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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, policy reforms such as supplemental caregiver benefits or in-kind transfers that cover formal care costs 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 the amount of time that spouses can allocate to market work due to time spent in caring for the disabled spouse. 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

¹Earlier 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 in 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 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 in the event of 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.

The model parameters are estimated by indirect inference. I show that the data patterns from the event study analyses can be used to infer the key preference parameters of the model. By using the results from the event study analyses as data moments, this method allows greater transparency in how the model parameters are identified and provides a tighter connection between the event study analyses and the estimated dynamic 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 2.16 hours (an 8.6% increase) and employment rate by 4.8 percentage points.

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 \$0.97 when I ignore that

²Regarding 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.

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 \$1.05 per each dollar of 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 7% higher than current levels. This implies that once we take into account that spousal care significantly reduces the insurance role of wives' labor supply, SSDI benefit levels 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, the increase in social welfare is higher when the supplemental caregiver benefit is implemented compared to introducing in-kind transfers. These findings suggest that adjusting benefit generosity 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). Most of these works model households as individual workers and do not explicitly model spouses.³ This paper extends the models proposed by earlier works. By explicitly

³Studies by Gallipoli and Turner (2011) and Autor et al. (2019) 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. My paper focuses on a different mechanism (wives' trade-off between caregiving and market work) and evaluates the full ex-ante insurance value of SSDI prior to the disability

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 using data on wives’ time spent in providing care. 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, 2017).⁴ I add to this literature by utilizing the rich information on caregiving hours in the HRS to measure how much the insurance role of wives’ labor supply is reduced due to caregiving for their disabled husbands.

The rest of the paper is organized as follows. Section 2 provides empirical evidence on wives’ labor supply and caregiving responses to their husbands’ disability shock using an event study framework. Section 3 describes a dynamic model of married households and Section 4 discusses the estimation method of the model parameters. Section 5 reports the parameter estimates of the model 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.⁵

onset.

⁴Some 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) finds that individuals decrease their labor supply when their spouses are diagnosed with cancer.

⁵Based 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.

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) is used for all analyses. The HRS is a biennial panel of a representative sample of Americans ages 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 is especially useful since it reports whether the respondent receives help from someone else to perform a set of (Instrumental) Activities of Daily Living (ADLs/IADLs), the caregiver’s relationship to the respondent (e.g., spouse, daughter, son, other relative, non-relative), the number of hours that they provide help, whether they are paid, and if so, the amount that 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, the Consumption and Activities Mail Survey (CAMS) is an off-year supplement on time use surveyed for a subsample of the HRS Core respondents. This survey provides information on non-market time use (including time spent in spousal care) conditional on the severity of spouses’ disability, which is generally not available in other datasets. Eight survey waves from 2001 to 2015 are used.⁶ In the CAMS survey, spousal care is measured as time spent in treating or managing a spouse’s medical condition, whereas in the Core survey, it is measured as helping a spouse perform a set of ADL/IADLs. I utilize both measures in my analyses.

⁶Time spent in caregiving is available from 2007 and onwards as this was not asked in earlier waves.

Finally, I merge restricted Social Security data which provides information on respondents' Social Security earnings history and disability benefit claims. Social Security earnings are reported annually and date back to 1954. The disability benefits claims data (Form 831 Disability Records) include detailed information on SSDI applications filed by HRS respondents and their outcomes.

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 the U.S. Census Bureau where I define individuals as “severely disabled” if they are disabled and satisfy one or more of the following seven criteria ([Brault, 2012](#)).

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 ADL/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 into any of the seven criteria listed above are classified as “moderately disabled.” Respondents who do not report being disabled are considered as being “healthy.”

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), then they are accepted into the program under medical allowance. 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). Vocational allowances have grown rapidly over the years such that since the early 2000s, about half of SSDI allowances have been based on vocational considerations ([Morton, 2015](#)).

Once awarded, SSDI beneficiaries receive a monthly benefit in which the amount is based on beneficiaries’ past average monthly earnings. The benefit amount does not depend on the severity of the disability since SSDI is designed to be eligible for workers whose impairments are severe enough (i.e., falls under the SSA’s definition of “disability”).⁷ 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.⁸ In 2014, the average monthly SSDI payment was \$1,145.61 for disabled workers. SSDI benefits automatically convert to Retirement benefits when beneficiaries reach full retirement age.

Lastly, SSDI beneficiaries are eligible for Medicare benefits after a two-year waiting period. Although Medicare provides coverage for various medical services, it does not cover most long-term care costs. It is important to note that this paper only analyzes the insur-

⁷This 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 recipients of SSDI are not truly work-limited.

⁸The average replacement rate is about 50%. Unlike Social Security retirement benefits, however, SSDI benefits are not adjusted for receiving benefits earlier than the full retirement age. Furthermore, up to five years of workers’ lowest earnings are excluded when computing past average earnings.

ance value of SSDI’s cash benefits and does not consider the insurance value from Medicare benefits.⁹

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 classified as being severely disabled. While employment rates drop significantly with the severity of the disability, 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 receives 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 that is associated with the reported disability. For both moderate and severely disabled husbands, musculoskeletal 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 that are 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 reveals that the Census severity definition aligns well with potential care needs. While the average moderately disabled husband does not have any ADLs or IADLs that are difficult to perform, the average severely disabled husband has difficulty in performing one ADL 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 far more often than moderately disabled husbands do (13 vs. 21 visits in two years). All of these facts

⁹To my knowledge, [Kitao \(2014\)](#) is the only paper that considers both the cash and in-kind Medicare benefits of the SSDI program using a dynamic life-cycle model of individual agents. The paper 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. Aside from the need to track the waiting period in the state space, 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 (for example, 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, measuring the insurance value of both cash and in-kind Medicare benefits for married households is left for future research.

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 that they receive increase with the severity of the disability. About 56% of severely disabled husbands receive their wives' help in performing ADL/IADLs with 14% of them 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

Table 1: Summary Statistics of Married Men by Disability Severity

	Healthy	Moderate	Severe
Age (mean)	57.7	58.7	58.3
Years of education (mean)	13.7	12.7	12.0
Employed (in %)	85.64	43.75	18.40
Receives SSDI (in %)	0.28	20.75	45.98
Household wealth (median, in \$1,000)	287.66	181.05	91.70
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) [§]	0.03	0.19	1.19
Number of IADLs difficult to perform (mean) [§]	0.03	0.04	1.00
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
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
Person-year observations	28,908	3,320	2,860
(%)	78.62	11.48	9.89

Notes: Results are based on a sample of married men from ages 50 to 64 in the HRS (1992-2014). All summary statistics are weighted by HRS sample weights. Dollar values are in 2015 dollars.

[†] The three most common health condition groups for the 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).

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

	Help their husbands perform at least one ADL/IADL [†]		Help treat or manage their husbands' medical condition(s) [‡]	
	Moderate	Severe	Moderate	Severe
(0, 25] hours per week	-	41.76	18.53	35.75
Greater than 25 hours per week	-	14.40	1.53	5.46
Person-year observations	-	1,750	364	271

Notes: Results are based on a sample of wives in the HRS whose husbands are from ages 50 to 64. All summary statistics are weighted by HRS sample weights.

[†] This information is from the HRS Core data (2000-2014, 8 waves). If a disabled husband receives help in performing one or more (Instrumental) Activities of Daily Living (ADL/IADL), then by definition, he is classified as severely disabled (due to the fourth criteria described in Section 2.1.2). Therefore, this information is not available for moderately disabled individuals.

[‡] This information is from the HRS CAMS data (2007-2015, 5 waves). Since the CAMS survey is a supplementary survey of a random subsample of the HRS Core respondents, the sample size is significantly smaller.

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. Here I restrict the sample to severely disabled men aged 50 to 64, conditional on receiving help from someone else to perform at least one ADL/IADL. The most striking difference between single and married men comes from who provides the care that they receive. For married men, 97% receive care from their wives. Only 5% receive care from non-relative caregivers such as caregivers from organizations or institutions, paid helpers, and professional helpers. Also, while 16% of married men have Medicaid coverage, only 1% of married men utilize caregivers covered by Medicaid. In contrast, 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.

Table 3: Summary Statistics of Severely Disabled Men Receiving Care

	Single*	Married
Number of caregivers (in %):		
One	61.97	73.60
Two	24.09	16.46
Three or more	13.94	9.94
Caregivers' relationship to respondent [‡] (in %)		
Wives	-	97.35
Daughters	18.54	9.95
Sons	8.64	9.62
Other relatives	44.54	11.84
Non-relatives [†]	51.49	5.02
Has Medicaid coverage (in %)	43.23	16.05
Receives care from Medicaid-covered caregiver(s) (in %)	17.07	1.45
Person-year observations	495	1,152

Notes: Results are based on a sample of severely disabled men from ages 50 to 64 in the HRS Core survey who report receiving help from someone else in performing one or more (Instrumental) Activities of Daily Living (ADL/IADLs) (2000-2014). All summary statistics are weighted by HRS sample weights.

* "Singles" include men who are either divorced, separated, widowed or never married.

[†] Includes caregivers from organizations or institutions, paid helpers, and professional helpers.

[‡] Since respondents may have multiple caregivers, this does not necessarily add up to 100%.

2.2 Event Study Framework and Results

In this section, I use an event study framework to report changes in wives' labor supply responses 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 as follows:

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

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 which 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.

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).

Figure 1a depicts changes in husbands' weekly working hours pre- and post-onset of the shock. 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.

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' displacement and these estimates are statistically significant. Since the average weekly working hours prior to their husbands' displacement is about 25 hours, this is equivalent to a 12% increase in working hours. This is consistent with 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.

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, 2017).

Next, columns (1) and (2) of Table 4 report changes in wives' weekly hours spent in providing care for their husbands. As the measures of time spent in caregiving in the Core and CAMS data are different, both results are shown in columns (1) and (2), respectively. Results from both data sources are quantitatively similar where wives spend on average 2 to

Figure 1: Changes in Weekly Hours Worked by Onset Year

(a) Husbands

(b) Wives

Notes: Results are based on a sample of married households in the HRS (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. Figure 1(b) additionally controls for wives' disability status. The vertical lines through each dot indicate 95% confidence intervals.

Table 4: Wive's Weekly Caregiving Hours by Husbands' Disability Onset and Severity

	(1) FE (Core) [†]	(2) FE (CAMS) [‡]	(3) OLS (CAMS)
Panel A: By Onset Year			
Year = -4, -3	-0.209 (0.461)	-	
Year = -2, -1	0.029 (0.423)	0.845 (0.645)	
Year = 0, 1	2.205*** (0.829)	1.930** (0.857)	
Year = 2, 3	3.800*** (1.216)	1.806** (0.868)	
Year = 4, 5	2.108*** (0.900)	-	
Panel B: By Severity			
Moderate			2.246** (1.109)
Severe			5.277*** (1.607)
R-sq.	0.016	0.069	0.061
Observations	11,540	1,595	2,849

Notes: Results are based on a sample of married households where both spouses are under age 65. Column (1) is based on data from the HRS Core survey (2000-2014) while columns (2) and (3) are based on the HRS CAMS data (2007-2015). The event study regressions for columns (1) and (2) 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, wives' disability severity, census division, and year and household fixed effects. OLS regression for column (3) controls for a quartic in age, education, and race of both spouses, dummies for each spouse indicating whether their age is 62 or above, wives' disability severity, household size, length of current marriage, census division, and year fixed effects. Standard errors in parentheses, clustered at the household level. ***, **, * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

[†] Measure of caregiving: time spent in helping the husband in performing (Instrumental) Activities of Daily Living (ADL/IADLs).

[‡] Measure of caregiving: time spent in treating or managing the husband's medical condition(s). Due to the CAMS data having a smaller sample size and shorter survey waves, column (2) reports changes in caregiving hours up to 3 years post-onset relative to 3 or more years before the husband's disability.

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 (3 hours per week as shown in Figure 1b).

Finally, column (3) of Table 4 shows the difference in spousal caregiving hours by the severity of husbands' disability. A simple OLS regression indicates that even wives of moderately disabled husbands spend a sizable amount of time in caregiving activities (about 2.2 hours per week). As expected, wives of severely disabled husbands spend more than twice the amount of time in caregiving (5.3 hours per week) than those of moderately disabled husbands.

