sample of married households with a male head between ages 30 and 57 in the PSID, the sample is not directly comparable to mine. Nevertheless, they report 0.121 – 0.22 (men) and 0.157 – 0.225 (women) as the range of estimates for the standard deviation of the permanent wage shock. For the standard deviation of the transitory wage shock, the range of estimates are 0.128 – 0.208 for men and 0.105 – 0.160 for women. Finally, the range of the covariance between the two spouses are -0.008 – 0.0072 for permanent wage shocks and 0.0007 – 0.0124 for transitory wage shocks.

Table A.14: Second Stage Estimates of the Model Parameters II

	(a) Baseline		(b) "No-care"†	
Husbands' care needs	$s^h = 1$	$s^h = 2$		
$\mu_\eta(s^h)$ Average ($\times 10^{-5}$)	3.072	9.515	-	
	(0.367)	(2.606)		
$\rho_\eta(s^h)$ Auto-regressive persistence	0.060	0.607	-	
	(0.064)	(0.094)		
σ_{ξ,s^h} SD of white noise ($\times 10^{-4}$)	0.065	4.196	-	
	(0.018)	(0.674)		
Husbands' weight on leisure utility ($\times 10^{-3}$), ψ_h	1.988		1.707	
	(0.213)		(0.096)	
Wives' weight on leisure utility ($\times 10^{-3}$), ψ_w	1.511		1.423	
	(0.162)		(0.160)	
Terminal utility function				
Weight on terminal utility, ψ_v	20.94		22.86	
	(1.812)		(2.225)	
Terminal utility shifter, k_v (\$2015)	46,839		53,246	
	(9,308)		(10,848)	
Disutility of SSDI application when moderately disabled ($\times 10^{-4}$), $\iota(1)$	3.001		2.562	
	(0.891)		(0.874)	
Hourly wage offer function	Husband	Wife	Husband	Wife
Age	0.097	0.090	0.111	0.085
	(0.025)	(0.025)	(0.014)	(0.015)
$(\text{Age}/10)^2$	-0.106	-0.104	-0.124	-0.102
	(0.024)	(0.024)	(0.015)	(0.018)
Education type	0.799	0.690	0.800	0.555
	(0.160)	(0.187)	(0.130)	(0.196)
SD of permanent shock ($\sigma_{\nu,j}$)	0.181	0.100	0.181	0.100
	(0.018)	(0.015)	(0.020)	(0.019)
SD of transitory shock ($\sigma_{\epsilon,j}$)	0.144	0.166	0.141	0.162
	(0.016)	(0.015)	(0.016)	(0.017)
Covariance of permanent shock ($\sigma_{\nu_{h,w}}$)	-0.010		-0.010	
	(0.002)		(0.003)	
Covariance of transitory shock ($\sigma_{\epsilon_{h,w}}$)	0.010		0.010	
	(0.002)		(0.003)	

Notes: Standard errors are in parentheses. Refer to Appendix G.3 on how standard errors are computed.
† Parameter estimates when the model abstracts from husbands' care needs (i.e., $\eta_t(s^h)$ is always zero such that time inputs to care (both in the form of wives' time and paid helpers) are always zero and wives allocate their time to leisure and market work only).

H Other Wage Moments

This section provides further technical details on how some of the wage moments were generated.

Fixed effect regression coefficients – For each spouse, I first regress log hourly wages on a quadratic in age, dummies for health status, and household fixed effects. To get coefficients on high education type (i.e., having a bachelor's degree or higher), I take the residuals and regress them on an indicator for being a high education type.

Variance and covariance of wage shocks – For each spouse j, rewrite the wage offer function (equations (8) and (9)) as

$$\log w_{it}^j = X_{it}^{j\prime}\alpha^j + \zeta_{it}^j + \epsilon_{it}^j + \upsilon_{it}^j \tag{33}$$

where ζ_{it}^j and ϵ_{it}^j are equivalent to those in equations (10) and (11), and υ_{it}^j denotes measurement error. I assume that υ_{it}^j is classical measurement error with variance $\sigma_{\upsilon,j}^2$ and assume zero covariance between measurement error of the two spouses.

