Canadian Labour Economics Forum

WORKING PAPER SERIES

Household Responses to Disability Shocks: Spousal Labor Supply, Caregiving, and Disability Insurance

Siha Lee (McMaster University)

Conference Volume CLEF – 2020, WP # 21

Household Responses to Disability Shocks:
Spousal Labor Supply, Caregiving, and Disability Insurance

Siha Lee*

McMaster University

This version: November 28, 2019
First version: January 10, 2019

Abstract

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. First, I find that while spousal labor supply responses to husbands' disability are small, wives spend a sizable amount of time in spousal care after their husbands become disabled. Motivated by these facts, I develop a dynamic model of married households that incorporates husbands' disability status, wives' time allocation choices, health state dependent utility, and the institutional features of SSDI. Counterfactual experiments indicate that caregiving needs substantially attenuate spousal labor supply responses and increase the insurance value of SSDI relative to its costs. Furthermore, policy reforms such as supplementary caregiving benefits can improve social welfare.

Keywords: disability, social security, spousal labor supply, caregiving

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

---

*Department of Economics, McMaster University, Hamilton, Ontario, L8S 4M4, Canada. lees223@mcmaster.ca. I am deeply indebted to John Kennan, Ananth Seshadri, and Christopher Taber for their invaluable support and guidance. I also thank seminar participants at Wisconsin, McMaster, HEC Montreal, Arizona State, Louisiana State, Dallas Fed, RAND, Upjohn Institute, KDI, KIPF, KIF, KIET, SOLE Annual Meeting, ARIA Annual Meeting, and Washington University in St. Louis for helpful comments. I gratefully acknowledge financial support from the Alfred P. Sloan Foundation Pre-doctoral Fellowship on the Economics of an Aging Workforce, awarded through the NBER, and from the Wisconsin Alumni Research Foundation. This project has benefited from the excellent computing resources at the UW-Madison Center For High Throughput Computing (CHTC) and Compute Canada. All remaining errors are my own.

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 (Stephens, 2002; Blundell et al., 2016).

As I show in this paper, however, wives' labor supply responses in the event of their husbands' disability are small and statistically insignificant. This is contrary to what standard economic models would predict, given that disability shocks are generally persistent and result in a significant decrease in household earnings. These facts suggest that the household insurance mechanism against wage shocks due to health shocks is considerably different from that against wage shocks generally studied in the literature.

An important difference between a job displacement shock and a disability shock is that the latter may reduce the time that spouses allocate to market work due to caregiving activities. Therefore, 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. Despite SSDI being one of the largest social insurance programs in the US with 9 million working age beneficiaries, little is known about the insurance value that SSDI provides, especially in the context of married households. This paper seeks to fill this gap by examining the insurance value of SSDI among 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 an event study to provide evidence that while wives' weekly working hours increase by 4 hours in response to their husbands' layoff, labor supply responses in the event of their husbands' disability are small and statistically insignificant. In contrast, I show that wives spend a significant amount of time in caregiving once their husbands become disabled, and the magnitude of this response is similar to the increase in wives' labor supply in the event of their husbands' layoff.

While informative, these facts alone are limited in answering how much of spousal labor supply responses are attenuated due to time spent in spousal care versus other competing forces and what its implications are for evaluating the insurance value of SSDI relative to its costs. Here, I consider two alternative mechanisms that could also explain the small spousal labor supply responses to husbands' disability: 1) the income effects of SSDI benefits and 2) health state dependent utility where the marginal utility of consumption in the disabled state is different from that in the healthy state.[1]

To answer the questions described above, I develop a dynamic model of married households which incorporates 1) husbands' disability and layoff shocks, 2) wives' time allocation to market hours, leisure, and caregiving, 3) health state dependent utility, and 4) the institutional features of SSDI. Importantly, health state dependence in consumption utility directly affects the insurance value of SSDI since the optimality of an insurance program depends on making transfers from the "good" state to the "bad" state such that the marginal utility of consumption in the two states is equal.

The model parameters that govern health state dependence are estimated using indirect inference where I use two types of moments: 1) changes in wives' labor supply in the event of their husbands' disability, and 2) wives' caregiving choices. Intuitively, this is because changes in wives' market hours across their husbands' health states partially reflect how much households value consumption across health states since wives choose market hours in each state such that the marginal utility of their leisure (per dollar) equals the marginal utility of consumption. However, since caregiving increases wives' marginal disutility of work when their husbands become disabled, spousal labor supply responses and spousal care choices need to be *jointly* matched in order to correctly estimate the health state dependence in consumption utility.

The model parameter estimates indicate positive health state dependence in both moderately and severely disabled states where the marginal utility of consumption is 8% and 18% higher than that in the healthy state, respectively. In contrast, the marginal utility of consumption in the disabled state is significantly underestimated when the model abstracts from caregiving and only the spousal labor supply responses across health states are matched. In this case, I find that the marginal utility of consumption is 9% *lower* when husbands are severely disabled compared to when they are healthy. This is because a model that does not account for spousal care will interpret the small spousal labor supply responses as households valuing consumption less in the disabled state when in fact they are due to a large fraction of wives spending time in spousal care.

Using the estimated model, two sets of counterfactual experiments are performed. First,

[1] In other words, the marginal utility of consumption would decline with deteriorating health if consumption goods (such as travel) are complements to good health. Notice that spouses have less incentive to increase their labor supply in response to their husbands' disability if the marginal utility of household consumption is lower when husbands are disabled compared to when they are healthy.

I find that about 50% of spousal labor supply responses are attenuated due to time spent in providing care for disabled husbands. Second, I perform various welfare analyses by computing the ex-ante insurance value of SSDI among married households relative to its costs. One of the main findings is that accounting for spousal care increases the insurance value of SSDI relative to its costs such that under the baseline model, married households value SSDI by $0.97 per dollar of SSDI benefits whereas the insurance value of SSDI drops to $0.91 per dollar of SSDI benefits when time spent in spousal care is not accounted for. This is because spousal care significantly reduces the insurance role of wives' labor supply in the event of their husbands' disability, and this is reflected as an increase in the parameter estimates that govern the marginal utility of consumption in the disabled states. 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 11.1% higher than current levels. This implies that once we consider the fact that spouses respond to disability shocks by allocating time to caregiving rather than increasing labor supply, optimal 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.

Furthermore, under the baseline model with time allocation to spousal care, each dollar of SSDI benefits entails an additional fiscal cost of 10 cents due to behavioral responses. Therefore, net of fiscal costs, each dollar of SSDI benefits is valued as 88 cents among married households and in order to make this equal to $1, SSDI benefits needs to be 17.4% lower than current levels. However, I show that instead of reducing SSDI benefits by 17.4% across the board, it is possible to improve utilitarian social welfare given the same government budget by reducing SSDI benefits but providing a flat amount of supplementary caregiving benefits to eligible SSDI beneficiaries. These results imply that adjusting benefit generosity based on the degree of required care could be one possible modification of the current SSDI system to provide households with the welfare benefits of SSDI while managing the growth of SSDI rolls.

This paper is related to three broad strands of literature. The first is what is known as the "added worker effect" literature which examines the extent to which the secondary earner's labor supply increases in response to a negative earnings shock of the primary earner. Earlier works have focused mostly 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; Haan and Prowse, 2015; Blundell et al., 2016).

Most of these works, however, do not distinguish whether the wage shock has been induced by a health shock or not.[2] I contribute to this literature by focusing on a mechanism that (to my knowledge) has not been explicitly accounted for, namely, wives' time allocation to caregiving, and examine the extent to which this can explain the small added worker effects in the event of husbands' disability.

The second strand is the large literature on social disability insurance (DI) programs. This literature has mainly evolved around exploring the disincentive effect of the receipt of DI 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 DI policies (Bound et al., 2004; Chandra and Samwick, 2005; Bound et al., 2010; Meyer and Mok, 2013; Jacobs, 2015; Kostøl and Mogstad, 2015; Low and Pistaferri, 2015; Autor et al., 2017).[3] However, most of these works model households as singles and ignore the additional source of insurance provided by spouses.[4]

Lastly, this paper is related to the empirical literature on state dependent utility functions (Viscusi and Evans, 1990; Evans and Viscusi, 1991; Lillard and Weiss, 1997; Edwards, 2008; Finkelstein et al., 2009, 2013; Brown et al., 2016). While it has been long recognized that variation in the shape of the utility function by health status has important economic implications (e.g., optimal structure of insurance, optimal life-cycle savings), there is little empirical consensus on the direction and magnitude of health state dependence. This is due to differences in identification strategies across previous studies as well as data limitations

[2]A smaller number of studies have explored the effect of health shocks on spousal labor supply responses including Parsons (1977), Berger and Fleisher (1984), Haurin (1989), Charles (1999), Coile (2004), Gallipoli and Turner (2011), Fadlon and Nielsen (2017), and Jeon and Pohl (2017).

[3]There is also a growing literature on the causes and consequences of the growth in DI rolls; see Autor and Duggan (2003), Autor and Duggan (2006), and Liebman (2015).

[4]One exception is a recent work by Autor et al. (2017). Based on Norwegian data, the authors find that DI denial has little impact on household income or consumption of married applicants since spousal earnings and benefit substitution entirely offset the loss in DI benefits. This leads to the conclusion that households' valuation of DI receipt is considerably greater for singles than for married couples. An important caveat of their results is that their analysis is restricted to DI appellants (i.e., applicants who appeal their initial DI denial) and it is reasonable to assume that appellants are more likely to be marginally disabled and thus do not require spouses to spend additional time in spousal care. This paper differs by modeling the intertemporal labor supply of the two spouses both pre- and post-disability as well as pre- and post-SSDI application and explicitly considering wives' choices between market work and caregiving.

(especially broad-based panel data on consumption with health measures). A recent work by Fadlon and Nielsen (2018) proposes using spousal labor supply responses across health status as sufficient statistics to infer welfare gains of social insurance programs since individual labor supply responses are arguably better measured and widely available in most datasets. I complement this literature by using both spousal labor supply responses and spousal care choices to estimate health state dependence and show that matching only spousal labor supply responses is imperfect when wives spend a sizable amount of time in 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 which incorporates husbands' disability process, wives' time allocation to leisure, market work, and caregiving, and the institutional details of SSDI. Section 4 discusses the estimation method of the model parameters. Section 5 reports the parameter estimates of the model as well as the key simulation results of this paper. Section 6 concludes.