Robustness

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 that are receiving SSDI benefits. Also, 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. In addition, one may be concerned that spousal labor supply and caregiving responses to husbands' disability are driven by wives with weak labor force attachment. These concerns are addressed in Appendix A, where I show that 1) spousal labor supply responses to husbands' disability are small even when the first two 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.

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 also allows the household to hire paid caregivers from the market.

3.1 Model Setup

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 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 $\delta_{m,t}^j(s_{t-1}^j, e^j)$ which depends on their age, health status (s_{t-1}^j), and education type (e^j). Education type is exogenously given and its values are discretized to 0 (without a bachelor's degree) and 1 (bachelor's degree or higher). The household can also dissolve through divorce with probability $\delta_d(s_{t-1}^h, s_{t-1}^j)$ 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 $s_t^h \in \{0, 1, 2\}$ (healthy, moderate, and severe) and the wife's health status $s_t^w \in \{0, 1\}$ (healthy, disabled) are realized.¹³ The household health status $s_t = (s_t^h, s_t^w)$ evolves each period according to a Markov

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

¹¹This improves computational tractability as separately tracking both spouses' ages substantially increases the state space.

¹²I assume that 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.

¹³Since 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.

process and I allow for possible 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 $\delta_{jd}(s_{t-1}^h, e^h)$ 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.

Preferences – The household period utility is specified as follows.

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

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). The household incurs a disutility $\iota(s^h)$ (e.g., “stigma” costs) when applying for SSDI benefits where $App \in \{0, 1\}$ indicates whether the household is applying for SSDI benefits in the given period. For simplicity, I assume that $\iota(2) = 0$.

$\theta(s^h)$ is included as a tractable way of accounting for health state dependence in consumption utility.¹⁴ 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.

¹⁴To reduce the number of parameters that needs to be estimated, I assume that $\theta(\cdot)$ only depends on the husband's health status and not on the wife's health status. Therefore, conditional on s^h , $\theta(s^h)$ captures the “average” degree of health state dependence over the two health states of the wife.

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). One possible interpretation 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). κ is assumed to be produced according to the following production function.

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

Furthermore, (tc, fc) is discretized into the following six choices: $(0,0)$, $(\text{part-time},0)$, $(0, \text{part-time})$, $(\text{full-time},0)$, $(0,\text{full-time})$, and $(\text{full-time},\text{full-time})$.¹⁵

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) when the husband has a higher degree of care needs. η differs across households and time by assuming that it evolves according to the following process.

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

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

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 which follows a standard AR(1) process. I assume that healthy individuals do not have any care needs by setting $\eta_t(0) = 0$. ϵ_t allows for (unobservable) heterogeneity in care needs even conditional on disability status s^h .¹⁶ 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

¹⁵In particular, $(\text{part-time}, \text{part-time})$, $(\text{full-time}, \text{part-time})$, and $(\text{part-time}, \text{full-time})$ are not included in the set of available choices. This modeling choice is guided by the data patterns in my sample. 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.

¹⁶In the absence of the heterogeneity coming from ϵ_t , it is difficult to match the joint distribution of husbands' employment choices and wives' caregiving choices as observed in the data.

¹⁷Among 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.

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 (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 following time constraints,

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

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

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 hours worked in the labor market, respectively. h^h and h^w are discretized as zero, part-time, and full-time hours.

Equation (6) indicates that husbands allocate their time to leisure and market hours but incur a time loss¹⁹ of $\phi^h(s^h) + \phi_\eta^h(s^h) \cdot g(\eta, s^h)$ and a fixed time cost of working, $\phi_{emp}^h(s^h) + \phi_{emp,\eta}^h(s^h) \cdot g(\eta, s^h)$. 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 or no care. Both of these time costs depend on health status and the degree of care needs where $g(\cdot, s^h)$ is a monotonically increasing function of η . In practice, I set $g(\cdot, s^h)$ 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 time cost of $\phi_\eta^h(s^h)$ and fixed cost of working $\phi_{emp,\eta}^h(s^h)$ compared to the husbands in the middle tertile. I assume that healthy husbands do not incur additional time costs such that $\phi^h(0) = \phi_\eta^h(0) = \phi_{emp}^h(0) = \phi_{emp,\eta}^h(0) = 0$.

Finally, husbands incur a time cost $\phi_w^h(s^w)$ depending on their wives' health status. This can be thought of as the husband's time spent in caregiving when their wives become disabled.²⁰ This time cost is assumed to be zero when wives are healthy ($\phi_w^h(0) = 0$).

¹⁸About 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.

¹⁹This can be thought of as "sick time" which burns some of the husband's leisure time (e.g. experiencing pain, being bedridden, visiting doctors)

²⁰In order to maintain computational tractability, I abstract from additionally modeling the husband's time allocation choice between leisure, market work, and spousal care. Instead, the model accounts for the

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, $\phi_{emp}^w(s^w)$ when they are disabled. These time costs are assumed to be zero when wives are healthy ($\phi^w(0) = \phi_{emp}^w(0) = 1$). Due to the time cost $\phi^w(s^w)$, the wife's marginal disutility of providing care for her husband will be higher when she is disabled compared to when she is healthy.

Terminal Utility Upon Household Dissolution – Individual behavior after a dissolution of a married household (either through divorce or the death of one or both spouses) is not explicitly modeled.²¹ Instead, the surviving individual j receives a terminal utility $v^j(a_t^j, y_t)$ specified as below.

$$v_t^j(a_t^j, y_t) = \psi_v \frac{\left(W_t^j(a_t^j, y_t)\right)^{1-\gamma}}{1-\gamma}, \quad j \in \{h, w\} \quad (8)$$

$W_t^j(a_t^j, y_t)$ denotes the present discounted value of individual wealth (a_t^j) and future retirement benefits based on the husband's average lifetime earnings at age t , y_t . a_t^j differs between widow/ers and divorcees since 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%.²²

Disability Insurance – Key features of the Social Security Disability Insurance (SSDI) are modeled in order to incorporate the complexities of the program.²³ First, husbands are

possibility of husbands spending time in spousal care in the form of time costs $\phi_w^h(s^w)$.

²¹This 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.

²²In 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 (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.

²³Note that the model abstracts from SSDI beneficiaries being eligible for Medicare benefits after a two-

required to choose whether to apply for SSDI ($App_t \in \{0, 1\}$).²⁴ Application is costly since the household incurs a disutility $\iota(s^h)$ and it requires the husband to be non-employed ($h_t^h = 0$) as well as not being able to receive wage offers during the application period.²⁵ Conditional on applying, SSDI is awarded with some probability $Pr(DI_{t+1} = 1 | s_t^h, t, App_t)$ which depends on the husband's current health status and age. This reflects the fact that although the SSA determines whether an applicant is eligible for disability benefits based on medical and vocational considerations, it cannot perfectly observe the true disability status of the applicant. I assume that the probability of receiving SSDI benefits if the husband is healthy is zero ($Pr(DI_{t+1} = 1 | s_t^h = 0, t, App_t = 1) = 0$) such that husbands never apply for benefits in the healthy state.²⁶

Successful applicants who applied in period t start receiving benefits from period $t + 1$. Husbands are not allowed to work while receiving disability benefits.²⁷ Benefit amount is calculated in the same manner as computing Social Security Retirement benefits which is a monotonic function of average lifetime earnings at age t , y_t .²⁸ Finally, receiving SSDI is an absorbing state (i.e., 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 fact that only a small fraction of SSDI awards are terminated due to recipients returning to work.²⁹

year waiting period. Refer to footnote 9 for further discussion.

²⁴Although SSDI application choices are explicitly modeled for husbands only, I take into account that wives may also receive SSDI income by including the wife's SSDI income as one source of household non-labor income in the budget constraint (see equation (13)).

²⁵This mimics the first step of SSA's disability determination process where applicants who are working and earning more than the substantial gainful activity (SGA) limit (\$1,070 per month in 2014) are automatically denied of benefits. Average application processing time is roughly 4~6 months for initial determinations but becomes significantly longer for appeals.

²⁶In my sample from the HRS data, 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.

²⁷This reflects the SSDI program rule that earnings above the substantial gainful activity (SGA) threshold will lead to the termination of disability benefits.

²⁸See Appendix B for details of how benefits are computed. In reality, SSDI benefit calculation differs slightly from that of Retirement benefits as it allows up to five years with the lowest earnings (including zero earnings) to be excluded from the calculation of benefits. I abstract from incorporating 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 SSDI benefit amount.

²⁹In 2012, only 5% of SSDI terminations were due to beneficiaries working above the SGA earnings

Offered Wages, Labor Market Frictions, and Unemployment Insurance – Husbands who are employed face the risk of being displaced with probability $\delta_{jd}(s_t^h, e^h)$. Non-employed husbands who are neither applying nor receiving SSDI benefits receive wage offers with probability λ . Displaced husbands receive a one-period unemployment insurance (UI) benefit which is set as 23% of previous period’s earnings.³⁰

Each household i receives wage offers such that they evolve according to the following process.

$$\log w_{it}^h = \alpha_0^h + \alpha_1^h \cdot t + \alpha_2^h \cdot t^2 + \alpha_3 \cdot e_i^h + \sum_{s=1}^2 \varphi_s^h \cdot \mathbf{1}(s_{it}^h = s) + \zeta_{it}^h + \epsilon_{it}^h \quad (9)$$

$$\log w_{it}^w = \alpha_0^w + \alpha_1^w \cdot (t-3) + \alpha_2^w \cdot (t-3)^2 + \tilde{\alpha}_3 \cdot e_i^w + \varphi^w \cdot \mathbf{1}(s_{it}^w = 1) + \zeta_{it}^w + \epsilon_{it}^w \quad (10)$$

$$\zeta_{it}^j = \zeta_{i,t-1}^j + \nu_{it}^j, \quad \nu_{it}^j \sim N(0, \sigma_{\nu,j}^2), \quad Cov(\nu_{it}^h, \nu_{it}^w) = \sigma_{\nu_{h,w}}, \quad j \in \{h, w\} \quad (11)$$

$$\epsilon_{it}^j \sim N(0, \sigma_{\epsilon,j}^2), \quad Cov(\epsilon_{it}^h, \epsilon_{it}^w) = \sigma_{\epsilon_{h,w}}, \quad j \in \{h, w\} \quad (12)$$

For both spouses, log wages depend on their own age, education type, and health status.³¹ 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.³² 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 decide to “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 65.³³ If husbands retire before age 65, their

threshold. In contrast, 55% of terminations were due to SSDI benefits rolling over to Retirement benefits once beneficiaries reached full retirement age and 35% due to the death of the recipient (Morton, 2014).

³⁰Average UI replacement rates were about 0.46 during the period of year 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 as 0.23.

³¹To maintain tractability, note that 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 relatively younger households.

³²In 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.

³³Conditional on claiming Social Security Retirement benefits, less than 10% of husbands in my data

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 are three years younger than their husbands and all husbands retire by the age of 65, wives are assumed to retire at age 62.³⁴

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 which is the sum of the husband's benefit and the wife's spousal benefits.³⁵ Following the SSDI program rules, SSDI benefits are automatically converted to retirement benefits once the husband turns age 65.

Budget Constraint – The household faces the following budget constraint each period.

$$A_{t+1} = (1 + r)A_t + \sum_{j \in \{h, w\}} w_t^j h_t^j + UI_t + b_t + I_t + T_t - \tau_t - m_t - c_t - p_{fc} \cdot f c_t \quad (13)$$

UI_t denotes a one-period UI benefit when husbands are displaced. $b_t = b(t, y_t, DI_t, ER_t)$ denotes household Social Security benefits (either Disability or Retirement) as a function of age t , the husband's average lifetime earnings y_t , whether the husband was awarded with disability benefits ($DI_t = 1$), and whether the husband has chosen early retirement ($ER_t = 1$). Note that b_t reflects the sum of both spouses' retirement benefits when both are retired.

$I_t = I(t, e^h, e^w, s_t^h, s_t^w)$ denotes all other sources of household non-labor income including pensions, annuities, veteran benefits, and other lump sum income of both spouses as well as the wife's SSDI and unemployment benefits. Note that 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 .³⁶ I assume that I_t is a function of age, education type, and health status of both spouses.

sample claim benefits after full retirement age (age 65 for most HRS respondents and age 66 for some respondents with later birth years).

³⁴This assumption is based on the observation that conditional on claiming Social Security Retirement benefits, 55% of wives in my data sample claim at age 62 whereas for husbands, the claiming age is relatively more spread out over age 62 to full retirement age.