Denote residual log hourly wage as $\omega_{it}^j = \log w_{it}^j - X_{it}^{j\prime}\alpha^j = \zeta_{it}^j + \epsilon_{it}^j + \upsilon_{it}^j$. Due to the HRS data being biennial, I use second differences and denote them using Δ_2. Therefore, the two-period growth in residual log hourly wages can be expressed as

$$\Delta_2\omega_{it}^j = \omega_{it}^j - \omega_{i,t-2}^j = \nu_{it}^j + \nu_{i,t-1}^j + \epsilon_{it}^j - \epsilon_{i,t-2}^j + \omega_{it}^j - \omega_{i,t-2}^j. \tag{34}$$

Then, equations (35) to (38) are informative of $\sigma_{\epsilon,h}^2$, $\sigma_{\nu,h}^2$, $\sigma_{\epsilon,w}^2$, $\sigma_{\nu,w}^2$, $\sigma_{\epsilon_{h,w}}$, and $\sigma_{\nu_{h,w}}$.

$$E(\Delta_2\omega_{i,t}^j\Delta_2\omega_{i,t+2}^j) = -\sigma_{\epsilon,j}^2 - \sigma_{\upsilon,j}^2, \qquad \forall j \in \{h,w\} \tag{35}$$

$$E\big(\Delta_2\omega_{i,t}^j(\Delta_2\omega_{i,t-2}^j + \Delta_2\omega_{i,t}^j + \Delta_2\omega_{i,t+2}^j)\big) = 2\sigma_{\nu,j}^2, \qquad \forall j \in \{h,w\} \tag{36}$$

$$E(\Delta_2\omega_{i,t}^h\Delta_2\omega_{i,t+2}^w) = -\sigma_{\epsilon_{h,w}} \tag{37}$$

$$E\big(\Delta_2\omega_{i,t}^h(\Delta_2\omega_{i,t-2}^w + \Delta_2\omega_{i,t}^w + \Delta_2\omega_{i,t+2}^w)\big) = \sigma_{\nu_{h,w}} \tag{38}$$

As described in footnote 25, I assume that a predetermined fraction of the variance of the residual log hourly wage growth is due to measurement error. This value is set as $\alpha_{err} = 0.304$ based on estimates from Bound et al. (1994). Then, the variance of first-differenced residual log hourly wage can be expressed as $Var(\Delta\omega_{it}^j) = \sigma_{\nu,j}^2 + 2\sigma_{\epsilon,j}^2 + 2\sigma_{\upsilon,j}^2$.

Since $\frac{2\sigma^2_{\upsilon,j}}{\sigma^2_{\nu,j}+2\sigma^2_{\epsilon,j}+2\sigma^2_{\upsilon,j}} = \alpha_{err}$ holds, $\sigma^2_{\upsilon,j}$ and therefore the right-hand side of equation (35) can be expressed using $\sigma^2_{\epsilon,j}$ and $\sigma^2_{\nu,j}$.

I Model Fit of Targeted and Untargeted Moments

Tables A.15 to A.17 report the model fit of remaining targeted moments. Table A.18 and Figures A.11 and A.12 report the model fit of various untargeted moments. For Table A.18, I report asset profiles by health status (healthy vs. disabled) rather than by disability severity (healthy/moderate/severe) as dividing the sample by disability severity and education results in some cells with a small number of observations.

Figure A.12 uses the HRS CAMS to generate household consumption measures. The CAMS collects information on 39 expenditure categories that were chosen to closely match the Consumer Expenditure Survey (CEX). I use the RAND CAMS classification to aggregate the expenditure data into four categories: durables,[39] nondurables,[40] transportation,[41] and housing.[42] Unlike the RAND CAMS classification, I exclude expenditures on health services, medical supplies, and prescription drugs since the model-generated consumption measure does not include out-of-pocket medical expenses. Total expenditure is defined as the sum of spending on these four aggregate categories.

[39]Durables include the following five categories: refrigerator, washer/dryer, dishwasher, television, and computer.