2 Empirical Evidence

This section provides empirical evidence on how wives' labor market and caregiving hours respond to their husbands' wage shocks, namely disability and layoff shocks. All analysis is restricted to the event of husbands' wage shocks since husbands are the "main earners" for most married households in my data sample.[5]

2.1 Background

Before presenting the empirical patterns regarding wives' time allocation to market work and caregiving, I discuss the dataset that I use throughout this paper and how I categorize individuals in my sample as "disabled." I also provide a brief overview of the institutional

[5]Based on the dataset described in Section 2.1.1, I use various definitions of "main earner" (e.g., share of total earnings during marriage, number of years in which one spouse earned more than the other spouse, 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. In addition, Merkurieva (2014) reports that although there is no evidence of husbands increasing working hours in the event of their wives' layoff, sizable added worker effects can be observed once the analysis is restricted to the layoff of wives who contributed 40% or more of household lifetime earnings. This aligns with economic intuition as it is less likely to observe added worker effects in response to wage shocks of the secondary earner.

settings of SSDI and report summary statistics.

2.1.1 Data

I use data from the Health and Retirement Study (HRS) for all of my analysis. HRS is a biennial panel of a representative sample of Americans ages 50 and over as well as their spouses. The Core survey contains rich information on health, assets, labor market outcomes, disability benefits, and caregivers. The caregiver data is especially useful since it reports whether the respondent receives help from someone else in performing a given list of (Instrumental) Activities of Daily Living (ADLs/IADLs)[6], the identity of the caregivers in relation to the respondent, the number of hours that they provide help, whether they are paid, and if so, the amount that they are paid. I use 12 survey waves of the data from 1992 to 2014. I utilize caregiver data from 2000 to 2014 (8 waves) due to inconsistencies in earlier survey waves that make it difficult to identify spouse caregivers.

Two other HRS data products are merged with the Core survey. First, 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 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.[7] Second, 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 applications filed by HRS respondents and their outcomes. Merging the three data products results in a unique panel dataset that contains rich information on disability status, labor market outcomes, non-market time use, and interactions with disability insurance programs.

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

[6]Six ADLs and five IADLs are included. ADLs include walking across a room, dressing, bathing or showering, eating, getting in and out of bed, and using the toilet. IADLs include preparing hot meals, shopping for groceries, making phone calls, taking medications, and managing money (e.g., paying bills and keeping track of expenses).

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

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 an individual to be "severely disabled" if he is disabled and satisfies 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 with a local SSA field office in order to be considered for benefits.

In practice, the disability determination process consists of multiple stages and applicants can be awarded with benefits 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 the 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).

Finally, 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").[8] The formula for SSDI benefits is almost identical to that for Social Security Retirement benefits where replacement rates are lower for beneficiaries with higher past earnings.[9] 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.

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 20% of severely disabled husbands still report being employed. Also, disabled husbands are more likely to be less educated and have less wealth. A sizable portion of disabled husbands receive SSDI benefits, roughly 18% and 40% 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,

[8]This does not imply that SSA can perfectly screen out non-meritorious claims. Since disability status is private information, sizable errors may arise in the screening process. For example, Nagi (1969) finds that 19% of initial allowances were undeserving and 48% of denied applicants were truly disabled. Using the HRS data, Benitez-Silva et al. (2006) conclude that over 40% of recipients of SSDI are not truly work limited.

[9]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.

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 caregiving needs. While the average moderately disabled husband do 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

Table 1: Summary Statistics of Married Men by Disability Severity

	Healthy	Moderate	Severe
Age (mean)	57.7	58.7	58.4
Years of education (mean)	13.7	12.7	12.0
Employed (in %)	85.64	43.74	18.41
Receives SSDI (in %)	0.22	18.23	39.85
Household wealth (median, in $1,000)	287.26	181.05	91.39
Associated primary health condition (top 3, in %)†			
1) Musculoskeletal system	-	58.27	43.56
2) Heart, circulatory and blood conditions	-	18.51	16.06
3) Neurological and sensory conditions	-	1.30	14.77
4) Respiratory system conditions	-	6.68	4.45
Number of ADLs difficult to perform (mean)	0.03	0.19	1.20
Number of IADLs difficult to perform (mean)	0.02	0.04	1.01
Stayed overnight in hospital (last 2 years, in %)	13.03	31.18	43.40
Number of hospital nights (last 2 years, mean)‡	4.82	8.06	14.98
Made any doctor visit (last 2 years, in %)	88.73	95.03	96.56
Number of doctor visits (last 2 years, mean)*	6.19	12.88	21.02
Person-year observations	23,498	3,402	2,943
(%)	78.74	11.40	9.86

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 moderate (1, 2, and 4) and severely disabled (1, 2, and 3) are reported. Refer to Appendix A for a list of detailed health conditions included in each group.
‡ 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.

Table 2: Share of Wives Providing Care for their Husbands

	Husbands' Disability	
	Moderate	Severe
Help their husbands perform at least one ADL/IADL[†] (%)		
$(0, 25]$ hours per week	-	41.64
Greater than 25 hours per week	-	14.34
Person-year observations	-	1,808
Help treat/manage their husbands' medical condition(s)[‡] (%)		
$(0, 25]$ hours per week	18.41	34.52
Greater than 25 hours per week	1.49	5.34
Person-year observations	386	281

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 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 which only includes a random subsample of the HRS Core respondents, the sample size is significantly smaller.

within a two-year period, severely disabled husbands frequent doctors far more often than moderately disabled husbands do (12.88 vs. 21.02 visits in two years). All of these facts suggest that individuals with severe disabilities are more likely to require help from another person to perform basic daily activities as well as 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. Here, I identify husbands receiving care from their wives using information from both the Core survey and the CAMS dataset where the Core survey reports the amount of time that husbands received help from their wives in performing ADL/IADLs while the CAMS data reports wives' time spent in treating or managing their husbands' medical conditions. About 60% of severely disabled husbands receive their wives' help in performing ADL/IADLs with 15% 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 conditions, although the number of hours is smaller. This suggests that wives spend a sizable amount of time in caregiving once their husbands become disabled.

Finally, I document substantial differences between single and married men in terms of

Table 3: Summary Statistics of Caregivers of Severely Disabled Men

	Single*	Married
Number of caregivers (in %):		
One	61.97	73.60
Two	24.09	16.47
Three or more	13.94	9.93
Caregivers' relationship to respondent‡ (in %)		
Wives	-	97.35
Daughters	18.54	9.94
Sons	8.64	9.64
Other relatives	44.54	11.85
Non-relatives†	51.49	5.02
Has Medicaid coverage (in %)	43.23	16.03
Receives care from Medicaid-covered caregiver(s) (in %)	17.07	1.44
Person-year observations	502	1,197

Notes: Results are based on a sample of severely disabled men from ages 50 to 64 in the HRS who report receiving help from someone else in performing 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%.

their caregivers in Table 3. Here I restrict the sample to severely disabled men aged 50 to 64, conditional on receiving help from someone else to perform ADL/IADLs. The most striking difference between single and married men comes from who they receive care from. For married men, 97% receive care from their wives. Only 5% receive care from non-relative caregivers which includes 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.

2.2 Event Study Framework and Results

In this section, I use an event study framework to document changes in labor supply responses and caregiving hours of wives in the event of their husband's earnings shock (layoff or disability). Layoffs are defined as job separations due to either closure of the business or being laid off/let go.[10]

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

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

where y_{it} denotes the dependent variable of interest, γ_t are year dummies, and X_{it} includes a quartic in both spouses' ages, census division dummies, household size, and length of the current marriage (in years). I_{itk} denotes an indicator for being k years since the onset of the wage shock (disability or layoff). I control for 4 years prior and 5 years after the onset of the wage shock. Therefore, δ_k measures the change in the dependent variable at k years of onset relative to 5 or more years before the onset of the shock.

Figure 1a depicts changes in husbands' weekly working hours pre- and post-onset of the shock.[11] For both layoffs and disability shocks, husbands significantly reduce working hours at the onset of the shock and this persists even after four years since the shock occurred. This implies that disability shocks as well as layoff shocks 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. For wives whose husbands are laid off, they increase their weekly working hours by 4 hours and the estimates are statistically significant. Given that the average weekly working hours prior to their husbands' layoff is about 26 hours, this is a 15% increase in working hours, which is a sizable magnitude. This is consistent with intuition as well as the magnitude of the response being similar to that reported by Stephens (2002) who used a sample of working age married women in the Panel Study of Income Dynamics (PSID).

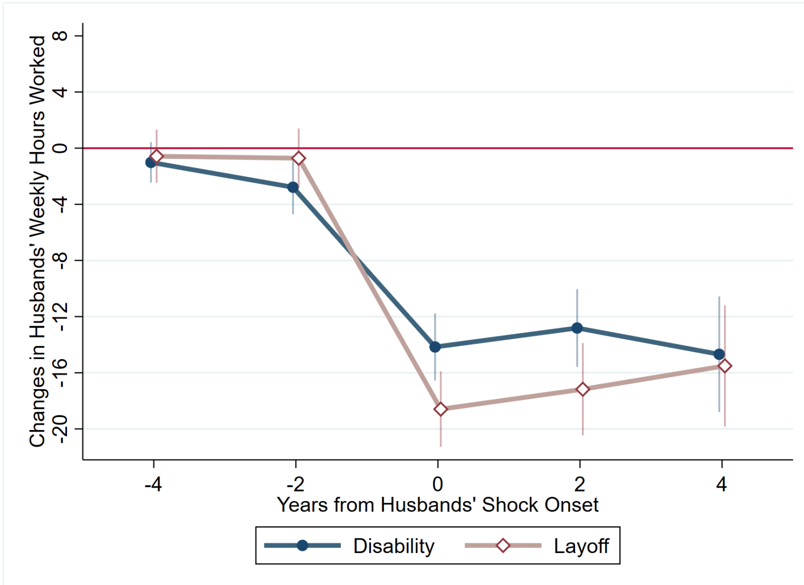
In contrast, wives with disabled husbands do not increase their labor supply. Point estimates indicate that wives reduce working hours by 2 hours compared to 5 or more years before their husbands' disability onset and all of the coefficients are statistically insignificant.

[10] Workers who list all other separation reasons (e.g., quit, health, family, new job, retirement) are not classified as being laid off.