³⁵See footnote 22 regarding the use of husbands' average lifetime earnings to compute wives' retirement benefits. See Appendix B for details on how benefits are computed.

³⁶This allows for computational tractability since the paper's primary focus is on the analysis of household responses to the husband's health shock.

$\tau_t = \tau(A_t, w_t^h h_t^h, w_t^w h_t^w, UI_t, b_t, I_t)$ denotes payroll and federal income taxes.³⁷ $m_t = m(t, s_t^h, s_t^w, e^h, e^w)$ denotes the sum of exogenous out-of-pocket medical expenses incurred by the husband and the wife and is a function of age, health status, and education type of both spouses. $p_{fc} \cdot fc_t$ denotes household expenditures on formal care where $p_{fc} = 24$ is the hourly market price of formal care³⁸ and fc_t is the annual hours of formal care that the household purchases.

For low-income households, government transfers T_t provides a minimum consumption level $\underline{c}_g$ which satisfies the following equation.

$$T_t = \max \left\{ 0, \underline{c}_g - \left((1+r)A_t + \sum_{j \in \{h,w\}} w_t^j h_t^j + UI_t + b_t + I_t - \tau_t - m_t - p_{fc} \cdot fc_t \right) \right\} \quad (14)$$

$$\underline{c}_g = \begin{cases} \underline{c}_{low} & \text{if } fc_t > 0 \\ \underline{c}_{high} & \text{if } fc_t = 0 \end{cases} \quad (15)$$

$\underline{c}_g$ is a tractable 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. \(1995\)](#).³⁹ I incorporate the fact that Medicaid covers the cost of formal care for eligible individuals by allowing $\underline{c}_g$ to take two values, $\underline{c}_{low}$ and $\underline{c}_{high}$ (equation (15)). I assume that $\underline{c}_{low} < \underline{c}_{high}$ due to Medicaid's stricter financial eligibility criteria.⁴⁰

³⁷State income taxes are not modeled due to wide variation in state tax codes. See Appendix C for details on how taxes are computed.

³⁸Based on average annual rates of home care in 2016 ([MetLife, 2017](#))

³⁹Although 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 benefits are a flat monthly amount which 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 (14) incorporates the nature of SSI while maintaining tractability.

⁴⁰In reality, home health care costs are covered through Home and Community Based Services (HCBS)

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 illegal to borrow against future SSDI/retirement benefits and means-tested program benefits.

Model Solution – Define the vector of state variables at period t as $\mathbf{X}_t = \{A_t, s_t^h, s_t^w, y_t, \vartheta_t, DI_t, ER_t, e^h, e^w, \zeta_t^h, \zeta_t^w, \epsilon_t\}$ 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 ($e^h, e^w \in \{\text{high}, \text{low}\}$), idiosyncratic wage shocks of both spouses (ζ_t^h, ζ_t^w), and the idiosyncratic shock to care needs (ϵ_t). For each period t , households solve the following problem subject to time and budget constraints (6), (7), (13), (14), and (15).

$$\begin{aligned}
V_t(\mathbf{X}_t) = & \max_{\substack{c_t, l_t^h, l_t^w, \\ tc_t, fc_t, App_t}} u(c_t, l_t^h, l_t^w, tc_t, fc_t, App_t; s_t) \\
& + \beta \left\{ (1 - \delta_{m,t}^h(s_t^h, e^h))(1 - \delta_{m,t}^w(s_t^w, e^w))(1 - \delta_d(s_t^h, s_t^w)) E_t[V_{t+1}(\mathbf{X}_{t+1} | \mathbf{X}_t)] \right. \\
& + (1 - \delta_{m,t}^h(s_t^h, e^h))(1 - \delta_{m,t}^w(s_t^w, e^w)) \delta_d(s_t^h, s_t^w) \left(\sum_{j \in \{h, w\}} v_{t+1}^j(\frac{1}{2}A_{t+1}, y_{t+1}) \right) \\
& + (1 - \delta_{m,t}^h(s_t^h, e^h)) \cdot \delta_{m,t}^w(s_t^w, e^w) \cdot v_{t+1}^h(A_{t+1}, y_{t+1}) \\
& \left. + \delta_{m,t}^h(s_t^h, e^h) \cdot (1 - \delta_{m,t}^w(s_t^w, e^w)) \cdot v_{t+1}^w(A_{t+1}, y_{t+1}) \right\}
\end{aligned} \tag{16}$$

The model requires to be solved numerically as there is no analytical solution. This is done by solving the value functions at the terminal period t_T and iterating backwards such that I solve for the value functions and the decision rules for each period.

3.2 Discussion of the Model

This section discusses some of the key model mechanisms and their implications for evaluating the welfare benefits of SSDI policies. First, health state dependence in consumption utility, $\theta(s^h)$, has important implications for determining the insurance value of SSDI benefits. 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

Medicaid Waivers and/or state Medicaid programs. Although there are some variations across states and programs, in general, the income and asset limit for HCBS Medicaid Waivers in 2021 were \$2,382 per month and \$2,000, respectively. For state Medicaid programs, the income limit is often lower than that for HCBS Medicaid Waivers ([American Council on Aging, 2022a](#)).

of consumption in both states are equal. Therefore, if $\theta(s^h) > 1$ in the disabled state (i.e., positive health state dependence), this increases the insurance value of SSDI given the SSDI benefit amount since the marginal value of \$1 of consumption is higher when husbands are disabled compared to when they are healthy. The opposite logic holds if $\theta(s^h) < 1$ in the disabled state (i.e., negative health state dependence).

Next, wives' time allocation to market work and spousal care in the event of their husbands' disability has implications for the household insurance mechanism against disability shocks. Compared to a job displacement, a disability shock is an earnings shock that also entails care needs. This implies that while wives would insure against their husbands' job displacement by increasing working hours, this is not necessarily true in the event of their husbands' disability since wives' time endowment can also be used in spousal care to produce the domestic good $\kappa(tc, fc; s^h)$.

Another implication of wives' time allocation to market work and spousal care is that it provides inference for $\theta(s^h)$. For the purpose of illustration, consider a static environment where the period utility is specified as equation (2). Assuming interior solutions, first order conditions indicate a direct link between household consumption and wives' leisure since the following holds (i.e., the marginal utility of wives' leisure per dollar equals the marginal utility of household consumption).

$$\theta(s^h) \cdot c^{-\gamma} = \frac{\psi_w \cdot l_w^{-\gamma_w}}{w_w}, \quad \forall s^h \quad (17)$$

Notice that if the model ignores that disabled husbands also have care needs (i.e., $\eta_t(s^h) = 0$), wives will allocate all of their time endowment to leisure and market work only. Therefore, wives' market hours h_w can be mapped into the marginal utility of consumption in each health state since equation (17) can be expressed as follows using equation (7) (assuming $\phi^w(s^w) = \phi_{emp}^w(s^w) = 0$ for the simplicity of exposition).

$$\theta(s^h) \cdot c^{-\gamma} = \frac{\psi_w \cdot (\bar{L} - h_w)^{-\gamma_w}}{w_w}, \quad \forall s^h \quad (18)$$

This implies that conditional on the realization of each health state s^h , h_w is chosen such that it reveals how much consumption is valued in the form of spousal earnings, allowing one to use the changes in spousal labor supply responses across husbands' health states to recover $\theta(s^h)$.⁴¹ This is extremely useful since the data requirements for estimating health

⁴¹This argument is also illustrated by [Fadlon and Nielsen \(2019\)](#) who propose using spousal labor supply

state dependence from consumption data are high since it requires a sufficiently large panel dataset that provides a comprehensive measure of household consumption in each health state.⁴² The mapping between wives' market hours and the marginal utility of consumption circumvents this issue and provides inference for $\theta(s^h)$ which is the key parameter of interest.

However, a crucial point is that wives' time endowment is not solely used for market work and leisure when their husbands become disabled. If wives also spend their time in spousal care, their choice of h_w cannot fully capture the marginal utility of consumption in the disabled states. This can be shown from the following,

$$\theta(s^h) \cdot c^{-\gamma} = \frac{\psi_w \cdot (\bar{L} - h_w - \mathbf{t}\mathbf{c})^{-\gamma_w}}{w_w}, \quad \forall s^h \in \{1, 2\} \quad (19)$$

which indicates that the marginal disutility of h_w is higher in the disabled state since tc reduces the time endowment that can be allocated to leisure. Since the direct mapping between wives' market hours and the marginal utility of consumption in the disabled state does not hold, wives' time allocation to both market work *and* spousal care needs to be considered in order to correctly infer $\theta(s^h)$.

4 Estimation

4.1 Estimation Method

To estimate the parameters of the model, I employ a two-step estimation method which is 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 can be identified without explicitly using the model. Given the parameter values from the first step, the remaining preference parameters are estimated by indirect inference. 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

responses across different states as sufficient statistics to infer welfare gains from social insurance programs.

⁴²In most panel datasets, consumption is often measured with error and available for a limited number of items (such as food consumption). Due to data limitations and differences in identification strategies across previous studies, there is wide variation in the empirical estimates of health state dependence ([Viscusi and Evans, 1990](#); [Evans and Viscusi, 1991](#); [Lillard and Weiss, 1997](#); [Edwards, 2008](#); [Finkelstein et al., 2009, 2013](#); [Low and Pistaferri, 2015](#); [Brown et al., 2016](#)).

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 θ_f and those that are estimated in the second stage as θ_s . Then, the estimate $\hat{\theta}_s$ is chosen such that it minimizes the weighted distance between the vector of data moments m_d and the vector of simulated moments $m_s(\hat{\theta}_f, \theta_s)$ where the weight is specified by the matrix $\hat{W}$.

$$\hat{\theta}_s = \arg \min_{\theta_s} (m_d - m_s(\hat{\theta}_f, \theta_s))' \hat{W} (m_d - m_s(\hat{\theta}_f, \theta_s)) \quad (20)$$

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.

4.1.1 Estimation Sample and Initial Conditions

When simulating households, I control for initial conditions by using the first observation of each married household in the HRS sample as the state vector and simulate forward. Table 5 provides a summary of this initial distribution. I make additional sample restrictions such that both spouses are white. This is because the HRS mostly consists of white respondents⁴³ and even after controlling for average lifetime earnings, mortality and disability processes differ significantly for non-whites.

4.1.2 First Stage Parameters

Annual time endowments, and part- and full-time hours – Annual time endowment $\bar{L}$ is set as 5,840 hours (16 hours $\times$ 365 days). For both spouses' market hours (h_t^h, h_t^w), I define annual full- and part-time labor market hours as 2,000 hours (40 hours $\times$ 50 weeks) and 1,000 hours (20 hours $\times$ 50 weeks), respectively. Annual full- and part-time caregiving hours are defined as 2,000 hours and 350 hours (7 hours $\times$ 50 weeks), respectively. This is because the average weekly caregiving hours of wives and paid caregivers in the HRS who provide care for more than zero but 25 hours or less is roughly 7 hours.

Coefficient of relative risk aversion – Following [Low and Pistaferri \(2015\)](#), γ is set as 1.5. I set

⁴³82% of married couples in my HRS sample are those in which both spouses are white. Only 0.7% of couples consist of one white spouse and one black spouse. About 5.8% of couples consist of one white spouse and one spouse who is neither white nor black (race only has three categories – white, black, and other – in the HRS).

$\gamma_h = 1$ and $\gamma_w = 1$ such that both spouses' utility from leisure is specified as a log function.⁴⁴

Rate of return and discount factor – Real interest rate for assets is set as $r = 0.03$ and the discount factor is set as $\beta = \frac{1}{1.03}$, which are commonly assumed values in the literature (Gourinchas and Parker, 2002; Cagetti, 2003; Brown and Finkelstein, 2008; Low and Pistaferri, 2015; Autor et al., 2019).