[40]Nondurables include the following 23 categories: electricity, water, heating fuel for the home, telephone/cable/internet, health insurance, housekeeping supplies, housekeeping/dry cleaning/laundry services, gardening and yard supplies, gardening and yard services, food and beverages, dining and/or drinking out, clothing and apparel, trips and vacations, tickets to movies/sporting events/performing arts, hobbies and leisure equipment, sports equipment, contributions to organizations, cash or gifts to family and friends outside the household, personal care products and services, health services, medical supplies, and prescription drugs, and household furnishings and equipment.

[41]Transportation includes the following five categories: purchase/lease vehicle, car payments, vehicle insurance, gasoline, and vehicle maintenance.

[42]Housing includes the following six categories: mortgage, home insurance, property tax, rent, home repair supplies, and home repair services.

Table A.15: Model Fit of Targeted Moments – Employment

	Model	Data	Model	Data
Panel A: Husbands' Employment Rates by Own Health				
	Employment Rate		Part-time Employment Rate	
Healthy	0.862	0.870 [#20] (0.005)	-	-
Moderate	0.499	0.491 [#21] (0.017)	0.107	0.114 [#23] (0.010)
Severe	0.224	0.228 [#22] (0.017)	0.062	0.059 [#24] (0.010)
Panel B: Wives' Employment Rate by Own Health				
	Employment Rate		Part-time Employment Rate	
Healthy	0.764	0.764 [#25] (0.007)	-	-
Disabled	0.336	0.336 [#26] (0.016)	0.160	0.162 [#27] (0.011)
Panel C: Husbands' Employment Rate (by Own Health × Wives' Care)				
	Moderate		Severe	
No Care	0.486	0.477 [#28] (0.056)	0.273	0.278 [#30] (0.034)
Part-time Care	0.360	0.352 [#29] (0.083)	0.195	0.202 [#31] (0.034)
Full-time Care	-	-	0.110	0.064 [#32] (0.031)
Panel D: Husbands' Part-time Emp. Rate (by Own Health × Wives' Care)				
	Moderate		Severe	
No Care	0.127	0.110 [#33] (0.033)	0.064	0.084 [#35] (0.019)
Part-time Care	0.068	0.061 [#34] (0.039)	0.062	0.058 [#36] (0.023)
Full-time Care	-	-	0.051	0.030 [#37] (0.023)

Notes: Standard errors are in parentheses. The numbers in brackets are moment indices that correspond to Figures 2, 3, and A.7 to A.10. All moments are computed conditional on both spouses being younger than age 65.

Table A.16: Model Fit of Targeted Moments – Wage

	Model	Data	Model	Data
Panel A: Fixed Effect Regressions of Log Hourly Wages†				
	Husbands		Wives	
Age	0.097	0.113 [#50] (0.038)	0.089	0.084 [#55] (0.032)
$(\text{Age}/10)^2$	-0.096	-0.106 [#51] (0.033)	-0.087	-0.070 [#56] (0.029)
Moderate disability	-0.017	-0.017 [#52] (0.023)	-	-
Severe disability	-0.019	0.009 [#53] (0.042)	-	-
Disabled	-	-	-0.007	0.001 [#57] (0.017)
High education type	0.527	0.532 [#54] (0.023)	0.625	0.570 [#58] (0.027)
Panel B: Other Wage Moments‡				
	Husbands ($j = h$)		Wives ($j = w$)	
$E(\Delta\omega^j_{i,t} \cdot \Delta\omega^j_{i,t+2})$	-0.044	-0.047 [#59] (0.005)	-0.039	-0.042 [#61] (0.007)
$E\big(\Delta\omega^j_{i,t} \cdot (\Delta\omega^j_{i,t-2} + \Delta\omega^j_{i,t} + \Delta\omega^j_{i,t+2})\big)$	0.033	0.037 [#60] (0.006)	0.009	0.009 [#62] (0.006)
	Couples			
$E(\Delta\omega^h_{i,t} \cdot \Delta\omega^w_{i,t+2})$	-0.009	-0.008 [#63] (0.004)		
$E\big(\Delta\omega^h_{i,t} \cdot (\Delta\omega^w_{i,t-2} + \Delta\omega^w_{i,t} + \Delta\omega^w_{i,t+2})\big)$	-0.008	-0.008 [#64] (0.005)		

Notes: Standard errors are in parentheses. The numbers in brackets are moment indices that correspond to Figures 2, 3, and A.7 to A.10. All moments are conditional on both spouses being younger than 65.
†,‡ Refer to Appendix H for further technical details.