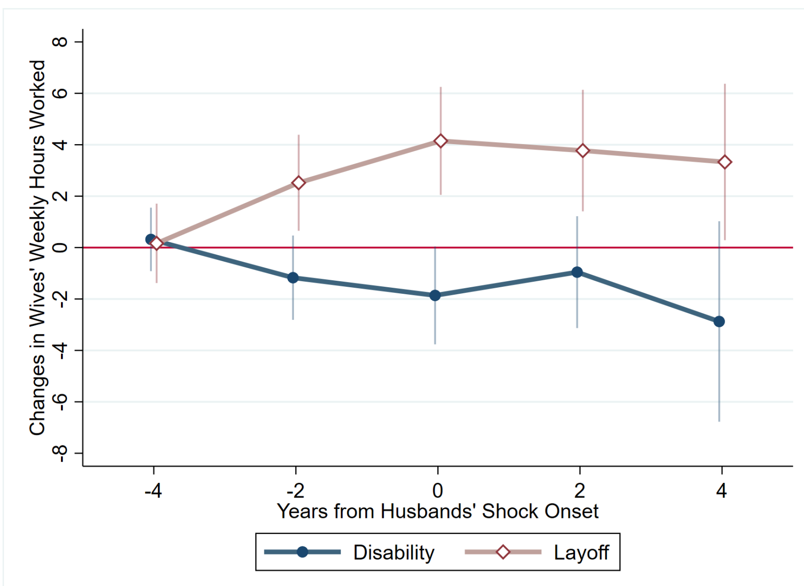
[11] When regressing husbands' weekly working hours on layoff onset indicators, I restrict the control group (i.e., husbands who did not experience a layoff shock) to those who are employed. This is because by definition, layoffs occur conditional on being employed in the previous period.

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. The vertical lines through each dot indicate 90% confidence intervals.

† Average weekly working hours before shock onset: 36.2 (disability), 43.8 (layoff)

‡ Average weekly working hours before their husbands' shock onset: 23.4 (disability), 25.9 (layoff).

Given that husbands' disability shocks lead to a persistent drop in household earnings (as implied by Figure 1a), the small spousal labor supply responses to husbands' disability shocks imply that wage shocks due to disability shocks elicit household responses that are different from that in the event of layoffs.

Next, columns (1) and (2) of Table 4 document changes in wives' hours spent in caregiving 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; by the second year of husbands' disability onset,

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

	(1) Event Study (Core)†	(2) Event Study (CAMS)‡	(3) OLS (CAMS)
Panel A: By Onset Year			
Year = -2, -1	0.082	0.537	
	(0.394)	(0.822)	
Year = 0, 1	1.711*	2.510**	
	(0.883)	(1.271)	
Year = 2, 3	3.450***	2.968*	
	(1.225)	(1.737)	
Panel B: By Severity			
Moderate			2.286**
			(1.109)
Severe			5.270***
			(1.615)
R-sq.	0.016	0.076	0.059
Observations	10,604	1,326	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, household size, length of current marriage, census division and year fixed effects, and household fixed effects. OLS regression for column (3) controls for a quartic in age, education, and race of both spouses, the wife's disability status, household size, length of current marriage, and 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 ADL/IADLs.

‡ Measure of caregiving: time spent in treating or managing the husband's medical condition(s).

wives spend on average 3 hours more per week on spousal care. Given that the increase in wives' labor supply when their husbands are laid off is 4 hours per week (as shown in Figure 1b), this is a sizable magnitude that may influence wives' decisions to increase their working hours.

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 (roughly 2.3 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 documents that added worker effects in the event of husbands' disability are small and statistically insignificant, it is possible that this may be due to a number of confounding factors. First, this may be due to disability status being correlated between the two spouses – wives of disabled husbands are more likely to be disabled and thus decrease labor supply in the event of their husbands' disability. Also, the results may be driven by households that are receiving SSDI benefits. Finally, 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. These concerns are addressed in Appendix B, where I show that spousal labor supply responses to husbands' disability are small even when these concerns are accounted for.

3 Dynamic Model of Married Households

Although the empirical evidence provided in Section 2 is informative, it is not able to provide a decomposition of the forces that contribute to the small spousal labor supply responses in the event of husbands' disability. Moreover, it is not able to answer how these forces interact with evaluating the ex-ante insurance value of SSDI relative to its costs. Therefore, I develop a dynamic model of married households which incorporates the three main factors that could explain the small added worker effects in the event of husbands' disability: 1) the disincentive for wives to work due to the income effects of SSDI benefits, 2) time spent in spousal care, and 3) health state dependent consumption utility. I incorporate health state dependence since it is reasonable to expect small spousal labor supply responses when consumption is valued less in the disabled state than the healthy state.

3.1 Model Setup

All households enter the model as married consisting of a husband and a wife denoted as $j \in \{h, w\}$.[12] I assume unitary households where households are single decision-making units.[13] 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.[14] The model period starts at t_1 and households die with certainty at t_T. A period is a year. Households dissolve through (exogenous) death or divorce, and I assume that there is no remarriage.[15]

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

1. Mortality and divorce shocks: The husband dies with probability $\delta^h_{m,t-1}(s_{t-1}, f^h)$ which depends on his age t, health status s_{t-1}, and individual type f^h, which is fixed and exogenous in the model. f^h is determined based on the husband's average lifetime earnings and accounts for ex-ante heterogeneity that affects his probability of survival (as well as his health transition probability and wage offers as described below). I

[12] Since this paper focuses on understanding responses to disability shocks among married couples, the model abstracts from endogenous marriage and separation over the life-cycle. Although understanding how disability shocks affect individuals' choices to marry and to divorce is an interesting question, this is left for future research.

[13] The unitary model is the most commonly used intertemporal household model as it can account for the intertemporal allocation of resources at the household level while maintaining computational tractability. Alternatively, there are recent works that use intertemporal collective models where the joint household utility is the sum of each spouse's utility weighed by their Pareto weight ("decision power") and within each period, resources are allocated between couples in a Pareto-efficient manner. Often, in these types of models, household members have limited commitment such that the marriage can break apart if the individual utility from staying in marriage is lower than leaving the household and taking the best outside option. These types of models are more suitable for exploring intra-household allocation of resources over time as well as household formation or dissolution processes. While these are certainly attractive features, implementing these features significantly complicates the estimation in this paper's setting. Since the objective of this paper is to develop a household model with time allocation to leisure and spousal care and use this model to evaluate the ex-ante insurance value of SSDI at the household level, I abstract from the intra-household allocation of consumption and focus on the unitary model. Exploring how disability shocks affect marital stability and the intra-household allocation of resources among spouses is saved for future research.

[14] This is due to computational tractability as separately tracking both spouses' ages substantially increases the state space.

[15] Although this is a simplifying assumption, assuming no remarriage is more reasonable for older couples since remarriage rates drop significantly among the older population. This is one reason why the starting period of the model, t_1, is set as age 50 when estimating the model parameters (see Section 4.1.2).

discretize f^h to two types: "high" and "low." The wife dies with probability $\delta^w_{m,t-1}$ which is a function of her age. The household dissolves through divorce with probability $\delta_d(s_{t-1})$ which also depends on the husband's health status.

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

2. Disability shock: The husband's health status $s_t \in \{0, 1, 2\}$ (healthy, moderate, and severe) is realized. The health transition probability is a function of s_{t-1}, t, and his individual type, f^h. I abstract from modeling the wife's health status.

3. Layoff shocks and job arrivals: Husbands who were working in the previous period receive a layoff shock with probability $\delta_j(s_{t-1})$ which depends on his health status. Jobs arrive at a rate of λ (there is no job search).

4. Wage shocks: The husband's wage offer depends on his age t, health status s_t, and individual type f^h. The wife's wage offer depends on her age, $t-3$. In addition, both spouses receive an idiosyncratic wage shock each period.

Preferences – The household period utility is specified as follows.

$$u_t(c, l^h, l^w, tc; s) \quad = \quad \theta(s)\,\frac{c^{1-\gamma}-1}{1-\gamma} + \psi_h\,\frac{(l^h)^{1-\gamma_h}-1}{1-\gamma_h} + \psi_w\,\frac{(l^w)^{1-\gamma_w}-1}{1-\gamma_w} + \omega_t(tc; s) \quad (2)$$

The household receives utility from household consumption c, leisure of each spouse l^h and l^w, and caregiving provided by the wife's time input tc.[16] The husband's health status is denoted as $s \in \{0 \text{ (healthy)}, 1 \text{ (moderate disability)}, 2 \text{ (severe disability)}\}$. $\theta(s)$ is included as a tractable way of accounting for health state dependence in consumption utility. Normalizing $\theta(0) = 1$, if $\theta(s)$ is greater than 1 in the disabled states, this implies positive health state dependence since the marginal utility of consumption is multiplied by $\theta(s)$. I do not make any a priori assumption on the direction of the health state dependence in consumption utility.

[16]It is possible to generate caregiving utility through either the wife's time input or expenditures on hiring professional caregivers (or a combination of both). However, as shown in Table 3, almost all husbands (97%) who receive help in performing ADL/IADLs report that they receive care from their wives. Only 5% of husbands report hiring non-relative caregivers. Also, while 16 % of severely disabled husbands are eligible for Medicaid, only 1% of husbands receive care from Medicaid-paid caregivers. Therefore, assuming that caregiving utility is solely produced by the wife's time inputs is reasonable in the context of this model.

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

$$l^h + (1+\phi(s)) \cdot h^h = \bar{L} \quad (3)$$

$$l^w + h^w + tc = \bar{L} \quad (4)$$

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 is discretized such that husbands choose to either not work at all or work full-time. h^w and tc are discretized as zero, part-time, and full-time hours.

Equation (3) indicates that the husband allocates his time to leisure and market hours but incurs a (per-unit) time cost of working, $\phi(s)$, which depends on his health status s.[17] I assume $\phi(0) = 0 < \phi(1) < \phi(2) < \bar{L}$, which implies that working in the disabled states yields a greater disutility for the husband.

The wife allocates her time to leisure l_w, market work h_w, and spousal care tc. tc is chosen based on the caregiving utility that it generates, $\omega_t(tc; s)$. Assume $\omega_t(tc; s)$ as follows.[18]

$$\omega_t(tc; s) = \begin{cases} 0 & \text{if } s = 0 \text{ or } tc \leq 1 \\ \omega_{c,t}(s) \cdot \log(tc) & \text{if } s \in \{1, 2\} \text{ and } tc > 1 \end{cases} \quad (5)$$

The caregiving utility weight $\omega_{c,t}(s)$ differs across households and time by assuming that $\omega_{c,t}(s)$ evolves according to the following process.

$$\omega_{c,t}(s) = \mu_c(s) + \epsilon_t \quad (6)$$

$$\epsilon_t = \rho(s) \cdot \epsilon_{t-1} + \xi_t, \quad \xi_t \sim N(0, \sigma^2_{\xi,s}) \quad (7)$$

Equations (6) and (7) indicate that households place a weight of $\mu_c(s)$ on average but face an additional idiosyncratic shock ϵ_t which follows a standard AR(1) process. ϵ_t allows for the fact that there exists unobservable heterogeneity in caregiving needs even conditional on disability status s.[19] For example, variation in associated health conditions may lead to

[17]For example, working in the disabled states aggravates physical pain such that it takes additional time to recover or requires visiting doctors.