Table 5: Summary Statistics of the Initial Distribution by Husbands' Health Status

	Husbands' Health Status		
	Healthy	Moderate	Severe
Husbands' characteristics			
Age (mean)	55.27	55.89	55.82
Average lifetime earnings (mean, in \$)	29,998	26,418	23,145
Hourly wages (mean, in \$) [†]	29.54	25.44	22.98
Has a bachelor's degree (or higher) (in %)	27.68	17.70	12.12
Wives' characteristics			
Age (mean)	52.13	52.35	52.71
Hourly wages (mean, in \$) [†]	18.95	17.12	16.30
Disabled (in %)	13.12	20.57	26.77
Has a bachelor's degree (or higher) (in %)	27.68	17.70	12.12
Household characteristics			
Assets (median, in \$1,000)	243.27	191.58	112.46
Observations	2,088	209	198
	(83.69%)	(8.38%)	(7.94%)

Notes: This table reports summary statistics of the initial sample that is 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. All dollar values are in 2015 dollars.

[†] For respondents who were not working in their first year of observation, I use their most recent wage in their last job as a proxy.

⁴⁴Assuming 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 to three choices (non-employment, part-time and full-time employment). 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 this period. This labor supply elasticity will be smaller than the Frisch labor supply elasticity due to wealth effects. Given the estimated model parameter values, the resulting labor supply elasticities are 0.18 (husbands) and 0.54 (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).

Job displacement and job arrival 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.5. 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. 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.⁴⁵

Divorce rates – Biennial divorce rates $\tilde{\delta}_m(s_t^h, s_t^w)$ 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 $\delta_m(s_t^h, s_t^w)$ from the biennial rates $\tilde{\delta}_m(s_t^h, s_t^w)$, I assume that annual divorce rates between the survey waves are equal and use the relationship $1 - \tilde{\delta}_m(s_t^h, s_t^w) = (1 - \delta_m(s_t^h, s_t^w))^2$. The resulting parameter values are reported in Table A.6.

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.1 in the Appendix 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 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.2 and A.3 in the Appendix report fitted biennial health transition probabilities for husbands and wives,

⁴⁵Low et al. (2010) estimate a quarterly job arrival rate of 0.73 from the PSID. Merkurieva (2019) reports a monthly job arrival rate of 0.24 based on the CPS data.

respectively.

SSDI award probabilities – Using the merged administrative data on respondents’ disability benefit claims, I compute the annual SSDI award probabilities for husbands who apply for benefits. These results are reported in Table A.7.

Annual household medical expenses – I compute household medical expenses as the sum of out-of-pocket medical expenses of the husband and the wife. $m_t = m(t, s_t^h, s_t^w, e^h, e^w)$ 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.8 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 55/62/65,⁴⁶ 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.9 reports the estimated coefficients.

Husbands’ time costs when wives are disabled – The husband’s leisure time cost when his wife is disabled, $\phi_w^h(s^w)$, is included in his time constraint (equation (6)) to account for the possibility of husbands spending time in caring for their disabled wives. I set $\phi_w^h(s^w = 1) = 220.48$, the average annual hours that husbands spend on caring for their disabled wives.

4.1.3 Second Stage Parameters and Targeted Data Moments

Given the first stage parameters, the remaining model parameters are estimated using indirect inference. There are a total of 43 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 (ψ_j ,

⁴⁶I 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.

$j \in \{h, w\}$), the husband and wife's time costs by disability status ($\phi^j(s^j), \phi_{emp}^j(s^j), \phi_\eta^h(s^h), \phi_{emp,\eta}^h(s^h), j \in \{h, w\}, s^h \in \{1, 2\}, s^j = 1$), the weight on terminal utility (ψ_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 level provided by government transfers ($\underline{c}_{low}, \underline{c}_{high}$), the disutility of applying for SSDI when moderately disabled ($\iota(1)$), and parameters that govern the wage offer functions of the two spouses (a total of 15 parameters). This section discusses how certain targeted moments are informative of the second stage parameters.

First, *jointly* matching wives' labor supply responses and caregiving choices following their husbands' disability is informative of the health state dependence in consumption utility, $\theta(s^h)$. As discussed in Section 3.2, this is because the direct mapping between wives' marginal disutility of working and the marginal utility of consumption in each health state does not hold in the presence of spousal care since time spent in caregiving increases wives' marginal disutility of working by reducing the time endowment that can be allocated to leisure and market work. For wives' labor supply responses, I run fixed effect regressions of wives' employment and weekly hours on a quartic in both spouses' ages, dummies for husbands' disability severity, a dummy for wives' disability status, interactions of husbands' and wives' disability status, and household fixed effects. I use the coefficients on the dummies for husbands' disability severity (main effects) as moments.

The husband's weight on leisure utility (ψ_h) and his time costs in the disabled states ($\phi^h(s^h), \phi_\eta^h(s^h), \phi_{emp}^h(s^h), \phi_{emp,\eta}^h(s^h), s^h \in \{1, 2\}$) are pinned down by matching husbands' average employment rates and part-time employment rates. I not only match these moments by husbands' health status but also jointly by husbands' health and wives' caregiving choices. In particular, husbands' employment rates by their health status and wives' caregiving choices are informative of $\phi_\eta^h(s^h)$ and $\phi_{emp,\eta}^h(s^h)$ since husbands with greater care needs are more likely to receive care from their wives as well as less likely to work.

The wife's weight on leisure utility (ψ_w) and time costs ($\phi^w(s^w), \phi_{emp}^w(s^w), s^w = 1$) can be recovered by matching wives' average employment rates and part-time employment rates by disability status.

Next, median household asset profiles by age are matched to infer the weight on terminal utility, ψ_v , as this parameter governs the household's wealth holdings over the remaining life-cycle given γ . The minimum household consumption floor $\underline{c}_{high}$ can be recovered by matching household asset profiles by age at the 25th percentile since $\underline{c}_{high}$ affects the savings decisions of households with low levels of assets. Since $\underline{c}_{low}$ is the consumption floor applicable

for household 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.

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 various data moments regarding wives’ caregiving choices. Specifically, $\rho(s^h)$ governs the persistence in wives’ caregiving choices and σ_{ξ, s^h} affects the fraction of part- and full-time caregivers since wives will be more likely to choose full-time caregiving when their husbands receive a higher idiosyncratic shock in care needs. For the parameters that govern the production of the domestic good $(\alpha_\kappa, \gamma_\kappa)$, I match the fraction of severely disabled husbands who hire paid helpers as well as the fraction who receive care from their wives and hire paid helpers at the same time. In particular, the latter moment will be informative of the degree of complementarity between spousal care and paid formal care.

The disutility of applying for benefits when moderately disabled, $\iota(1)$, is inferred by matching the percentage of SSDI applicants by health status. Since the SSDI award probability conditional on applying is given in the first stage, $\iota(1)$ directly affects the number of husbands who decide to apply for benefits. This ensures that both the award probabilities and the flow into the SSDI program are consistent with what is observed in the data.

Finally, the wage parameters governing equations (9), (10), (11), and (12) are recovered by matching fixed effect regression coefficients of log hourly wages for each spouse. 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 age and health status. Then, I take the residuals and regress them on a dummy for having a bachelor’s degree in order to get the wage coefficient on education. For parameters that govern the variance and covariance of the permanent and transitory shocks (equations (11), (12)), I match wage moments as described in Appendix F. Since wages in the data are only observed for respondents selecting into employment, I also only use wages of employed individuals in the simulated data when generating wage moments.

5 Results

5.1 Model Fit and Parameter Estimates

Tables 6 through 10 report the estimated parameter values and model fit of the targeted moments. Parameter estimates of the baseline model specified in Section 3 are reported

in column (a) of Tables 6 and 7. Next, I re-estimate the model where husbands' care needs $\eta_t(s^h)$ is 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 chooses caregiving and only allocates her time between leisure and market hours. The goal of this exercise is to highlight the potential bias in the estimates of key preference parameters when we do not take into account that disability shocks additionally entail care needs and increases the household's demand for spousal and/or market-purchased care. The corresponding parameter estimates are reported in column (b) of Tables 6 and 7, and the model fit is reported in Tables A.10 and A.11 in the Appendix. When I estimate the “no-care” model, I use the same moments as described in Section 4.1.3 except for moments that involve wives' caregiving choices and households' formal care choices.

The key preference parameter that has significant implications for evaluating the welfare benefits of SSDI is the health state dependence in household consumption utility, $\theta(s^h)$. For the moderately disabled state, both the baseline and “no-care” model estimates indicate that the marginal utility of consumption is lower (about 13%) than in the healthy state. However, compared to the baseline model, $\theta(2)$ is significantly underestimated under the “no-care” model. While the baseline model suggests that the marginal utility of consumption in the severely disabled state is 60% higher than in the healthy state, the “no-care” model indicates that it is only 24% higher. By omitting the fact that wives of severely disabled husbands are spending 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. Panel A of Table 8 and Panels A and B of Table 9 show that the model can replicate wives' labor supply and caregiving choices in response to their husbands' disability shocks as observed in the data.

Next, the parameter estimates for husbands' leisure time costs indicate that both sick time and fixed cost of working increase with disability severity and the degree of care needs. Panels D and E of Table 9 show that the model can replicate the negative correlation between husbands' care needs and labor supply. Similarly, wives' sick time and fixed time cost of working are sizable when they are disabled. Panel C of Table 8 indicates that the model can closely replicate wives' employment patterns by their disability status.

Parameter estimates of the baseline model indicate that on average, care needs are higher and exhibit greater persistence for severely disabled husbands compared to those who are moderately disabled. 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

Table 6: Second Stage Estimates of the Model Parameters I

(by husbands' disability $s^h \in \{1(\text{moderate}), 2(\text{severe})\}$)	(a) Baseline		(b) "No-care" [†]	
	$s^h = 1$	$s^h = 2$	$s^h = 1$	$s^h = 2$
Health state dependence in consumption utility, $\theta(s^h)$	0.867 (0.026)	1.601 (0.027)	0.866 (0.009)	1.242 (0.012)
Husbands' leisure time costs (in hours)				
$\phi^h(s^h)$	1,677 (205.8)	2,175 (227.0)	1,764 (117.7)	2,238 (344.1)
$\phi_\eta^h(s^h)$	5.22 (46.99)	3.29 (41.39)	-	-
$\phi_{emp}^h(s^h)$	3.07 (95.02)	353.2 (136.2)	0.108 (0.021)	369.9 (140.0)
$\phi_{emp,\eta}^h(s^h)$	149.9 (61.87)	185.9 (41.54)	-	-
Husbands' care needs				
$\mu_\eta(s^h)$ Average ($\times 10^{-5}$)	4.192 (0.384)	13.72 (3.671)	-	-
$\rho_\eta(s^h)$ Auto-regressive persistence	0.622 (0.236)	0.833 (0.096)	-	-
σ_{ξ,s^h} Variance of white noise ($\times 10^{-4}$)	0.058 (0.068)	5.988 (1.239)	-	-
Husbands' weight on leisure utility ($\times 10^{-3}$), ψ_h	3.427 (0.194)		3.252 (0.175)	
Wives' weight on leisure utility ($\times 10^{-3}$), ψ_w	2.522 (0.157)		2.453 (0.099)	
Wives' leisure time costs (in hours)				
$\phi^w(s^w = 1)$	2,338 (105.0)		2,393 (111.6)	
$\phi_{emp}^w(s^w = 1)$	162.9 (37.01)		152.5 (44.97)	
Production function of the domestic good				
α_κ Weight on wives' time input	0.720 (0.300)		-	
γ_κ Substitution parameter	0.433 (0.340)		-	

Notes: Standard errors in parentheses. Refer to Appendix E 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).

Table 7: Second Stage Estimates of the Model Parameters II

Parameters	(a) Baseline		(b) “No-care” [†]	
	Husband	Wife	Husband	Wife
Wage offer function				
Age	0.115 (0.034)	0.072 (0.022)	0.120 (0.043)	0.080 (0.027)
(Age/10) ²	-0.114 (0.034)	-0.075 (0.024)	-0.120 (0.052)	0.084 (0.028)
Education type	0.684 (0.101)	0.173 (0.063)	0.797 (0.138)	0.177 (0.074)
Moderate disability	-0.096 (0.040)	-	-0.091 (0.032)	-
Severe disability	-0.137 (0.057)	-	-0.107 (0.009)	
Disabled	-	-0.073 (0.042)	-	-0.058 (0.034)
Standard deviation of permanent shock ($\sigma_{\nu,j}$)	0.104 (0.020)	0.068 (0.021)	0.108 (0.017)	0.040 (0.012)
Standard deviation of transitory shock ($\sigma_{\epsilon,j}$)	0.188 (0.015)	0.185 (0.025)	0.188 (0.013)	0.187 (0.014)
Covariance of permanent shock ($\sigma_{\nu_{h,w}}$)		-0.006 (0.001)		-0.010 (0.009)
Covariance of transitory shock ($\sigma_{\epsilon_{h,w}}$)		0.009 (0.002)		0.010 (0.003)
Weight on terminal utility, ψ_v		13.82 (0.935)		14.97 (1.246)
Minimum consumption floor (\$2015)				
$\underline{c}_{high}$		30,590 (2,392)		31,731 (2,024)
$\underline{c}_{low}$		25,969 (3,700)		-
Disutility of SSDI application when moderately disabled ($\times 10^{-4}$), $\iota(1)$		3.359 (1.108)		3.256 (0.991)

Notes: Standard errors in parentheses. Refer to Appendix E 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).