Table A.17: Model Fit of Targeted Moments – Other

	Model	Data	Model	Data
Panel A: 25th Percentile of Household Assets (by husbands' age, in $1,000)				
Ages 50 - 54	107.15	93.03 [#8] (5.423)		
Ages 55 - 59	119.94	114.87 [#9] (4.104)		
Ages 60 - 64	138.94	129.04 [#10] (5.001)		
Panel B: SSDI Application Rates by Husbands' Disability				
Moderate	0.078	0.079 [#38] (0.006)		
Panel C: Spousal Care Transition Rates (year $t \to t+2$, by husbands' health)				
	Moderate		Severe	
No Care → No Care	0.900	0.908 [#43] (0.043)	0.675	0.637 [#45] (0.048)
Care → Care	0.614	0.420 [#44] (0.078)	0.701	0.735 [#46] (0.038)

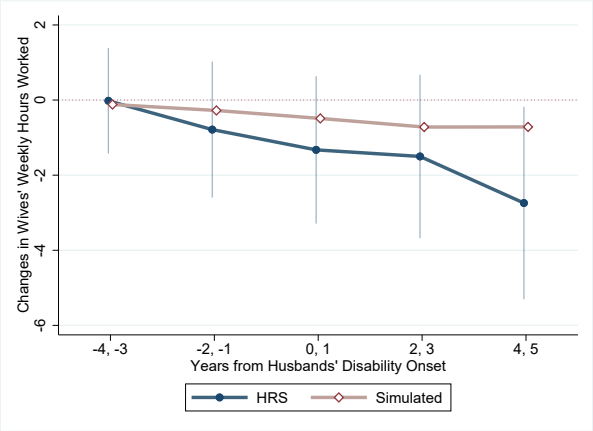
Notes: Standard errors are in parentheses. The numbers in brackets are moment indices that correspond to Figures 2, 3, and A.7 to A.10. All moments are conditional on both spouses being younger than 65. Dollar values are in 2015 dollars.

Table A.18: Untargeted Moments: Median Household Assets by Husbands' Education and Health Status

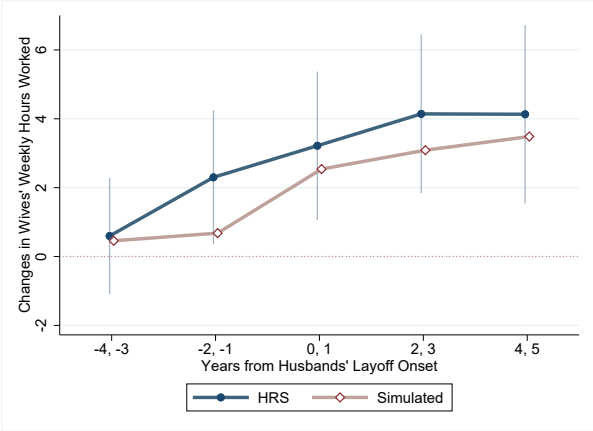
	Model	Data	Model	Data
Panel A: Without a bachelor's degree				
	Healthy		Disabled	
Ages 50 - 54	195.91	205.77 (9.137)	134.63	158.72 (17.33)
Ages 55 - 59	238.73	235.08 (6.988)	141.05	166.55 (10.264)
Ages 60 - 64	292.21	281.48 (7.230)	171.81	167.06 (8.586)
Panel B: Bachelor's degree or higher				
	Healthy		Disabled	
Ages 50 - 54	403.66	392.60 (22.42)	195.74	190.90 (73.19)
Ages 55 - 59	486.38	492.63 (16.81)	353.21	356.45 (37.74)
Ages 60 - 64	569.87	588.92 (15.39)	431.51	442.92 (30.63)

Notes: Standard errors are in parentheses. All moments are conditional on both spouses being younger than age 65. Dollar values are in 2015 dollars.