[18]I assume caregiving utility to be zero for $tc \leq 1$ in order to ensure $\omega_t(tc; s) \geq 0$ for all values of tc. Given that the annual time endowment is set as $\bar{L} = 8,760$ hours (see Section 4.1.2), $tc \leq 1$ is a small number such that $\omega_t(tc; s)$ being zero for these values of tc is reasonable.

[19]In the absence of the heterogeneity coming from ϵ_t, it is difficult to match wives' caregiving choices as observed in the data.

differences in caregiving needs.[20] Also, conditional on disability state s and health conditions, some husbands may not receive care from their wives but instead use equipments such as wheelchairs and walkers.[21] Disability may also worsen or multiple conditions may develop over time such that severely disabled husbands who initially did not receive care and relied on equipments end up requiring help from their spouses. Equations (6) and (7) incorporate these types of heterogeneity in a tractable way since $\rho(s)$ can capture the persistence in caregiving utility coming from the nature of the health condition and ξ_t captures any idiosyncratic differences in caregiving needs including preferences for using equipments or development of multiple health conditions over time.

Individual behavior after a dissolution of a married household (either through death or divorce) is not modeled.[22] Instead, the surviving individual j receives a terminal utility $v_t^j(a_t^j, y_t)$ specified as below.

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

$W_t^j(a_t^j, y_t)$ 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 males are computed based on his 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 her deceased husband's Primary Insured Amount (PIA) while divorcees receive 50%.[23]

[20]Among severely disabled husbands in the HRS, 58% of those with neurological and sensory conditions (e.g., blind, deaf, multiple sclerosis) report having difficulty in any ADL/IADLs compared to 80% of those with musculoskeletal conditions and 83% of those with heart, circulatory, and blood conditions. This is suggestive of substantial heterogeneity in caregiving needs stemming from differences in the associated health conditions.

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

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

[23]In practice, it is possible for wives to receive retirement benefits computed from 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

Disability Insurance – Key features of the Social Security Disability Insurance (SSDI) are modeled in order to incorporate the complexities of the program. First, households are required to choose whether to apply for SSDI ($App_t \in \{0, 1\}$). Although there are no monetary costs for applying, application is costly in the sense of requiring the husband to be non-employed ($h_t^h = 0$) as well as not being able to receive wage offers during the application period.[24] Conditional on applying, SSDI is awarded with some probability $Pr(DI_{t+1} = 1|s_t, App_t)$ which depends on the applicant's current health status. This reflects the fact that although the SSA determines whether an applicant is eligible for disability benefits based on medical and other supporting evidence, it cannot perfectly observe the true disability status of the applicant. I assume that the probability of receiving SSDI benefits if the applicant is healthy is zero ($Pr(DI_{t+1} = 1|s_t = 0, App_t = 1) = 0$) such that husbands never apply for benefits in the healthy state.[25]

Successful applicants who applied in period t start receiving benefits from period $t + 1$.[26] 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

the main earners in most married households (roughly 85% in the HRS), wives' entitled spousal benefits are generally greater than their primary benefits. This is one reason why auxiliary beneficiaries (i.e., beneficiaries receiving benefits based on someone else's earning history) are mostly females (along with the fact that on average, wives live longer than their husbands). 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.

[24]This 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.

[25]In my sample from the HRS data, less than 0.5% of healthy husbands report applying for SSDI. Also, conditional on being an 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.

[26]In reality, SSDI has a five-month waiting period where benefits are paid out 5 months after "disability onset" (the date of "disability onset" is also determined by the SSA as part of the application process). In many cases, the disability onset date is equivalent to the application date. Therefore, the five-month waiting period is already over by the time benefits are awarded since it generally takes about 4∼6 months to process initial applications. Also, given that a period is a year in the model, the assumption that successful applicants receive benefits the following period is reasonable.

[27]This reflects the fact that earnings above a certain threshold lead to termination of disability benefits.

[28]See Appendix C on details of how benefits are computed. In reality, SSDI benefit calculation differ

an absorbing state (i.e., husbands continue receiving SSDI benefits each period and do not 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]

Offered Wages and Labor Market Frictions – Husbands who are employed face the risk of being laid off with probability $\delta(s_t)$. Non-employed husbands who are neither applying nor receiving SSDI benefits receive wage offers with probability λ. Laid off husbands receive a one-period unemployment insurance (UI) benefit which is set as 23% of previous period's earnings.[30] I abstract from labor market frictions for wives and assume that wives always receive wage offers each period.

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

$$\log w_{it}^h = \alpha_1 \cdot t + \alpha_2 \cdot t^2 + \alpha_3 \cdot \mathbf{1}(f_i^h = \text{high}) + \sum_{s=1}^{2} \varphi_s \cdot \mathbf{1}(s_{it} = s) + \zeta_{it}^h \tag{9}$$

$$\log w_{it}^w = \tilde{\alpha}_1 \cdot (t-3) + \tilde{\alpha_2} \cdot (t-3)^2 + \zeta_{it}^w \tag{10}$$

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

For the husband, offered log wages depend on his age t, individual type f^h, and health status s_t. The wife's log wages depend only on her age since the model abstracts from tracking the wife's health status. Finally, each spouse receives a permanent wage shock which follows a random-walk process specified as equation (11). I assume that the idiosyncratic wage shock η_t^j is i.i.d. and correlated between the two spouses with covariance $\sigma_{\eta_{h,w}}$.

Retirement Period – The household retires (i.e., both spouses do not work) when the husband reaches age 65 (and age 62 for the wife). Therefore, household consumption is the only choice during this period. The household receives Social Security Retirement benefits based on the

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.

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

[30] Average UI replacement rates (measured as weekly UI benefits divided by the worker's weekly earnings) 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.

husband's average lifetime earnings at age 65 (y_{65}) until death. The household retirement benefit is the sum of the husband's benefit and the wife's spousal benefits, subject to the maximum family benefit amount.[31] SSDI benefits are automatically converted to retirement benefits upon retirement.

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

$$A_{t+1} = (1+r)A_t + \sum_{j\in\{h,w\}} w_t^j h_t^j + UI_t + b_t(y, DI_t) - \tau(A_t, w_t^h h_t^h, w_t^w h_t^w) + T_t - c_t \quad (12)$$

UI_t denotes a one-period UI benefit when husbands are laid off. b_t denotes Social Security benefits as a function of the husband's average lifetime earnings y_t and whether the household is receiving disability benefits ($DI_t = 1$) or retirement benefits ($t \geq 65$). $\tau(A_t, w_t^h h_t^h, w_t^w h_t^w)$ denotes payroll and federal income taxes.[32]

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

$$T_t = \max\Big\{0,\ \underline{c} - \big((1+r)A_t + \sum_{j\in\{h,w\}} w_t^j h_t^j + UI_t + b_t(y_t, DI_t) - \tau(A_t, w_t^h h_t^h, w_t^w h_t^w)\big)\Big\} \quad (13)$$

$\underline{c}$ is a tractable of way of incorporating the consumption floor provided by means-tested programs such as the Supplemental Security Income (SSI) and the Supplemental Nutrition Assistance Program (SNAP). This is a standard way of modeling means-tested programs in the literature following the work of Hubbard et al. (1995).[33]

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.

[31] See footnote 23 regarding the use of husbands' average lifetime earnings to compute wives' retirement benefits. See Appendix C for details on how benefits are computed.

[32] State income taxes are not modeled due to wide variation in state tax codes. See Appendix D for details on how taxes are computed.

[33] Although the disability determination process is the same for both SSDI and SSI, SSI requires applicants to hold less than $3,000 in assets in order to be eligible for benefits. However, most assets are excluded from this $3,000 limit including primary residence and adjacent land, and one vehicle. 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 a minimum consumption floor and thus benefits are deducted accordingly if the household has additional resources through unearned/earned income, equation (13) incorporates the nature of SSI while maintaining tractability.

Model Solution – Define the vector of state variables at period t as $\boldsymbol{X}_t = \{A_t, s_t, y_t, \vartheta_t, DI_t, f^h, \zeta_t^h, \zeta_t^w, \epsilon_t\}$ which consists of household assets (A_t), the husband's health status s_t, the husband's average lifetime earnings at age t (y_t), whether the husband is laid off ($\vartheta_t \in \{0, 1\}$), whether the husband is receiving SSDI benefits ($DI_t \in \{0, 1\}$), the husband's individual type ($f^h \in \{\text{high, low}\}$), idiosyncratic wage shocks of both spouses (ζ_t^h, ζ_t^w), and the idiosyncratic caregiving utility shock (ϵ_t). For each period t, households solve the following problem subject to time and budget constraints (3), (4), and (13).

$$
\begin{aligned}
V_t(\boldsymbol{X}_t) = \max_{\substack{c_t, h_{ht}, h_{wt}, \\ tc_t, App_t}} \; & u(c_t, l_{ht}, l_{wt}, tc_t; s_t) \\
& + \beta \Big\{ \big(1 - \delta_{m,t}^h(s_t)\big)\big(1 - \delta_{m,t}^w\big)\big(1 - \delta_d(s_t)\big) E_t\big[V_{t+1}(\boldsymbol{X}_{t+1} | \boldsymbol{X}_t)\big] \\
& \qquad + \big(1 - \delta_{m,t}^h(s_t)\big)\big(1 - \delta_{m,t}^w\big)\; \delta_d(s_t)\Big(\sum_{j \in \{h,w\}} v_{t+1}^j\big(\tfrac{1}{2} A_{t+1}, y\big)\Big) \\
& \qquad + \big(1 - \delta_{m,t}^h(s_t)\big) \cdot \delta_{m,t}^w \cdot v_{t+1}^h(A_{t+1}, y) \\
& \qquad + \delta_{m,t}^h(s_t) \cdot \big(1 - \delta_{m,t}^w\big) \cdot v_{t+1}^w(A_{t+1}, y) \; \Big\}
\end{aligned}
\tag{14}
$$

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. First, health state dependence in consumption utility, $\theta(s)$, has important implications for determining the optimal level 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 utility of consumption in both states are equal. If $\theta(s) > 1$ in the disabled state (i.e, positive health state dependence), household consumption needs to be higher in order to equate the marginal utility of consumption in the disabled state to that in the healthy state. Therefore, exhibiting positive health state dependence increases the insurance value of SSDI since it provides a transfer to the disabled state which is more valuable compared to when husbands are healthy. This also implies that the optimal level of benefits will be higher compared to when there is no health state dependence. The opposite holds if $\theta(s) < 1$ in the disabled state (i.e., negative health state dependence): since consumption is valued less in the disabled state than in the healthy state, households do not require as much transfers in the disabled state, and therefore optimal benefit levels are lower (i.e., the insurance value of SSDI is lower).