Table 8: Targeted Moments I

	Model	Data	Model	Data
Panel A: Changes in Wives' Labor Supply by Husbands' Disability [†]				
	Wives' Employment Rate		Wive's Weekly Hours (in hours)	
Moderate	-0.011	-0.021 (0.013)	-0.002	-0.240 (0.495)
Severe	-0.015	-0.002 (0.018)	-0.317	0.032 (0.628)
Panel B: Husbands' Employment Rates by Own Health Status				
	Employment Rate		Part-time Employment Rate	
Healthy	0.857	0.861 (0.005)	-	-
Moderate	0.457	0.466 (0.018)	0.117	0.119 (0.011)
Severe	0.222	0.237 (0.017)	0.063	0.062 (0.009)
Panel C: Wives' Employment Rate by Own Health Status				
	Employment Rate		Part-time Employment Rate	
Healthy	0.752	0.752 (0.006)	-	-
Disabled	0.329	0.330 (0.014)	0.154	0.154 (0.011)
Panel D: Household Assets (by husbands' age, in \$1,000)				
	50th Percentile		25th Percentile	
Ages 50 - 54	224.22	245.93 (7.542)	109.05	101.63 (4.180)
Ages 55 - 59	282.14	296.63 (5.912)	124.91	120.27 (3.067)
Ages 60 - 64	334.46	323.66 (7.229)	155.69	129.06 (4.007)
Panel E: SSDI Application Rates by Husbands' Disability				
	Moderate		Severe	
	0.078	0.079 (0.006)	0.116	0.143 (0.008)

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

[†] Based on fixed effect regressions of labor supply variables on indicators of husbands' disability severity, a quartic in both spouses' ages, a dummy for wives' disability, interactions of husbands' and wives' disability status, and household fixed effects. The reported moments are the regression coefficients for the indicators of husbands' disability severity.

Table 9: Targeted Moments II – Care Choices by Husbands' Disability

	Model	Data	Model	Data
	Moderate		Severe	
Panel A: Fraction of Wives Providing Care				
Part-time	0.197	0.203 (0.037)	0.427	0.421 (0.024)
Full-time	0.004	0.000 (0.000)	0.111	0.103 (0.014)
Panel B: Spousal Care Transition Rates (year $t \rightarrow t + 2$)				
No Care $\rightarrow$ No Care	0.900	0.908 (0.046)	0.675	0.637 (0.049)
Care $\rightarrow$ Care	0.614	0.420 (0.172)	0.701	0.735 (0.038)
Panel C: Formal Care Usage Among Severely Disabled Husbands (in %)				
Use formal care	-	-	0.165	0.264 (0.133)
Use both spousal and formal care	-	-	0.065	0.109 (0.090)
Use formal care covered by Medicaid	-	-	0.053	0.041 (0.041)
Panel D: Husband's Employment Rates by Wives' Caregiving Choices				
No Care	0.486	0.477 (0.046)	0.273	0.278 (0.023)
Part-time Care	0.360	0.352 (0.091)	0.195	0.202 (0.024)
Full-time Care	-	-	0.110	0.064 (0.049)
Panel E: Husband's Part-time Employment Rates by Wives' Caregiving Choices				
No Care	0.127	0.110 (0.028)	0.064	0.084 (0.014)
Part-time Care	0.068	0.061 (0.055)	0.062	0.058 (0.015)
Full-time Care	-	-	0.051	0.030 (0.030)

Notes: Standard errors in parentheses. All moments are computed conditional on both spouses being younger than age 65.

Table 10: Targeted Moments III – Wage Moments

	Model	Data	Model	Data
	Husbands		Wives	
Panel A: Fixed Effect Regressions of Log Hourly Wages [†]				
Age	0.097	0.113 (0.039)	0.089	0.084 (0.033)
(Age/10) ²	-0.096	-0.106 (0.034)	-0.087	-0.070 (0.030)
Moderate disability	-0.017	-0.017 (0.021)	-	-
Severe disability	-0.019	0.009 (0.040)	-	-
Disabled	-	-	-0.007	0.001 (0.016)
High education type	0.527	0.532 (0.023)	0.625	0.570 (0.027)
Panel B: Other Wage Moments [‡] ($j \in \{h, w\}$)				
$E(\Delta\omega_{i,t}^j \Delta\omega_{i,t+2}^j)^{\ddagger}$	-0.044	-0.047 (0.005)	-0.039	-0.042 (0.007)
$E\big(\Delta\omega_{i,t}^j (\Delta\omega_{i,t-2}^j + \Delta\omega_{i,t}^j + \Delta\omega_{i,t+2}^j)\big)^{\ddagger}$	0.033	0.037 (0.006)	0.009	0.009 (0.008)
$E(\Delta\omega_{i,t}^h \Delta\omega_{i,t+2}^w)^{\ddagger}$	-0.009	-0.008 (0.004)	-0.009	-0.008 (0.004)
$E\big(\Delta\omega_{i,t}^h (\Delta\omega_{i,t-2}^w + \Delta\omega_{i,t}^w + \Delta\omega_{i,t+2}^w)\big)^{\ddagger}$	-0.008	-0.008 (0.005)	-0.008	-0.008 (0.005)

Notes: Standard errors in parentheses. All moments are computed conditional on both spouses being younger than age 65.

[†] This panel matches fixed effect regression coefficients of log hourly wages for each spouse. 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.

[‡] $\Delta\omega_{i,t}^j$ is the second difference of residual log hourly wage of spouse j in household i , i.e., $\Delta\omega_{i,t}^j = (\zeta_{it}^j + \epsilon_{it}^j) - (\zeta_{i,t-2}^j + \epsilon_{i,t-2}^j)$. I use second differences due to the HRS data being biennial. Refer to Appendix F for more technical details.

wives from choosing market work to make up for the loss in their husbands' earnings. Panels A and B of Table 9 show that the model does a good job of replicating wives' caregiving choices.

Based on the parameter estimates of the production function of the domestic good, one can infer that 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). Furthermore, $\alpha_\kappa = 0.72$ indicates that the weight on spousal care is significantly higher than that on formal care. This can be interpreted as husbands having a stronger preference for receiving care from family members such that spousal care contributes more towards husbands' well-being. Panel C of Table 9 indicates that formal care usage among severely disabled husbands is very low (0.264% in the data). Nonetheless, the model can reasonably replicate the formal care choices observed in the data. Note that the percentage of severely disabled husbands receiving Medicaid-covered formal care is informative of c_{low} .

Tables 7 and 10 report the second stage parameter estimates of the wage offer function and the model fit of wage moments, respectively. Under the baseline model, husbands' offered hourly wages are reduced by 9.6% and 13.7% when they are moderately and severely disabled, respectively. These magnitudes are roughly in line with 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 wage by 7.3% under the baseline which is smaller in magnitude than that of husbands. 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).⁴⁷ Table 10 indicates that given the estimated wage parameters, the model can generate wage moments that are similar to those observed in the data.

Finally, given that the SSDI award rate for moderately disabled husbands in the data can be as high as 62% (see Table A.7), the disutility of applying when moderately disabled is estimated to be strictly positive in order to match SSDI application rates. Panel E of Table 8 shows that although the model slightly underpredicts the SSDI application rates among severely disabled husbands, it closely matches the SSDI application behavior for moderately

⁴⁷Since 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 $0.121 \sim 0.22$ (men) and $0.157 \sim 0.225$ (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 $0.128 \sim 0.208$ for men and $0.105 \sim 0.160$ for women. Finally, the range of the covariance between the two spouses are $-0.008 \sim 0.0072$ for permanent wage shocks and $0.0007 \sim 0.0124$ for transitory wage shocks.

disabled husbands.

Untargeted Moments: Assets and Consumption Patterns

As robustness, I simulate median asset profiles by husbands' disability severity using the baseline model and report the model fit in Table A.12. Although these moments were not matched in the estimation procedure, Table A.12 shows that the model can generate asset patterns for married households with moderately and severely disabled husbands as observed in the data.

Next, I compare household consumption responses to husbands' disability that the baseline model generates to those observed in the HRS data. This is done by estimating the event study equation (1) using the simulated data and the HRS data where the dependent variable is log household consumption. The results are shown in Figure A.4. Unlike the information on caregiving hours which is available in both the Core and CAMS data, household expenditure data is only available in the CAMS data in which the sample size is substantially smaller than the Core survey. Therefore, I additionally construct imputed household consumption measures based on the method proposed by Skinner (1987) using the variables available in the HRS Core survey.

Figure A.4 indicates that due to the lack of statistical significance, there is inconclusive evidence of household consumption responses to husbands' disability for both consumption measures in the HRS. However, the simulated data is able to mimic the point estimates from the imputed HRS Core data which were not targeted in the estimation procedure.

5.2 Simulated Added-Worker-Effects When Spousal Care Needs Are Reduced

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 the simulated added-worker effects under two scenarios using the baseline model estimates (column (a) of Table 6). In the first scenario, I set $\eta_t(s^h)$ to be zero such that the household never allocates resources to the husband's care (in the form of spousal care and/or formal care). This is an extreme case in which the need for spousal care is completely removed. In the second scenario, I assume that SSDI beneficiaries are additionally eligible for a long-term care (LTC) insurance program that covers all formal care costs.

The results are reported in Table 11. First, under both scenarios, simulated added-worker effects are modest when husbands become moderately disabled. However, reducing spousal care needs increases added-worker effects considerably when husbands become severely disabled. When spousal care needs are completely removed (column (1)), wives increase weekly working hours by 2.16 hours and employment rate by 4.8 percentage points in response to their husbands' severe disability. Even when spousal care needs are partially removed through the LTC program for SSDI beneficiaries (column (2)), the increase in wives' weekly working hours and employment rate is 0.813 hours and 1.7 percentage points, respectively. This implies that husbands' care needs play a sizable role in attenuating wives' labor supply responses.

Table 11: Simulated Added-Worker Effects Using Baseline Model Estimates
(by Husbands' Disability)

	(1) No care needs [†] ($\eta_t(s^h) = 0$)	(2) LTC program for SSDI recipients [‡]
Wives' weekly hours		
Moderate	0.554	0.326
Severe	2.162	0.813
Wives' employment rate		
Moderate	0.008	0.000
Severe	0.048	0.017

Notes: This table reports results from fixed effect regressions of wives' labor supply on indicators of husbands' disability severity, a quartic in both spouses' ages, a dummy for wives' disability, and household fixed effects using model simulated data.

[†] Column (1) reports simulated added-worker effects using baseline model estimates but when care needs $\eta_t(s^h)$ is always zero such that the household never allocates resources towards husbands' care (spousal care and/or formal care).

[‡] Column (2) reports simulated added-worker effects when SSDI beneficiaries are additionally eligible for a long-term-care insurance program that covers all formal care costs.

5.3 Evaluating the Welfare Benefits of SSDI Policies

Next, I use the estimated model to analyze the welfare benefits of the current and counterfactual SSDI policies relative to their costs.⁴⁸ First, the ex-ante insurance value of SSDI is calculated using a compensating variation measure, x . I define x as the lump sum amount

⁴⁸One caveat to keep in mind when interpreting the results is that these counterfactual exercises are partial equilibrium analyses.

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 follows,

$$V_{50}(A_t, \Theta_t | \text{economy with SSDI}) = V_{50}(A_t + x, \Theta_t | \text{economy with no SSDI}) \quad (21)$$

where Θ_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 which sets husbands’ care needs to zero such that the household never allocates resources to spousal care or formal care (using corresponding parameter estimates reported in column (b) of Table 6). 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 12.