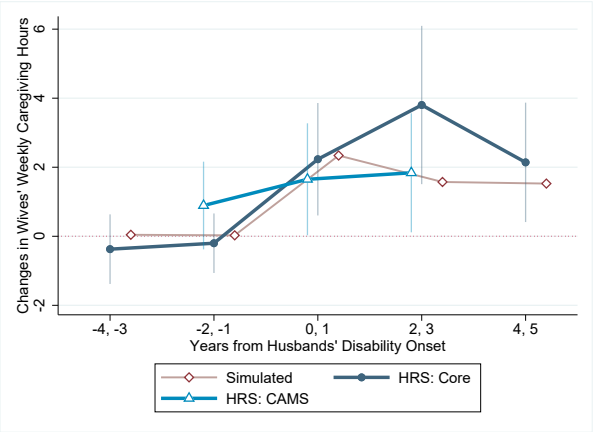
Figure A.11: Untargeted Moments: Spousal Responses to Husbands' Event Onset



(a) Weekly Working Hours (Disability)



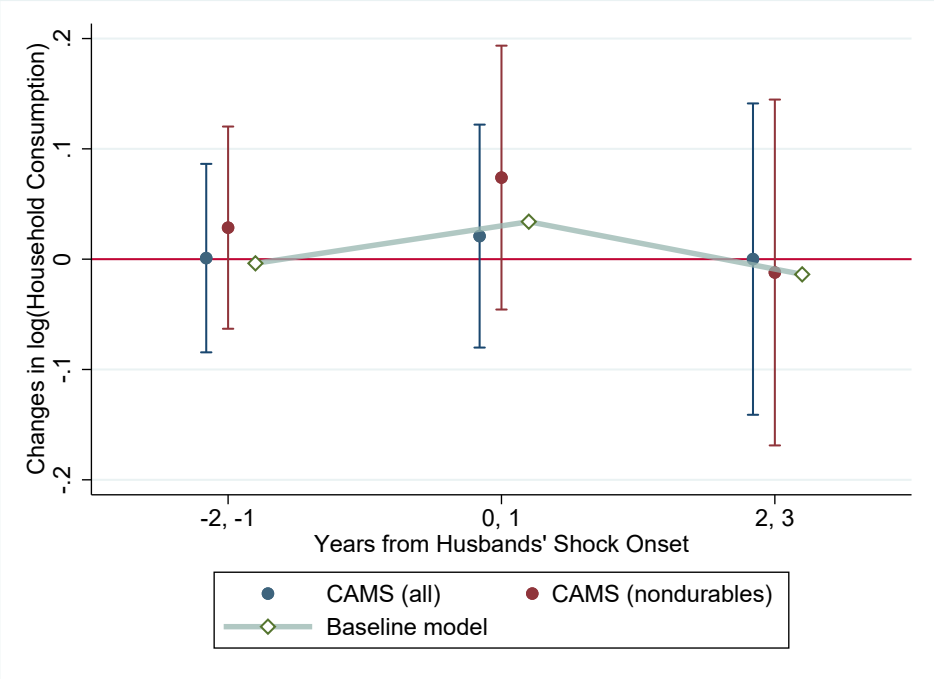
(b) Weekly Working Hours (Job Displacement)



(c) Weekly Caregiving Hours

Notes: This figure presents fixed effect event study coefficients based on the HRS and model-simulated data. The HRS sample (1992-2014) consists of married households where both spouses are under age 65. For subfigure (c), the HRS Core data span 2000-2014 while the CAMS data span 2007-2015. All event study regressions control for a quadratic in both spouses' ages and household fixed effects. Year fixed effects are additionally controlled for when using the HRS data. The vertical lines through each dot indicate 95% confidence intervals.

Figure A.12: Untargeted Moments: Changes in Log Household Consumption by Husbands' Disability Onset Year



Notes: The blue and red dots indicate event study regression coefficients using a sample of married households in the HRS CAMS data (2005-2015) where both spouses are under age 65. I use total household spending (blue dots) and household spending on nondurables (red dots) to construct the dependent variables. Both regressions control for a quadratic in both spouses' ages and year and household fixed effects. The vertical lines through each dot indicate 95% confidence intervals. The green dots indicate event study regression coefficients using simulated data from the baseline model. Refer to Appendix I regarding the expenditure categories available in the HRS CAMS.