Empirically, the direction and magnitude of $\theta(s)$ is ambiguous. For example, expenditures on vacations would drop when one becomes disabled which implies that $\theta(s)$ is less than one for expenditures on vacations. On the other hand, it is likely that consumption for taxis, wheelchairs, and medical services would increase in the disabled state, which implies $\theta(s)$ being greater than one for those consumption goods. Notice that $\theta(s)$ in the model is a catch-all measure which averages over all of the consumption goods at the household level.

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 layoff shock, a disability shock is an earnings shock that also entails receiving care, which is reflected in the model as a caregiving preference shock $\omega_{c,t}(s)$. This implies that while wives would insure against their husbands' layoff 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 generate utility $\omega_t(tc; s)$.[34]

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

$$\theta(s) \cdot c^{-\gamma} \;\; = \;\; \frac{\psi_w \cdot l_w^{-\gamma_w}}{w_w}, \qquad \forall s \tag{15}$$

Notice that if the model ignores caregiving such that wives allocate all of their time to leisure and market work only, wives' market hours can always be mapped into the marginal utility

[34]If caregiving utility could also be produced by expenditures on professional caregivers, then this would be a form of health state dependence in consumption utility since the demand for professional caregivers would be higher in the disabled state. Then, wives may choose to increase their working hours so that they can hire professional caregivers. However, as shown in Table 3, almost all of the care that husbands receive is provided by wives despite the existence of alternative market options (either because hiring professional caregivers is more expensive than wives' forgone earnings or husbands prefer to receive care from their wives rather than from professional caregivers). This implies that wives' time endowment is valuable not only because it can be used as market hours to make up for the loss in their husbands' earnings, but also because it can generate caregiving utility which has imperfect market substitutes.

of consumption in each health state since equation (15) can be expressed as follows.

$$\theta(s) \cdot c^{-\gamma} \quad = \quad \frac{\psi_w \cdot (\bar{L} - h_w)^{-\gamma_w}}{w_w}, \qquad \forall s \tag{16}$$

This implies that conditional on the realization of each health state, h_w is chosen such that it reveals how much consumption is valued in the form of spousal earnings. Therefore, changes in spousal labor supply responses across husbands' health states can recover $\theta(s)$. This is extremely useful since $\theta(s)$ is empirically challenging to estimate in the absence of panel data that provides a comprehensive measure of household consumption in each health state. The mapping between wives' market hours and the marginal utility of consumption circumvents this issue and provides inference for $\theta(s)$ 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,

$$\theta(s) \cdot c^{-\gamma} \quad = \quad \frac{\psi_w \cdot (\bar{L} - h_w - tc)^{-\gamma_w}}{w_w}, \qquad \forall s \in \{1, 2\} \tag{17}$$

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, the key implication is that wives' time allocation to both market work *and* spousal care needs to be considered in order to correctly infer $\theta(s)$.

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 model simulated moments and data moments, I update the parameter guess and repeat this process until I find the parameter values that generate the closest fit between the model simulated moments and the data moments.

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

$$\hat{\boldsymbol{\theta}}_{\boldsymbol{s}} = \arg\min_{\boldsymbol{\theta_s}} \left(\boldsymbol{m_d} - \boldsymbol{m_s}(\hat{\boldsymbol{\theta}}_{\boldsymbol{f}}, \boldsymbol{\theta_s})\right)' \hat{W} \left(\boldsymbol{m_d} - \boldsymbol{m_s}(\hat{\boldsymbol{\theta}}_{\boldsymbol{f}}, \boldsymbol{\theta_s})\right) \tag{18}$$

Following Pischke (1995), I use a diagonal weighting matrix $\hat{W}$ which uses the inverse of the variance-covariance matrix of the data along the diagonal and zero elsewhere.[35] 25,000 households are simulated to calculate the simulated moments $\boldsymbol{m_s}(\hat{\boldsymbol{\theta}}_{\boldsymbol{f}}, \boldsymbol{\theta_s})$.[36]

4.1.1 Estimation Sample and Initial Conditions

I use the same data as described in Section 2.1.1. I make the additional sample restriction where I focus on households in which husbands are white and hold less than a bachelor's degree. This is because even after controlling for average lifetime earnings, mortality and disability processes differ significantly for non-whites and four-year college degree holders. Furthermore, SSDI recipiency rates differ considerably for men with a bachelor's degree.[37] These differences in SSDI recipiency rates persist even after controlling for disability status. In my data sample, 85% of married households consists of husbands who are white and 75% of married white men hold less than a bachelor's degree. Therefore, the additional sample cut still covers the majority of the population of interest.

When simulating households, I control for initial conditions by using the first observation of each married household in the estimation sample as the state vector and simulate forward. Table 5 provides a summary of this initial distribution.

[35] This is because although the inverse of the variance-covariance matrix is asymptotically efficient, in practice it can be severely biased in small samples as shown in Altonji and Segal (1996). Therefore, the diagonal weighting matrix is a common weighting matrix used in empirical papers using SMM.

[36] Parameter estimates are robust to increasing the number of simulated households.

[37] In the HRS, the share of white men receiving SSDI for those with less than a high school degree and those with a GED is 13% and 13.3%, respectively. For white men whose highest level of education is a high school degree or some college education,[38] the recipiency rate drops to 6.8% and 6.6%, respectively, but the numbers are similar between the two education groups. In contrast, recipiency rates among white men with

Table 5: Summary Statistics of the Initial Distribution

	Healthy	Moderate	Severe
Husband's age (mean)	55.07	55.59	55.81
Wife's age (mean)	51.80	51.76	52.13
Husband's average lifetime earnings (mean, in \$)	28,498	23,669	21,195
Household assets (median, in \$1,000)	177.38	139.20	87.79
Fraction of "high type" husbands†	0.45	0.35	0.26
Observations	2,533	290	308

Notes: Dollar values are in 2015 dollars.
† Hubands' individual type f^h is measured using their average lifetime earnings. "High type" refers to husbands whose average lifetime earnings is greater than \$30,223 (median average lifetime earnings of males in the HRS).

4.1.2 First Stage Parameters

Model period, annual time endowments, and part- and full-time hours – I set $t_1 = 50$ and $t_T = 80$. Annual time endowment $\bar{L}$ is set as 8,760 hours (24 hours $\times$ 365 days).

For both spouses' market hours (h^h, h^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. For the wife's caregiving hours, 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 part-time caregivers in the HRS data, who I define as those spending more than zero but 25 hours or less in caregiving per week, is roughly 7 hours.

Coefficient of relative risk aversion with respect to leisure – I set $\gamma_h = 1$ and $\gamma_w = 1$ such that both spouses' utility from leisure is specified as a log function.[39]

a bachelor's degree drops to 2.7%.

[39] Assuming certainty and interior conditions, γ_h and γ_w govern the Frisch labor supply elasticities of the husband and wife. However, in the model, the husband's labor market hours are discretized to two choices (non-employment and full-time employment). Therefore, for given a parameter value of γ_h, we can always find a value of ψ_h that matches husbands' employment choices (at the extensive margin). The wife's labor market hours are discretized to three choices (non-employment, part-time, and full-time employment). I measure female labor supply elasticity by introducing a 20% increase in simulated female 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 model parameter values, the resulting female labor supply elasticity is 0.46, which is within the range of female (Marshallian) labor supply elasticities that have been estimated in the literature (see Keane (2011) for an excellent survey of the empirical literature on male and female labor supply elasticities). A recent work by Blundell et al. (2016) reports female Marshallian labor supply elasticities of 0.40 to 0.42, depending on specification, which is very similar to the female labor supply elasticity of 0.46 that my model generates.

Table 6: Annual Job Destruction and Divorce Rates by Husbands' Disability

Husbands' Disability	Job Destruction Rate $\delta_j(s)$	Divorce Rate $\delta_m(s)$
Healthy ($s = 0$)	.052	.0056
Moderate ($s = 1$)	.042	.0056
Severe ($s = 2$)	.075	.0094

Rate of return and discount factor – Real interest rate for assets is set as $r = 0.03$ and discount factor is set as $\beta = 0.975$, 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., 2017).

Job destruction and job arrival rates – Annual job destruction rates $\delta_j(s)$ are calculated from the HRS by measuring the fraction of workers that are laid off in the next 12 months, conditional on current disability status. These values are reported in the second column of Table 6. I use self-reported dates on when respondents left their previous employer due to either a business closure or layoff. Job arrival rate is set to $\lambda = 0.99$. This is very similar to job arrival rates estimated in previous works when converted to an annual basis.[40]

Divorce rates – Biennial divorce rates $\tilde{\delta}_m(s)$ are computed as the fraction of married couples in the HRS that divorced in the next survey wave, conditional on husbands' disability status. In order to get annual divorce rates $\delta_m(s)$ from the biennial rates $\tilde{\delta}_m(s)$, I assume that annual divorce rates between the survey waves are equal[41] and use the relationship $1 - \tilde{\delta}_m(s) = (1 - \delta_m(s))^2$. The resulting parameter values are reported in the third column of Table 6. Notice that annual divorce rates for healthy and moderately disabled husbands are the same but higher for severely disabled husbands.

Mortality rates – Husbands' annual survival rates are estimated from a logit regression model using reported death dates in the HRS data. Covariates include a quartic in age, disability status, and a dummy for whether average lifetime earnings are above the median of the distribution. Wives' annual survival rates are taken from the SSA Life Tables (Bell and Miller,

[40] Low et al. (2010) estimate a quarterly job arrival rate of 0.73 from the PSID. Merkurieva (2018) reports a monthly job arrival rate of 0.24 based on the CPS data.

[41] This assumption is due to the fact that HRS does not report actual divorce dates.

2005) since the model tracks neither wives' health status nor their average lifetime earnings. I use the reported survival rates for females born in 1930 since most wives in the estimation sample are born between the years 1930 and 1940.

Disability transition probabilities – Husbands' biennial disability transition probabilities are estimated from the HRS data using a multinomial logit regression model. Covariates include a quadratic in age, a dummy for whether average lifetime earnings are above the median of the distribution, and current disability status. Conditional on age and average lifetime earnings, I obtain a three by three matrix of annual transition probabilities Π_a from the matrix of biennial transition probabilities Π_b using the relationship $\Pi_a^2 = \Pi_b$.