Row (2) of Table 12 reports that under the baseline model, households value each dollar of SSDI benefits as \$1.05. 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 benefits as 97 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, row (3) reports the required percentage change in SSDI benefits such that the insurance value of SSDI equals to the value predicted by the “no-care” model. 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.

Next, I consider two different types of government-budget-neutral policy reforms which reduces SSDI benefit levels 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.⁴⁹ 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

Table 12: Ex-ante Insurance Value of SSDI for Married Households

	Model	
	Baseline	“No-care”*
Health state dependence estimates $(\theta(1), \theta(2))$	(0.87, 1.60)	(0.87, 1.24)
(1) Ex-ante insurance value of SSDI (in \$) [†]		
Mean	5,559	5,112
Median	4,132	3,710
25th percentile	2,126	1,714
75th percentile	7,406	6,962
(2) Ex-ante insurance value of SSDI per dollar of SSDI benefits (in \$) [‡]	1.05	0.97
(3) Required % change in SSDI benefits such that (2) equals 0.97	+7.00%	-

Notes: Reports the ex-ante insurance value of SSDI for married households that are first observed at ages 50 to 54. Nominal dollar amounts are in 2015 dollars.

* 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 6 are used.

[†] For each simulated household, the ex-ante insurance value is measured as the lump sum amount of asset which 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 (21) for a formal definition.

[‡] Computed as the average ex-ante insurance value over the average present discounted value of SSDI benefits.

⁴⁹In reality, monitoring the number of caregiving hours performed by the spouse may be challenging. 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 exclude their spouses from being hired as a paid caregiver. 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, 2022b). When interpreting the counterfactual results, it must be noted that administration and monitoring costs are not included in the analysis.

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 13.

Table 13 shows that compared to the current SSDI policy, reducing benefits for everyone by 14.85% but providing an annual caregiver allowance of \$33,669 for eligible SSDI beneficiaries can increase utilitarian social welfare while keeping the government budget the same. On average, the ex-ante insurance value of the reformed policy is about \$1,000 higher than that of the current policy (\$6,569 vs. \$5,559) and therefore, the increase in welfare benefits is sizable. Furthermore, Table 13 indicates that Policy (1) provides higher welfare benefits than the current policy across all income quintile groups. Lastly, the supplement for full-time spouse caregivers (\$33,669 annually) is lower than the cost of privately hiring a full-time home health aide (\$24 (average hourly rate in 2016) $\times$ 2,000 annual hours = \$48,000).

Next, Policy (2-1) reduces SSDI benefits by 14.13% for everyone but provides eligible beneficiaries with in-kind transfers that fully cover the cost of formal care. Compared to the current SSDI policy, Policy (2-1) also improves utilitarian social welfare given the same government budget although the magnitude of the increase is smaller than that of Policy (1). The smaller increase in welfare compared to Policy (1) can be explained by the fact that under the baseline model estimates, spousal care has a higher weight in the production of the domestic good than the time input from paid helpers ($\alpha_\kappa > 0.5$).

Finally, providing in-kind transfers that fully cover formal care costs for all beneficiaries requires SSDI benefits to be reduced by 44.20% in order to maintain budget neutrality (Policy (2-2)). Although providing in-kind transfers for formal care expenses increases wives’ labor supply responses to their husbands’ disability (as seen in column (2) of Table 11), this reform *lowers* welfare compared to the baseline policy due to its large reduction in benefits.

Tables 12 and 13 point toward a couple of important conclusions. First, Table 12 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 12 and 13 imply that utilitarian social welfare can be improved given the same government budget level by targeting resources to disabled beneficiaries with greater care needs (either in the form of supplemental caregiver benefits directly given to spousal caregivers or in the form of in-kind transfers that cover the cost of hiring paid caregivers).

Table 13: Counterfactual Budget-Neutral Policy Reforms

- Baseline: Current SSDI policy
- Government budget-neutral reform that maximizes social welfare*
 - (1) Caregiver benefits: Reduce SSDI benefits by 14.85% but provide annual caregiver benefits of \$33,669 to eligible SSDI beneficiaries[†]
 - (2-1) In-kind transfers: Reduce SSDI benefits by 14.13% but fully cover the cost of paid helpers for eligible SSDI beneficiaries[‡]
 - (2-2) In-kind transfers: Reduce SSDI benefits by 44.20% 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	\$5,559	\$6,569	\$5,694	\$3,418
By income quintiles [§]				
Q1 (bottom)	\$3,053	\$3,595	\$3,209	\$2,305
Q2	\$4,538	\$5,819	\$4,922	\$3,142
Q3	\$5,813	\$7,128	\$6,077	\$3,679
Q4	\$7,951	\$9,478	\$8,157	\$4,728
Q5 (top)	\$9,249	\$9,935	\$9,120	\$4,886

* 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 which 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 (21) 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).

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 in the form of either supplemental caregiver benefits or 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 of age 50 to 64). Although this is the primary age group of SSDI beneficiaries,⁵⁰ 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 one spouse’s 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.

⁵⁰In 2013, about 70% of SSDI awards were for individuals of age 50 to full retirement age (age 65 to 66 depending on birth year) ([Morton, 2015](#)).

References

- American Council on Aging (2022a). Answers to All of Your Questions about Medicaid Long Term Care. <https://www.medicaidplanningassistance.org/medicaid-long-term-care-faq/>.
- American Council on Aging (2022b). How to Receive Financial Compensation via Medicaid to Provide Care for a Loved One. <https://www.medicaidplanningassistance.org/getting-paid-as-caregiver/>.
- Autor, D., A. Kostol, M. Mogstad, and B. Setzler (2019). Disability Benefits, Consumption Insurance, and Household Labor Supply. *American Economic Review* 109(7), 2613–2654.
- Benitez-Silva, H., M. Buchinsky, and J. Rust (2004). How Large are the Classification Errors in the Social Security Disability Award Process? NBER Working Paper 10219, National Bureau of Economic Research, Cambridge, MA.
- Berger, M. C. and B. M. Fleisher (1984). Husband’s Health and Wife’s Labor Supply. *Journal of Health Economics* 3(1), 63–75.
- Blundell, R., L. Pistaferri, and I. Saporta-Eksten (2016). Consumption Inequality and Family Labor Supply. *American Economic Review* 106(2), 387–435.
- Bound, J. (1989). The Health and Earnings of Rejected Disability Insurance Applicants. *American Economic Review* 79(3), 482–503.
- Bound, J., C. Brown, G. J. Duncan, and W. L. Rodgers (1994). Evidence on the Validity of Cross-Sectional and Longitudinal Labor Market Data. *Journal of Labor Economics* 12(3), 345–368.
- Bound, J., J. B. Cullen, A. Nichols, and L. Schmidt (2004). The Welfare Implications of Increasing Disability Insurance Benefit Generosity. *Journal of Public Economics* 88(12), 2487–2514.
- Bound, J., T. Stinebrickner, and T. Waidmann (2010). Health, Economic Resources and the Work Decisions of Older Men. *Journal of Econometrics* 156(1), 106–129.
- Brault, M. W. (2012). Americans With Disabilities: 2010. Current Population Reports P70-131, U.S. Census Bureau.
- Brown, J. R. and A. Finkelstein (2008). The Interaction of Public and Private Insurance: Medicaid and the Long-Term Care Insurance Market. *American Economic Review* 98(3), 1083–1102.
- Brown, J. R., G. S. Goda, and K. McGarry (2016). Heterogeneity in State-Dependent Utility: Evidence from Strategic Surveys. *Economic Inquiry* 54(2), 847–861.

- Cagetti, M. (2003). Wealth Accumulation Over the Life Cycle and Precautionary Savings. *Journal of Business & Economic Statistics* 21(3), 339–353.
- Chandra, A. and A. Samwick (2005). Disability Risk and the Value of Disability Insurance. NBER Working Paper 11605, National Bureau of Economic Research, Cambridge, MA.
- Charles, K. (1999). Sickness in the Family: Health Shocks and Spousal Labor Supply. Unpublished manuscript.
- Charles, K. K. (2003). The Longitudinal Structure of Earnings Losses among Work-Limited Disabled Workers. *Journal of Human Resources* XXXVIII(3), 618–646.
- Charles, K. K. and P. Sevak (2005). Can family caregiving substitute for nursing home care? *Journal of Health Economics* 24(6), 1174–1190.
- Chen, S. and W. van der Klaauw (2008). The Work Disincentive Effects of the Disability Insurance Program in the 1990s. *Journal of Econometrics* 142(2), 757–784.
- Chetty, R. (2012). Bounds on Elasticities with Optimization Frictions: A Synthesis of Micro and Macro Evidence on Labor Supply. *Econometrica* 80(3), 969–1018.
- Chetty, R., A. Guren, D. Manoli, and A. Weber (2011). Are Micro and Macro Labor Supply Elasticities Consistent? A Review of Evidence on the Intensive and Extensive Margins. *American Economic Review* 101(3), 471–475.
- Coe, N. B., G. S. Goda, and C. H. Van Houtven (2015). Family spillovers of long-term care insurance. NBER Working Paper w21483.
- Coile, C. (2004). Health Shocks and Couples’ Labor Supply Decisions. NBER Working Paper 10810, National Bureau of Economic Research, Cambridge, MA.
- Cullen, J. B. and J. Gruber (2000). Does Unemployment Insurance Crowd Out Spousal Labor Supply? *Journal of Labor Economics* 18(3), 546–572.
- De Nardi, M., E. French, and J. B. Jones (2010). Why Do the Elderly Save? The Role of Medical Expenses. *Journal of Political Economy* 118(1), 39–75.
- Edwards, R. D. (2008). Health Risk and Portfolio Choice. *Journal of Business & Economic Statistics* 26(4), 472–485.
- Evans, W. N. and W. K. Viscusi (1991). Estimation of State-Dependent Utility Functions Using Survey Data. *Review of Economics and Statistics* 73(1), 94–104.
- Fadlon, I. and T. H. Nielsen (2017). Family Labor Supply Responses to Severe Health Shocks. NBER Working Paper 21352, National Bureau of Economic Research, Cambridge, MA.
- Fadlon, I. and T. H. Nielsen (2019). Household Labor Supply and the Gains from Social Insurance. *Journal of Public Economics* 171, 18–28.

- Finkelstein, A., E. F. P. Luttmer, and M. J. Notowidigdo (2009). Approaches to Estimating the Health State Dependence of the Utility Function. *American Economic Review: Papers & Proceedings* 99(2), 116–121.
- Finkelstein, A., E. F. P. Luttmer, and M. J. Notowidigdo (2013). What Good Is Wealth Without Health? The Effect of Health on the Marginal Utility of Consumption. *Journal of the European Economic Association* 11(S1), 221–258.
- French, E. and J. Jones (2011). The Effects of Health Insurance and Self-Insurance on Retirement Behavior. *Econometrica* 79(3), 693–732.
- French, E. and J. Song (2014). The Effect of Disability Insurance Receipt on Labor Supply. *American Economic Journal: Economic Policy* 6(2), 291–337.
- Gallipoli, G. and L. Turner (2011). Household Responses to Individual Shocks: Disability and Labor Supply. Unpublished manuscript.
- Garcia-Perez, J. I. and S. Rendon (2020). Family Job Search and Wealth: The Added Worker Effect Revisited. *Quantitative Economics*, forthcoming.
- Gourieroux, C., A. Monfort, and E. Renault (1993). Indirect Inference. *Journal of Applied Econometrics* 8(S1), S85–S118.
- Gourinchas, P.-O. and J. A. Parker (2002). Consumption Over the Life Cycle. *Econometrica* 70(1), 47–89.
- Gruber, J. (2000). Disability Insurance Benefits and Labor Supply. *Journal of Political Economy* 108(6), 1162–1183.
- Haan, P. and V. Prowse (2015). Optimal Social Assistance and Unemployment Insurance in a Life-Cycle Model of Family Labor Supply and Savings. Upjohn Institute Working Paper 15-240, W.E. Upjohn Institute.
- Haurin, D. R. (1989). Women’s Labor Market Reactions to Family Disruptions. *The Review of Economics and Statistics* 71(1), 54.
- Heckman, J. J. and T. E. MaCurdy (1980). A Life Cycle Model of Female Labour Supply. *Review of Economic Studies* 46(1), 47–74.
- Hubbard, G., J. Skinner, and S. Zeldes (1995). Precautionary Saving and Social Insurance. *Journal of Political Economy* 103(2), 360–399.
- Hyslop, D. R. (2001). Rising U.S. Earnings Inequality and Family Labor Supply: The Covariance Structure of Intrafamily Earnings. *American Economic Review* 91(4), 755–777.
- Jacobs, L. (2021). Occupations, Retirement, and the Value of Disability Insurance. mimeo.

- Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan (1993). Earnings Losses of Displaced Workers. *The American Economic Review* 83(4), 685–709. Publisher: American Economic Association.
- Jeon, S.-H. and R. V. Pohl (2017). Health and Work in the Family: Evidence from Spouses’ Cancer Diagnoses. *Journal of Health Economics* 52, 1–18.
- Juhn, C. and S. Potter (2007). Is There Still an Added-Worker Effect? Federal Reserve Bank of New York Staff Report 310, Federal Reserve Bank of New York, New York, NY.
- Keane, M. P. (2011). Labor Supply and Taxes: A Survey. *Journal of Economic Literature* 49(4), 961–1075.
- Kitao, S. (2014). A life-cycle model of unemployment and disability insurance. *Journal of Monetary Economics* 68, 1–18.
- Kostøl, A. R. and M. Mogstad (2015). Earnings, Disposable Income, and Consumption of Allowed and Rejected Disability Insurance Applicants. *American Economic Review* 105(5), 137–141.
- Layard, R., M. Barton, and A. Zabalza (1980). Married Women’s Participation and Hours. *Economica* 47(185), 51–72.
- Lillard, L. A. and Y. Weiss (1997). Uncertain Health and Survival: Effects on End-of-Life Consumption. *Journal of Business & Economic Statistics* 15(2), 254–268.
- Low, H., C. Meghir, and L. Pistaferri (2010). Wage Risk and Employment Risk over the Life Cycle. *American Economic Review* 100(4), 1432–1467.
- Low, H. and L. Pistaferri (2015). Disability Insurance and the Dynamics of the Incentive Insurance Trade-Off. *American Economic Review* 105(10), 2986–3029.
- Lundberg, S. (1985). The Added Worker Effect. *Journal of Labor Economics* 3(1), 11–27.
- Maestas, N., K. J. Mullen, and A. Strand (2013). Does Disability Insurance Receipt Discourage Work? Using Examiner Assignment to Estimate Causal Effects of SSDI Receipt. *American Economic Review* 103(5), 1797–1829.
- Maloney, T. (1987). Employment Constraints and the Labor Supply of Married Women: A Reexamination of the Added Worker Effect. *Journal of Human Resources* 22(1), 51–61.
- Maloney, T. (1991). Unobserved Variables and the Elusive Added Worker Effect. *Economica* 58(230), 173–187.
- Meghir, C. and L. Pistaferri (2004). Income Variance Dynamics and Heterogeneity. *Econometrica* 72(1), 1–32.

- Merkurieva, I. (2014). The Added Worker Effect and the Lifetime Labor Supply of Older Households. mimeo.
- Merkurieva, I. (2019). Late Career Job Loss and the Decision to Retire. *International Economic Review* 60(1), 259–282.
- MetLife (2017). Summary of 2016 Long Term Care Costs. Technical Report.
- Meyer, B. D. and W. K. Mok (2019). Disability, Earnings, Income and Consumption. *Journal of Public Economics* 171, 51–69.
- Mincer, J. (1962). Labor Force Participation of Married Women: A Study of Labor Supply. In *Aspects of Labor Economics*, pp. 63–105. Princeton, NJ: Princeton University Press.
- Morton, W. (2014). Primer on Disability Benefits: Social Security Disability Insurance (SSDI) and Supplemental Security Income (SSI). CRS Report RL32279, Congressional Research Service.
- Morton, W. R. (2015). Social Security Disability Insurance (SSDI) Reform: An Overview of Proposals to Manage the Growth in the SSDI Rolls. CRS Report R43054, Congressional Research Service.
- Nagi, S. (1969). *Disability and Rehabilitation: Legal, Clinical, and Self-concepts and Measurement*. Columbus, OH: Ohio State University Press.
- Parsons, D. (1977). Health, Family Structure, and Labor Supply. *American Economic Review* 67(4), 703–712.
- Parsons, D. O. (1980). The Decline in Male Labor Force Participation. *Journal of Political Economy* 88(1), 117–134.
- Pischke, J. (1995). Measurement Error and Earnings Dynamics: Some Estimates from the PSID Validation Study. *Journal of Business and Economic Statistics* 13(3), 305–314.
- Rhee, S. (2020). Disability and Occupational Labor Transitions: Evidence from South Korea. *SSRN Electronic Journal*.
- Skinner, J. (1987). A superior measure of consumption from the panel study of income dynamics. *Economics Letters* 23(2), 213–216.
- Skira, M. M. (2015). Dynamic Wage and Employment Effects of Elder Parent Care: Dynamic Effects of Caregiving. *International Economic Review* 56(1), 63–93.
- Spletzer, J. R. (1997). Reexamining the Added Worker Effect. *Economic Inquiry* 35(2), 417–427.
- Stephens, M. (2001). The Long-Run Consumption Effects of Earnings Shocks. *Review of Economics and Statistics* 83(1), 28–36.

- Stephens, Jr., M. (2002). Worker Displacement and the Added Worker Effect. *Journal of Labor Economics* 20(3), 504–537.
- Teshale, S., W. Fox-Grage, and K. Purington (2021). Paying Family Caregivers through Medicaid Consumer-Directed Programs: State Opportunities and Innovations. Technical Report, National Academy for State Health Policy.
- Van Houtven, C. H. and E. C. Norton (2004). Informal care and health care use of older adults. *Journal of Health Economics* 23(6), 1159–1180.
- Viscusi, W. K. and W. N. Evans (1990). Utility Functions That Depend on Health Status: Estimates and Economic Implications. *American Economic Review* 80(3), 353–374.
- von Wachter, T., J. Song, and J. Manchester (2011). Trends in Employment and Earnings of Allowed and Rejected Applicants to the Social Security Disability Insurance Program. *American Economic Review* 101(7), 3308–3329.

Appendix

A Robustness of Spousal Responses to Husbands' Disability Onset

This section provides additional analyses regarding wives' labor supply and caregiving responses to their husbands' disability. Table A.1 reports the effect of husbands' disability onset on their wives' weekly working hours. 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. 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 are receiving 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 are not mainly driven by households whose husbands are receiving SSI/DI benefits.

Another concern is that disabilities that are highly expected 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. Arguably, disabilities caused by accidents are less likely to be expected and therefore more likely to be regarded as an unexpected shock. Formally, the estimation model is as follows:

$$y_{it} = \alpha_i + \gamma_t + X'_{it}\beta + \sum_g \left(\sum_{k=-4}^5 \delta_k^g \cdot I_{itk}^g \right) + \epsilon_{it} \quad (22)$$

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 that disabilities occur.

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

Table A.1: The Effect of Husbands' Disability Onset on Wives' Weekly Hours Worked

	(1)	(2)	(3)	
			Cause of disability	
			Non-Accident	Accident
Year = -4, -3	0.321 (0.691)	0.332 (0.690)	0.601 (0.785)	-0.717 (1.384)
Year = -2, -1	-0.407 (0.878)	-0.370 (0.877)	0.106 (0.974)	-2.001 (1.844)
Year = 0, 1	-0.706 (0.959)	-0.565 (0.957)	-0.640 (1.057)	-0.611 (1.940)
Year = 2, 3	-0.697 (1.052)	-0.440 (1.068)	-0.230 (1.183)	-1.279 (1.966)
Year = 4, 5	-1.845 (1.238)	-1.526 (1.267)	-1.309 (1.372)	-2.370 (2.380)
Receiving SSDI	-	-1.625 (1.479)	-1.644 (1.485)	
Receiving SSI	-	-1.346 (2.630)	-1.390 (2.639)	
Observations	23,424	23,424	23,424	
R-sq	0.108	0.108	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 in parentheses, clustered at the household level.

in response to their husbands' earnings shock). The results shown in Table A.2 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. For wives of with high labor force attachment, point estimates indicate that those whose husbands experience a disability

Table A.2: 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 (1.045)	0.0112 (0.014)	0.091 (0.105)	0.490 (1.093)	0.002 (0.018)	-0.734 (1.544)
Year = -2, -1	-0.750 (1.373)	0.005 (0.020)	0.090 (0.222)	0.727 (1.387)	0.034 (0.025)	0.520 (1.321)
Year = 0, 1	-0.504 (1.450)	0.093*** (0.033)	1.028*** (0.349)	0.261 (1.508)	0.128*** (0.035)	2.569 (2.509)
Year = 2, 3	-0.988 (1.551)	0.110*** (0.036)	1.606** (0.707)	0.709 (1.691)	0.136*** (0.044)	7.263** (3.041)
Year = 4, 5	-2.435 (1.825)	0.097*** (0.037)	1.689** (0.787)	-0.878 (2.126)	0.176*** (0.058)	1.315 (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 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).

shock decrease their working hours, although all of the estimates lack statistical significance. Columns (2), (3), (2'), and (3') confirm that sizable increases in time spent in spousal care is observed for both groups.

B Social Security Benefit Computation

This section describes how Social Security Disability Insurance and (household) retirement benefits are computed in the model. Denote the age that the husband first receives Social Security benefits (either SSDI or retirement) as t_b . In reality, the individual's 35 highest years of earnings (including zero earnings) are used in computing benefits. Since keeping track of husbands' entire earnings histories is computationally infeasible, I approximate average lifetime earnings at age t_b as follows:

$$y_{t_b} = \frac{\sum_{t=t_0}^{t_b} e_t^*}{35} \quad (23)$$

where t_0 denotes the first year of earnings. e_t^* denotes period earnings subject to the maximum taxable earnings e^{max} :

$$e_t^* = \min\{w_t^h h_h^h, e^{max}\} \quad (24)$$

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 his average lifetime earnings (measured at age t_b) y_{t_b} divided by 12.

$$AIME(y_{t_b}) = \frac{y_{t_b}}{12} \quad (25)$$

In reality, indexed nominal earnings are used when computing the AIME in order to ensure 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 (25) provides a reasonable approximation of the AIME without the need of introducing a wage index for each calendar year.

Next, the Primary Insurance Amount (PIA) is computed from the AIME based on the following Social Security benefit formula.

$$\begin{aligned} PIA(y_{t_b}) = & 0.90 \times \min\{AIME(y_{t_b}), b_1\} \\ & + 0.32 \times \min\left\{\max\{AIME(y_{t_b}) - b_1, 0\}, b_2 - b_1\right\} \\ & + 0.15 \times \max\{AIME(y_{t_b}) - b_2, 0\} \end{aligned} \quad (26)$$

b_1 and b_2 denote bend points which reflect the three progressive replacement factors (90%,

32%, and 15%) that are applied to the three brackets of AIME. I use $b_1 = \$826$ and $b_2 = \$4,980$ based on the policy parameters for 2015.

Since the model period is annual, disability benefits are set as follows.

$$b_t(y_{t_b}, DI_t = 1) = 12 \times PIA(y_{t_b}) \quad (27)$$

Household retirement benefits are computed as the sum of both spouses' retirement benefits based on the husband's average lifetime earnings.⁵¹ I use the fact that wives are eligible for 50% of their husbands' PIA and calculate household retirement benefits as below.⁵²

$$b_t(y_{t_b}, DI_t = 0) = 12 \times (1.5 \times PIA(y_{t_b})) \quad (28)$$

C 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 ($\tau_t = \tau_{P,t}^h + \tau_{P,t}^w + \tau_{F,t}$).

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 follows.

$$\tau_{P,t}^j = 0.062 \times \min\{w_t^j h_t^j, e^{max}\} + 0.0145 \times w_t^j h_t^j, \quad j \in \{h, w\} \quad (29)$$

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

$$TI_t = \max\{rA_t + w_t^h h_t^h + w_t^w h_t^w + UI_t + tb_t + I_t - d, 0\} \quad (30)$$

⁵¹See footnote 22 regarding the use of the husband's average lifetime earnings to compute the wife's retirement benefits.

⁵²As noted in footnote 22, while wives can receive Social Security benefits based on either their own or spouses' earnings history (or both), I find that in my data sample, wives' Social Security retirement benefits are about half of that of their husbands' on average.

Table A.3: 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.

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.3.

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.4 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.4: 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.