Wage offer function – I follow the estimation method used by Low and Pistaferri (2015) to estimate the parameters of the wage offer equations (9) through (11). In order to correct for selection into employment, a two-step Heckman estimation procedure is employed. I use state and year variation in "residualized" SSDI award rates, potential UI benefits, and potential SNAP benefits as exclusion restrictions.[42] For husbands, I generate interactions of the exclusion restriction variables with disability status, and use these interaction terms as additional exclusion restrictions. The variance of the idiosyncratic wage shocks ($\sigma^2_{\eta,h}, \sigma^2_{\eta,w}$) and their covariance between the two spouses (σ_{η_h,η_w}) are estimated by GMM.

Parameter estimates reported in Table 7 indicate that for husbands, moderate and severe disabilities lead to a 12% and 21% decrease in hourly offered wages. These estimates are similar to those reported by Low and Pistaferri (2015).

4.1.3 Second Stage Moments and Identification of the Preference Parameters

Given the parameter values estimated in the first stage, the remaining preference parameters are estimated using indirect inference. There are a total of 17 parameters including the health state dependence in consumption utility ($\theta(s), s \in \{1,2\}$), the husband and wife's weight on leisure utility (ψ_j, $j \in \{h,w\}$), the husband's time cost of working in the disabled states ($\phi(s), s \in \{1,2\}$), the weight on terminal utility (ψ_v), the caregiving utility parameters ($\mu_c(s), \rho(s), \sigma_{\xi,s}, s \in \{1,2\}$), the minimum consumption level guaranteed by government

[42] Refer to Appendix E for details on the construction of the exclusion restrictions. Instead of using actual SSDI award rates, I use the "residualized" version by controlling for various state-level demographics that may be correlated with both disability benefit award rates and wages. Potential UI and SNAP benefits are computed based on formulae coded in federal and state legislation. By using potential benefits based on legislative formulae, only exogenous characteristics (state and year) are exploited.

Table 7: Estimates of the Wage Offer Function

	Male	Female
$s = 1$ (Moderate)	-0.119 (0.045)	-
$s = 2$ (Severe)	-0.205 (0.091)	-
Age	0.076 (0.023)	0.066 (0.032)
Age sq./100	-0.074 (0.023)	-0.067 (0.033)
High type†	0.232 (0.015)	-
Variance of wage shock ($\sigma^2_{\eta,j}$)	0.044 (0.008)	0.023 (0.007)
Covariance of spouses' wage shocks ($\sigma_{\eta_{h,w}}$)	.011 (0.002)	
Exclusion restrictions		
χ^2	14.41	12.02
p-value	0.025	0.003
Observations	15,245	18,105

Notes: Dependent variable: log hourly earnings. Results are based on a sample of HRS respondents who are white and under age 65, estimated separately for males and females. Controls for education, marital status, and year fixed effects. Standard errors in parentheses, computed via bootstrap to correct for first-stage estimation bias.

† Corresponds to hubands' individual type f^h, measured using their average lifetime earnings. "High type" refers to husbands whose average lifetime earnings are greater than \$30,223 (median average lifetime earnings of males in the HRS, in \$2015).

transfers ($\underline{c}$), the coefficient of relative risk aversion with respect to consumption (γ), and SSDI award probabilities by disability severity ($Pr(DI_{t+1} = 1 | App_t = 1, s_t)$, $s_t \in \{1, 2\}$). This section discusses how the targeted moments identify the preference parameters.

First, health state dependence in consumption utility $\theta(s)$ is identified by *jointly* matching 1) wives' labor supply responses in the event of their husbands' disability and 2) wives' caregiving choices. 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.

The husband and wife's weight on leisure utility (ψ_h, ψ_w) can be recovered by matching both spouses' employment rates when the husband is in the healthy state. Husbands' time cost of working in the disabled states ($\phi(s), s \in \{1, 2\}$) is identified by matching the changes in husbands' employment rates after a disability shock. I use fixed effect regression coefficients of husbands' employment on dummies of disability severity as the corresponding moments.

The coefficient of relative risk aversion with respect to consumption γ is identified by matching median household asset profiles by age for healthy households. This is because γ directly governs the speed in which assets are decumulated over the life-cycle. The minimum household consumption floor $\underline{c}$ can be recovered by matching household asset profiles by age at the 25th percentile since $\underline{c}$ affects the savings decisions of households with low levels of assets. The weight on terminal utility (ψ_v) is inferred from median household assets when the husband is age 65 (i.e., beginning of the retirement period in the model). Since consumption is the only choice that is made in the retirement period, ψ_v affects the speed that assets are decumulated in the retirement period. Therefore, ψ_v can be recovered from the amount of assets that households have when they enter the retirement period.

Caregiving utility weight parameters ($\mu_c(s), \rho(s), \sigma_{\xi,s}$) are identified by matching the percentage of part- and full-time caregivers as well as transition probabilities from caregiver to caregiver and non-caregiver to non-caregiver, conditional on health status s. This is because $\rho(s)$ governs persistence in wives' caregiving choices. Also, the variance of the idiosyncratic caregiving utility shock $\sigma_{\xi,s}$ affects the fraction of part- and full-time caregivers since households that receive a higher idiosyncratic shock will be more likely to choose full-time caregiving.

Finally, the probability of being awarded disability benefits $Pr(DI_{t+1} = 1|App_t, s_t)$ is identified by matching the percentage of SSDI applicants by health status.

5 Results

5.1 Model Fit and Parameter Estimates

Tables 8 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 Table 8. Next, I re-estimate the model without caregiving (i.e., caregiving utility is zero in all states such that wives never choose caregiving) and report the corresponding parameter estimates in column (b). The goal of this exercise is to highlight the potential bias in the estimates of key preference parameters when caregiving is omitted. When I estimate the model without caregiving, I use the same moments described in Section 4.1.3 except for wives' caregiving choices.

The key preference parameter that has significant implications for evaluating the optimality of social insurance benefits is the health state dependence in household consumption utility, $\theta(s)$. Under the baseline model, the marginal utility of consumption is 8% and 18% higher compared to that in the healthy state when husbands become moderately and severely disabled, respectively. Although empirical evidence on both the direction and magnitude of health state dependence in consumption utility is mixed, these values are in line with previous works that support positive health state dependence.[43]

Importantly, the "no-caregiving" model which omits wives' caregiving choices and does not match wives' caregiving choices underestimates the health state dependence in the marginal utility of consumption. Under the "no-caregiving" model, the marginal utility of consumption is 2% and 9% *lower* than that in the healthy state when husbands are moderately and severely disabled, respectively, which indicates negative health state dependence. This implies that changes in wives' labor supply responses across their husbands' health states are not sufficient to recover key preference parameters. By omitting the fact that wives are actually spending a significant amount of time in caregiving, the "no-caregiving" model incorrectly interprets the small spousal labor supply responses in the event of husbands' disability as households valuing consumption less in the disabled states.

Also, while almost all models in the literature do not consider wives' caregiving decisions, these results indicate that this will underestimate the insurance value that married households place on SSDI benefits. This is because models that ignore caregiving will incorrectly interpret the small spousal labor supply responses as households valuing consumption less in the disabled states and therefore conclude that government transfers to the disabled states are less valuable.

[43]See Finkelstein et al. (2009) for an overview of the empirical literature regarding health state dependence. Low and Pistaferri (2015) estimate a 25% and 57% increase in marginal utility of consumption in the moderately and severely disabled states, respectively. Lillard and Weiss (1997) find that the marginal utility in the sick state is 155% of that in the healthy state. Also, notice that there is no distinction between medical and non-medical consumption in this model. However, it is possible that there is negative health dependence in non-medical consumption but positive health dependence in medical consumption such that $\theta(s) > 1$ may be due to the magnitude of health dependence in medical consumption being larger than that in non-medical consumption. While interesting, measuring the health dependence for different types of consumption goods is left as future work.

Table 8: Estimates of the Model Parameters

Parameters	(a) Baseline	(b) "No-caregiving"†
Health state dependence in consumption utility		
$\theta(1)$ Moderately disabled	1.079 (0.033)	0.977 (0.013)
$\theta(2)$ Severely disabled	1.183 (0.017)	0.909 (0.015)
Coefficient of relative risk aversion (consumption), γ	1.458 (0.005)	1.460 (0.005)
Husbands' weight on leisure utility ($\times 10^{-3}$), ψ_h	7.029 (0.640)	6.928 (0.771)
Husbands' (per-unit) time cost of working		
$\phi(1)$ Moderately disabled	0.608 (0.068)	0.544 (0.190)
$\phi(2)$ Severely disabled	0.781 (0.147)	0.631 (0.197)
Wives' weight on leisure utility ($\times 10^{-3}$), ψ_w	4.721 (0.275)	4.626 (0.173)
Weight on terminal utility, ψ_v	0.646 (0.476)	0.900 (0.237)
Caregiving utility weight parameters		
Moderately disabled		
$\mu_c(1)$ Average ($\times 10^{-6}$)	4.666 (1.876)	-
$\rho(1)$ Auto-regressive persistence	0.637 (0.066)	-
$\sigma_{\xi,1}$ Variance of white noise ($\times 10^{-5}$)	3.711 (0.777)	-
Severely disabled		
$\mu_c(2)$ Average ($\times 10^{-4}$)	1.691 (0.538)	-
$\rho(2)$ Auto-regressive persistence	0.850 (0.140)	-
$\sigma_{\xi,2}$ Variance of white noise ($\times 10^{-4}$)	4.978 (0.555)	-
Minimum consumption floor ($2015), $\underline{c}$	23,798 (992)	23,165 (1,118)
Probability of receiving SSDI by disability status		
$Pr(DI_{t+1} = 1 \mid App_t = 1, s_t = 1)$ Moderate	0.108 (0.044)	0.107 (0.030)
$Pr(DI_{t+1} = 1 \mid App_t = 1, s_t = 2)$ Severe	0.550 (0.207)	0.591 (0.185)

Notes: Standard errors in parentheses. Refer to Appendix F on how standard errors are computed.
† Parameter estimates when caregiving is omitted (i.e., caregiving utility is always zero such that wives allocate their time to leisure and market work only).

Table 9: Targeted Moments I

	Model	Data	Model	Data
Panel A: Changes in Labor Supply by Husbands' Disability Severity†				
	Husbands' Employment			
Moderate	-0.205	-0.205		
		(0.016)		
Severe	-0.303	-0.294		
		(0.019)		
	Wives' Employment		Wive's Weekly Hours (in hours)	
Moderate	0.002	-0.020	0.150	-0.138
		(0.014)		(0.520)
Severe	0.003	-0.017	0.193	-0.315
		(0.018)		(0.634)
Panel B: Employment Rates when Husbands are Healthy				
	Husbands' Employment Rate		Wives' Employment Rate	
Healthy	0.838	0.835	0.655	0.651
		(0.006)		(0.009)
Panel C: Household Assets when Husbands are Healthy (by age, in $1,000)				
	50th Percentile		25th Percentile	
Ages 50 - 54	169.74	184.44	76.80	78.16
		(7.10)		(3.67)
Ages 55 - 59	211.93	223.50	100.27	96.57
		(6.04)		(3.33)
Ages 60 - 64	257.23	274.28	120.37	121.10
		(6.92)		(3.67)
Panel D: Median Household Assets at Retirement (Age 65)				
	262.25	249.16		
		(11.01)		
Panel E: SSDI Application Rate by Husbands' Disability				
	Moderate		Severe	
	0.089	0.083	0.137	0.142
		(0.007)		(0.009)

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, and household fixed effects. The reported moments are the regression coefficients for the indicators of husbands' disability severity.

Table 10: Targeted Moments II – Caregiving Choices

	Model	Data	Model	Data
	Moderate		Severe	
Panel A: Fraction of Spouse Caregivers by Husbands' Disability				
Overall	0.195	0.198	0.577	0.566
		(0.034)		(0.025)
Part-time	0.193	0.191	0.444	0.437
		(0.034)		(0.023)
Full-time	0.002	0.007	0.132	0.128
		(0.007)		(0.016)
Panel B: Caregiving Transition Rates by Husbands' Disability ($t \rightarrow t+2$)				
No Care $\rightarrow$ No Care	0.868	0.885	0.651	0.654
		(0.045)		(0.045)
Care $\rightarrow$ Care	0.505	0.450	0.732	0.741
		(0.155)		(0.034)

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

Next, the coefficient of relative risk aversion with respect to consumption is 1.458 which is within the range of reported values from previous studies as well as being close to 1.5 – a value commonly assumed in the literature.[44] Panel C of Table 9 shows that the model can generate median asset profiles by age reasonably close to that of the data.

The annual minimum consumption floor $\underline{c}$ is $23,798 in 2015 dollars. Given that $\underline{c}$ is the consumption floor for a two-member household, this estimate is within the range of values reported by previous works.[45] Finally, Table 10 indicates that estimates of the caregiving utility parameters generate reasonable fit. On average, caregiving generates greater utility and exhibits greater persistence for severely disabled households compared to moderately disabled households. As wives of severely disabled husbands are more likely to choose caregiving, this increases the marginal disutility of wives' market hours and discourages wives from choosing market work to make up for the loss in their husbands' earnings.

[44] Rust and Phelan (1997), Attanasio et al. (1999), Blau and Gilleskie (2006), and Banks et al. (2001) report estimates of 1.07, 1.57, 1.811, and 1.96 respectively. Blau and Gilleskie (2008) report a range of values from 1.011 to 1.04 depending on health and employment status.

[45] Using the CPI-U to convert to 2015 dollars, French and Jones (2011) and Merkurieva (2018) estimate $6,369 and $10,505 ($4,380 in 1998 dollars and $7,632 in 2000 dollars), respectively. Hubbard et al. (1995) set the consumption floor as $15,968 ($7,000 in 1984 dollars) based on calculating annual SSI and food stamp payments and verify that it matches asset profiles well compared to other values. All of these papers model households as single-member households.

5.2 Decomposing Added-Worker-Effects and Measuring the Insurance Value of SSDI

Building on parameter estimates that generate good model fit, I use the model to perform two sets of counterfactuals. First, in order to explore the extent to which added worker effects are attenuated by either caregiving or the existence of SSDI, I perform an event study regression of wives' labor supply on husbands' disability events under three scenarios: (1) baseline, (2) when SSDI is shut down[46], and (3) when SSDI is shut down and wives never choose to provide care.[47] Using the same specification as equation (1), I control for four years prior and five years after husbands' disability. Changes in wives' labor supply at the onset year of husbands' disability event are reported in Table 11.[48]

Under the counterfactual scenario of no-SSDI and no-spousal care, wives increase employment by 1.8% in response to their husbands' disability. This drops to 0.9% once wives optimally allocate their time between market work and spousal care (but still without SSDI).

Table 11: Simulated Added-Worker Effects (AWE) at Husbands' Disability Onset Year

	AWE at Year=0	
	Wives' Employment	Wives' Weekly Hours
Counterfactual		
No SSDI + No spousal care	0.018	0.884
No SSDI	0.009	0.482
Baseline: with SSDI & spousal care	0.002	0.242

Notes: Reports changes in wives' employment and weekly working hours upon their husbands' first disability onset. Estimates obtained via event study regressions using simulated data and controlling for four years prior and five years after husbands' first disability onset as well as a quartic in both spouses' ages. "No SSDI" is the counterfactual scenario where SSDI is shut down by assuming that SSDI benefits are always zero. "No spousal care" indicates the scenario where caregiving utility is imposed to be zero (i.e., wives never choose caregiving).

[46] SSDI is shut down by imposing that SSDI benefits are always zero. Both the payroll and federal income tax rates are kept the same as in the baseline scenario.

[47] While constraining wives such that they never choose caregiving is suboptimal, the goal of this exercise is to illustrate the magnitude in which the two mechanisms (spousal care and SSDI) contribute to the attenuation of wives' labor supply responses.

[48] When generating simulated data under the counterfactual scenarios, I assign wives' optimal employment choices, conditional on their husbands' choices being the same as those chosen in the baseline scenario. This is because the counterfactual scenarios also affect husbands' employment choices and thus does not provide a fair comparison for the purpose of decomposing whether the observed added worker effect is attributable to either caregiving choices or the existence of SSDI benefits.

This indicates that 50% of spousal labor supply responses are attenuated due to wives choosing to spend time in spousal care. Once we return to the baseline scenario with both SSDI and spousal care, wives' employment reduces by an additional 0.7 percentage points (i.e., 38% of the 1.8 percentage point observed in the "No SSDI+No spousal care" scenario) such that the increase in wives' employment in response to their husbands' disability is only 0.2%. Therefore, the fraction of spousal labor supply responses attenuated due to spousal care choices is larger compared to that due to the income effects of SSDI. We can observe a similar pattern when considering changes in wives' weekly hours as well (last column of Table 11).

These results further strengthen the importance of using both changes in spousal labor supply responses across husbands' disability status and spousal care choices in order to correctly infer how much households' valuation of consumption varies across health states. From observing small added worker effects, one may mistakenly conclude that this is partly due to consumption not being valuable in the disabled state when in fact, a large fraction of spousal labor supply responses is attenuated due to spousal care.

The second and final set of counterfactuals measures the ex-ante insurance value of SSDI relative to its costs among married households. To do this, for each simulated household, I calculate the amount of income y that needs to be annually given until death in the counterfactual world where SSDI does not exist such that the expected utilities under the baseline world with SSDI and the counterfactual world without SSDI are equal. Then, I compute the present discounted value of income stream y measured at age 50 (i.e., the start of the model). This present discounted value is the compensating variation that I use to measure the insurance value that each household places on SSDI. I divide the average compensating variation by the average present discounted SSDI benefits to get a measure of how much a dollar of SSDI benefits is valued (ex-ante) among married households. These numbers are reported in Table 12 for households that first enter the model as healthy. I consider two types of models: 1) baseline model using baseline estimates and 2) the "no-caregiving" model which omits caregiving (using corresponding parameter estimates reported in column (b) of Table 8). The key point of this exercise is to quantify the difference in the ex-ante insurance value of SSDI that each model predicts.

Row (1) of Table 12 reports the ex-ante insurance value of SSDI per each dollar of SSDI benefits for married households. Under the baseline model where consumption is valued higher in the disabled states than in the healthy state, households value a dollar of SSDI benefits as 97 cents. In contrast, the "no-caregiving" model predicts the insurance value relative to a dollar of SSDI benefits as 91 cents per SSDI benefit payments.

In order to interpret the magnitude of the difference in the insurance value of SSDI between the two models, row (2) reports the required percentage change in SSDI benefits such that the insurance value of SSDI equals to the value predicted by the "no-caregiving" model. Note that an increase in benefits will decrease the insurance value of SSDI relative to its direct costs (i.e., expenditure on SSDI benefit payments) as it creates a work disincentive for both husbands and wives. Row (2) indicates that SSDI benefits need to be 11.1% higher in order for the insurance value of SSDI per dollar of benefits to be decreased to \$0.91, which is a non-negligible magnitude. This implies that SSDI benefits for married households need

Table 12: Ex-ante Insurance Value of SSDI for Married Households (in 2015 dollars)

	Model	
	Baseline	"No-caregiving"*
Health state dependence estimates $(\theta(1), \theta(2))$	(1.08, 1.18)	(0.98, 0.91)
(1) Ex-ante insurance value of SSDI per dollar of SSDI benefits†	0.97	0.91
(2) Required % change in SSDI benefits such that (1) equals 0.91	+11.1%	-
(3) Additional fiscal costs per dollar of SSDI benefits	0.10	0.11
(4) Ex-ante insurance value of SSDI per dollar of SSDI benefits, net of fiscal costs $(= \frac{(1)}{1+(3)})$	0.88	0.82
(5) Required % change in SSDI benefits such that (4) equals 1	-17.4%	-

Notes: Reports the ex-ante insurance value of SSDI for married households that enter the model at age 50 as healthy.

* Alternative model without caregiving (i.e., caregiving utility is always zero) using the corresponding parameter estimates reported in column (b) of Table 8.

† Computed as the average compensating variation divided by the average present discounted SSDI benefits. For each simulated household, compensating variation is measured as the present discounted value of an annuity income stream y which should be given to households 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.

‡ Fiscal costs are measured by taking the difference in net government expenditures between the economy with SSDI and the counterfactual economy where SSDI is non-existent. Net government expenditures are measured as the sum of government transfers (which guarantees the minimum consumption floor) and SSDI payments, subtracted by tax revenues (payroll and income taxes). The difference in net government expenditure captures both the direct costs (SSDI benefit payments) and indirect costs (changes in transfers and tax revenues) induced by the existence of SSDI.

to be higher when we take into account that the insurance role of spousal labor supply is reduced due to time spent in caregiving.

While the results shown in Table 12 consider the direct costs of SSDI, SSDI has indirect costs since an increase in SSDI benefits disincentivizes both husbands and wives to work, which leads to a decrease in tax revenues. Also, an increase in SSDI benefits affects government transfers that provide the minimum consumption floor, since low asset households would have a stronger incentive to receive SSDI benefits rather than government transfers. In order to measure both the direct and indirect costs of SSDI, I compute the difference in net government expenditures (i.e., sum of SSDI benefit payments and government transfers that guarantee the minimum consumption floor, minus payroll and income taxes) between the scenarios with and without SSDI. The additional fiscal costs due to behavioral responses are reported in row (3).