D First Stage Parameters

This section provides further details on the first stage parameters used in the dynamic model. Tables A.5 and A.6 report the annual job destruction and divorce rates that are estimated from the HRS data.

Table A.7 reports the annual SSDI award probability conditional on the husband’s age and disability status at the year of application. SSDI eligibility is based on both medical and vocational considerations and since the vocational criteria become more lenient for applicants of ages 55 and over,⁵³ I use age 55 as a cutoff. Indeed, Table A.7 reports that while moderately

Table A.5: Husbands’ Annual Job Destruction Rates
by Disability and Education Type

Disability	Education type [†]	
	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.6: Annual Divorce Rates by Health Status

Husbands’ Disability	Wives’ 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.

⁵³Chen and van der Klaauw (2008) use this institutional feature to estimate the work disincentive effects of SSDI in a regression discontinuity framework.

Table A.7: Annual SSDI Award Rates by Husbands' Age and Disability

Husbands' Disability	Husbands' Age	
	Age < 55	55 ≤ 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 (1992-2014) who are white, under age 65, and hold less than a bachelor's degree. Merged administrative data on HRS respondents' disability benefit claims is primarily used. If information is not available from the administrative data, it is supplemented with the SSDI episodes data available in the public RAND HRS data.

disabled applicants younger than age 55 are significantly less likely to be awarded compared to their severely disabled counterparts, this pattern does not hold for applicants of ages 55 and older such that the award probabilities are similar for both moderately and severely disabled applicants.

Table A.8 reports the OLS estimates for the annual household medical expense function. Household medical expenses are the sum of both spouses' out-of-pocket medical expenses. 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. Table A.9 reports the OLS estimates for the annual household non-labor income function where 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.

Finally, Figure A.1 reports the fitted annual mortality rates based on logistic regressions on quadratic in age, health status, and education type. Figures A.2 and A.3 report fitted biennial health transition probabilities for husbands and wives, respectively.

E Computing Standard Errors of the Second Stage Model Parameters

Given the first stage parameter estimates ($\hat{\theta}_f$), the second stage estimates ($\hat{\theta}_s$) are chosen such that they minimize the weighted distance between the vector of data moments $\mathbf{m}_d$ and

Table A.8: Annual Household Medical Expenses (OLS Estimates)

Dependent variable: log(household out-of-pocket medical expenses) [†]	
Controls	Coefficients
<i>Husbands' characteristics</i>	
Moderate disability ($s^h = 1$)	0.520*** (0.188)
Severe disability ($s^h = 2$)	1.046*** (0.219)
Age	0.008*** (0.003)
Age $\times$ Moderate disability	-0.005* (0.003)
Age $\times$ Severe disability	-0.012*** (0.003)
Age 65+	0.011 (0.025)
Bachelor's degree or higher	0.141*** (0.026)
<i>Wives' characteristics</i>	
Disabled ($s^w = 1$)	0.976*** (0.142)
Age	0.009*** (0.003)
Age $\times$ 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 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 each spouses' reported out-of-pocket medical expenses.

Table A.9: Annual Household Non-labor Income (OLS Estimates)

Dependent variable: $\log(\text{household non-labor income})^\dagger$		
Controls	Coefficients	Std. Err.
<i>Husbands' characteristics</i>		
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 $\times$ Bachelor's degree or higher	0.023***	0.004
Age 55+	-3.681***	1.127
(Age 55+) $\times$ Age	0.069***	0.021
Age 62+	0.236***	0.054
(Age 62+) $\times$ Moderate disability	-0.129	0.108
(Age 62+) $\times$ Severe disability	-0.273**	0.127
Age 65+	0.360***	0.070
(Age 65+) $\times$ Moderate disability	-0.212***	0.080
(Age 65+) $\times$ Severe disability	-0.578***	0.095
<i>Wives' characteristics</i>		
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 $\times$ Bachelor's degree or higher	0.021***	0.004
Age 55+	-1.786**	0.883
(Age 55+) $\times$ Age	0.034**	0.016
Age 62+	0.067	0.054
(Age 62+) $\times$ Disabled	-0.188**	0.083
Age 65+	-0.023	0.070
(Age 65+) $\times$ 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.1: 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.

Figure A.2: 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.3: 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.

the vector of simulated moments $\mathbf{m}_s(\hat{\boldsymbol{\theta}}_f, \hat{\boldsymbol{\theta}}_s)$ where the weight is specified by the matrix $\hat{W}$:

$$\hat{\boldsymbol{\theta}}_s = \arg \min_{\boldsymbol{\theta}_s} (\mathbf{m}_d - \mathbf{m}_s(\hat{\boldsymbol{\theta}}_f, \boldsymbol{\theta}_s))' \hat{W} (\mathbf{m}_d - \mathbf{m}_s(\hat{\boldsymbol{\theta}}_f, \boldsymbol{\theta}_s)) \quad (31)$$

Standard errors of $\hat{\boldsymbol{\theta}}_s$ are computed based on the following formula (Gourieroux et al., 1993)

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

where H is the number of simulations, $J = \frac{\partial \mathbf{m}_s(\hat{\boldsymbol{\theta}}_f, \boldsymbol{\theta}_s)}{\partial \boldsymbol{\theta}_s}$, and S is the variance-covariance matrix of the data moments such that $S = var(\mathbf{m}_d)$. S is computed via bootstrap and J is computed using numerical derivatives (i.e., finite differences).

F Other Wage Moments

This section describes the data moments that are used to recover the variance of the permanent and transitory wage shocks for each spouse as well as the covariance of the permanent and transitory shocks between the two spouses.

For each spouse j , rewrite the wage offer function (equations (9) and (10)) as follows

$$\log w_{it}^j = X_{it}^{j'} \alpha^j + \zeta_{it}^j + \epsilon_{it}^j + v_{it}^j \quad (33)$$

where ζ_{it}^j and ϵ_{it}^j are equivalent to those in equations (11) and (12), and v_{it}^j denotes measurement error. I assume that v_{it}^j is classical measurement error with variance $\sigma_{v,j}^2$ and assume zero covariance between measurement error of the two spouses.

Denote residual log hourly wage as $\omega_{it}^j = \log w_{it}^j - X_{it}^{j'} \alpha^j = \zeta_{it}^j + \epsilon_{it}^j + v_{it}^j$. 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 follows.

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

Then, the following six moments are informative of $\sigma_{\epsilon,h}^2$, $\sigma_{\nu,h}^2$, $\sigma_{\epsilon,w}^2$, $\sigma_{\nu,w}^2$, $\sigma_{\epsilon,h,w}$, and $\sigma_{\nu,h,w}$.

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

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

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

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

As described in footnote 32, 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 $Var(\Delta\omega_{it}^j) = \sigma_{\nu,j}^2 + 2\sigma_{\epsilon,j}^2 + 2\sigma_{\nu,j}^2$. Since $\frac{2\sigma_{\nu,j}^2}{\sigma_{\nu,j}^2 + 2\sigma_{\epsilon,j}^2 + 2\sigma_{\nu,j}^2} = \alpha_{err}$ holds, $\sigma_{\nu,j}^2$ and therefore the right-hand side of equation (35) can be expressed using $\sigma_{\epsilon,j}^2$ and $\sigma_{\nu,j}^2$.

G Model Fit for the “No-care” Model and Untargeted Moments

Tables A.10 and A.11 report the model fit between the simulated and data moments for the “no-care” model where the model ignores husbands’ care needs (i.e., $\eta_t(s^h) = 0$) such that wives spend their time allocation to market work and leisure only. Table A.12 and Figure A.4 report the baseline model fit for a selected set of untargeted moments.

Table A.10: Targeted Moments for the “No-care” Model

	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	-0.021 (0.013)	-0.012	-0.240 (0.495)
Severe	-0.010	-0.002 (0.018)	0.003	0.032 (0.628)
Panel B: Husbands’ Employment Rates by Own Health Status				
	Employment Rate		Part-time Employment Rate	
Healthy	0.859	0.861 (0.005)	-	-
Moderate	0.454	0.466 (0.018)	0.121	0.119 (0.011)
Severe	0.205	0.237 (0.017)	0.065	0.062 (0.009)
Panel C: Wives’ Employment Rate by Own Health Status				
Healthy	0.754	0.752 (0.006)	-	-
Disabled	0.327	0.330 (0.014)	0.154	0.154 (0.011)
Panel D: Household Assets (by husbands’ age, in \$1,000)				
	50th Percentile		25th Percentile	
Ages 50 - 54	223.84	245.93 (7.542)	108.00	101.63 (4.180)
Ages 55 - 59	282.09	296.63 (5.912)	121.68	120.27 (3.067)
Ages 60 - 64	333.56	323.66 (7.229)	150.87	129.06 (4.007)
Panel E: SSDI Application Rates by Husbands’ Disability				
	Moderate		Severe	
	0.076	0.079 (0.006)	0.118	0.143 (0.008)

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

[†] Based on fixed effect regressions of labor supply variables on indicators of husbands’ disability severity, a quartic in both spouses’ ages, a dummy for wives’ disability, interactions of husbands’ and wives’ disability status, and household fixed effects. The reported moments are the regression coefficients for the indicators of husbands’ disability severity.

Table A.11: Targeted Wage Moments for the “No-care” Model

	Model	Data	Model	Data
	Husbands		Wives	
Panel A: Fixed Effect Regressions of Log Hourly Wages [†]				
Age	0.107	0.113 (0.039)	0.095	0.084 (0.033)
(Age/10) ²	-0.101	-0.106 (0.034)	-0.094	-0.070 (0.030)
Moderate disability	-0.013	-0.017 (0.021)	-	-
Severe disability	0.003	0.009 (0.040)	-	-
Disabled	-	-	-0.002	0.001 (0.016)
High education type	0.534	0.532 (0.023)	0.623	0.570 (0.027)
Panel B: Other Wage Moments [‡] ($j \in \{h, w\}$)				
$E(\Delta\omega_{i,t}^j \Delta\omega_{i,t+2}^j)^{\ddagger}$	-0.045	-0.047 (0.005)	-0.040	-0.042 (0.007)
$E\big(\Delta\omega_{i,t}^j (\Delta\omega_{i,t-2}^j + \Delta\omega_{i,t}^j + \Delta\omega_{i,t+2}^j)\big)^{\ddagger}$	0.036	0.037 (0.006)	0.003	0.009 (0.008)
$E(\Delta\omega_{i,t}^h \Delta\omega_{i,t+2}^w)^{\ddagger}$	-0.010	-0.008 (0.004)	-0.010	-0.008 (0.004)
$E\big(\Delta\omega_{i,t}^h (\Delta\omega_{i,t-2}^w + \Delta\omega_{i,t}^w + \Delta\omega_{i,t+2}^w)\big)^{\ddagger}$	-0.005	-0.008 (0.005)	-0.005	-0.008 (0.005)

Notes: Standard errors in parentheses. All moments are computed conditional on both spouses being younger than age 65.

[†] This panel matches fixed effect regression coefficients of log hourly wages for each spouse. 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.

[‡] $\Delta\omega_{i,t}^j$ is the second difference of residual log hourly wage of spouse j in household i , i.e., $\Delta\omega_{i,t}^j = (\zeta_{it}^j + \epsilon_{it}^j) - (\zeta_{i,t-2}^j + \epsilon_{i,t-2}^j)$. I use second differences due to the HRS data being biennial.

Table A.12: Model Fit: Untargeted Asset Moments

Median Household Assets by Husbands' Age and Disability Severity (in \$1,000)				
	Model	Data	Model	Data
	Moderate		Severe	
Ages 50 - 54	206.76	174.48 (22.92)	113.62	117.72 (17.64)
Ages 55 - 59	231.48	216.66 (15.30)	114.38	136.97 (13.80)
Ages 60 - 64	268.40	233.99 (14.23)	160.07	137.02 (10.79)

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

Figure A.4: 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 data where both spouses are under age 65. I use total household spending in the CAMS data (blue dots) and imputed household consumption in the Core data using the method proposed by [Skinner \(1987\)](#) (red dots) to construct the dependent variable. Both regressions control for a quartic in both spouses' ages, dummies for each spouse indicating whether their age is 62 or above, wives' disability status and its interaction with the onset dummies, household size, length of current marriage, census division, and year and household fixed effects. The vertical lines through each dot indicate 95% confidence intervals. The green dots indicate fixed effect event study regression coefficients using simulated data generated by the baseline model.