Both models indicate that a dollar of SSDI benefits induces an additional fiscal cost of approximately 10 cents. This indicates that a dollar of SSDI benefits net of indirect costs is valued as 88 cents (=0.97/1.10) under the baseline model and 82 cents (=0.91/1.11) under the "no-caregiving" model.[49] This implies that given the degree of moral hazard in the model, the total government costs (direct and indirect) of SSDI exceed the welfare benefits (i.e., ex-ante insurance value) that it provides to married households at age 50. The estimate in row (5) shows that under the baseline model, SSDI benefits needs to be decreased by 17.4% in order for the direct and indirect costs of SSDI to be equal to the insurance value that married households place on SSDI.

Row (5) of Table 12 shows that under the baseline model, one possible reform in order to make the insurance value of SSDI equal to the total government cost of providing SSDI would be to reduce SSDI benefit levels across the board by 17.4%. An alternative policy would be to reduce SSDI benefit levels by x% but provide a flat amount of annual caregiving benefits b_{care} to "deserving" SSDI beneficiaries. Providing a supplementary caregiving benefit for disability beneficiaries is a common feature in a number of OECD countries but not in the US. Instead of mimicking specific policies, I consider a hypothetical policy where SSDI

[49] To my knowledge, Bound et al. (2004) is the only paper on SSDI that reports estimates that can be compared with the ones reported in Table 12. Bound et al. (2004) assumes that individual preferences exhibit constant relative risk aversion and are separable in consumption and leisure. Given these preferences, for male workers of ages 45 to 61 and with less than a college degree, individuals' willingness to pay for a dollar of SSDI benefits net of fiscal costs is \$0.83 ~ \$0.90 when the coefficient of relative risk aversion (γ) is 1 and \$1.02 ~ \$1.22 when $\gamma = 2$. Given that the estimated coefficient of relative risk aversion in this paper is $\gamma = 1.458$, the values reported in row (4) of Table 12 are reasonably within the range that is reported by Bound et al. (2004).

Table 13: Policy Reform: Introducing Supplementary Caregiving Benefits

$*$ Baseline policy: Reducing SSDI benefits by 17.4%
$*$ Alternative reform: Reducing SSDI benefits by x% but providing annual caregiving benefits b_{care} to eligible beneficiaries[†]

Government budget-neutral and utilitarian welfare-improving combinations of (x, b_{care})	
x	b_{care}
21	\$6,090
45	\$37,737
50	\$42,372

[†] In this policy experiment, beneficiaries eligible for caregiving benefits are defined as those whose caregiving utility weight $\omega_{c,t}(s)$ is above some threshold z. In line with the fact that about 4% of severely disabled men in my data are completely unable to perform one or more ADL, I set z such that 4% of severely disabled households are eligible for this caregiving benefit.

beneficiaries are eligible for a flat amount of b_{care} in the periods where their caregiving utility weight $\omega_{c,t}(s)$ is greater than some threshold z. In my data sample, about 4% of severely disabled men are completely unable to perform one or more ADL. Since it is natural to expect that this subgroup would require a greater degree of caregiving and be more identifiable as being "severely disabled," I set z such that 4% of severely disabled households are eligible for this caregiving benefit.[50] Table 13 reports combinations of x and b_{care} in which the government budget is the same as under the baseline policy (i.e., reducing benefits across the board by 17.4%) but generate higher utilitarian social welfare.

The results reported in Tables 12 and 13 point toward a couple of important conclusions. First, Table 12 shows that even under the estimates for the baseline model with caregiving, the ex-ante insurance value of SSDI among married households is lower than the total government cost of providing SSDI which suggests that SSDI generosity should be reduced. However, Table 13 implies that this can be done in a way such that government resources are targeted to a certain population (in this case, disabled beneficiaries requiring significant degree of care from others) and that this can improve (utilitarian) social welfare.[51] This

[50]Note that this is based on interpreting $\omega_{c,t}(s)$ as unobservable heterogeneity in caregiving needs (conditional on disability severity s). A higher $\omega_{c,t}(s)$ leads to households spending more time in spousal care and variation in $\omega_{c,t}(s)$ across time and households is what allows the model to generate simulated wives' caregiving choices as observed in the data.

[51]A important caveat is that this analysis abstracts from distributional concerns.

is because household welfare increases when more resources are transferred to the severely disabled states due to positive health state dependence. In addition, reducing overall benefits discourages marginal individuals from applying but the supplementary caregiving benefit targets resources to severely disabled individuals who require receiving care from others (and these individuals are more likely to be inframarginal).

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 illustrates its implications for evaluating the insurance value of SSDI. The key results of this paper are twofold. First, spousal labor supply responses to husbands' disability are attenuated by a large extent due to time spent in caregiving. Second, the insurance value of SSDI relative to its costs is considerably higher when I account for the fact that caregiving needs substantially reduce the insurance role of spousal labor supply. Furthermore, counterfactual policy experiments indicate that for a given government budget, it is possible to improve (utilitarian) social welfare by reducing overall SSDI benefit levels but introducing a supplementary caregiving benefit to eligible SSDI beneficiaries with significant caregiving needs.

Between 1980 to 2013, the number of SSDI beneficiaries and their eligible dependents rose from 4.7 million to 11 million. During the same time period, spending on benefits increased from 0.54% to 0.84% of gross domestic product, putting a significant strain on the DI trust funds (Morton, 2015). This has raised concerns among policymakers and subsequently, various reforms to the current SSDI program have been proposed. Given that SSDI benefit amounts are computed based on individuals' past earnings and do not vary by severity under the current system, these results imply that further adjusting benefit generosity based on the degree of required care may be an effective method to address the rapid growth of SSDI while providing households with valuable insurance.

References

Altonji, J. G. and L. M. Segal (1996). Small-Sample Bias in GMM Estimation of Covariance Structures. *Journal of Business and Economic Statistics 14*(3), 353–366.

Attanasio, O. P., J. Banks, C. Meghir, and G. Weber (1999). Humps and Bumps in Lifetime Consumption. *Journal of Business & Economic Statistics 17*(1), 22–35.

Autor, D., A. Kostol, M. Mogstad, and B. Setzler (2017). Disability Benefits, Consumption Insurance, and Household Labor Supply. mimeo.

Autor, D. H. and M. G. Duggan (2003, February). The Rise in the Disability Rolls and the Decline in Unemployment. *The Quarterly Journal of Economics 118*(1), 157–206.

Autor, D. H. and M. G. Duggan (2006, May). The Growth in the Social Security Disability Rolls: A Fiscal Crisis Unfolding. *Journal of Economic Perspectives 20*(3), 71–96.

Banks, J., R. Blundell, and A. Brugiavini (2001). Risk Pooling, Precautionary Saving and Consumption Growth. *Review of Economic Studies 68*(4), 757–779.

Bell, F. and M. Miller (2005). Life Tables for the United States Social Security Area 1900-2100. Actuarial Study No. 120, Social Security Administration.

Benitez-Silva, H., M. Buchinsky, and J. Rust (2006, August). How Large Are the Classification Errors in the Social Security Disability Award Process?

Berger, M. C. and B. M. Fleisher (1984). Husband's Health and Wife's Labor Supply. *Journal of Health Economics 3*(1), 63–75.

Blau, D. M. and D. B. Gilleskie (2006). Health Insurance and Retirement of Married Couples. *Journal of Applied Econometrics 21*(7), 935–953.

Blau, D. M. and D. B. Gilleskie (2008). The Role of Retiree Health Insurance in the Employment Behavior of Older Men. *International Economic Review 49*(2), 475–514.

Blundell, R., L. Pistaferri, and I. Saporta-Eksten (2016, February). 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., 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 WP 11605, National Bureau of Economic Research, Cambridge, MA.

Charles, K. (1999). Sickness in the Family: Health Shocks and Spousal Labor Supply. mimeo.

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.

Coile, C. (2004). Health Shocks and Couples' Labor Supply Decisions. NBER WP 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 WP 21352, National Bureau of Economic Research, Cambridge, MA.

Fadlon, I. and T. H. Nielsen (2018). Household Labor Supply and the Gains from Social Insurance. *Journal of Public Economics* (forthcoming).

Finkelstein, A., E. F. P. Luttmer, and M. J. Notowidigdo (2009, April). Approaches to Estimating the Health State Dependence of the Utility Function. *American Economic Review 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. mimeo.

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, December). 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 WP 15-240.

Haurin, D. R. (1989, February). 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. (2015). Occupational Choice, Retirement, and the Effects of Disability Insurance. mimeo.

Jeon, S.-H. and R. V. Pohl (2017, March). 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? Staff Report No. 310, Federal Reserve Bank of New York.

Keane, M. P. (2011, December). Labor Supply and Taxes: A Survey. *Journal of Economic Literature 49*(4), 961–1075.

Kostøl, A. R. and M. Mogstad (2015, May). 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.

Liebman, J. B. (2015, May). Understanding the Increase in Disability Insurance Benefit Receipt in the United States. *Journal of Economic Perspectives 29*(2), 123–150.

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.

Merkurieva, I. (2014). The Added Worker Effect and the Lifetime Labor Supply of Older Households. mimeo.

Merkurieva, I. (2018). Late Career Job Loss and the Decision to Retire. *International Economic Review* (forthcoming).

Meyer, B. and W. K. Mok (2013). Disability, Earnings, Income and Consumption. NBER WP 18869, National Bureau of Economic Research, Cambridge, MA.

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 Disablity 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, February). 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.

Rust, J. and C. Phelan (1997). How Social Security and Medicare Affect Retirement Behavior In a World of Incomplete Markets. *Econometrica 65*(4), 781–831.

Spletzer, J. R. (1997). Reexamining the Added Worker Effect. *Economic Inquiry 35*(2), 417–427.

Stephens, Jr., M. (2002). Worker Displacement and the Added Worker Effect. *Journal of Labor Economics 20*(3), 504–537.

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 Detailed Health Conditions

The following are the detailed health conditions that are included in the aggregated health condition groups reported in Table 1. These are the aggregate groupings used in the HRS Master Codes.

Musculoskeletal system and connective tissue conditions

1. Arthritis; rheumatism; bursitis
2. Back/neck/spine problems: chronic stiffness, deformity or pain; disc problems; scoliosis; spina bifida
3. Stiffness, deformity, numbness or chronic pain in foot, leg, arm or hand; knee/hip problems; hip replacement
4. Missing legs, feet, arms, hands, or fingers (from amputation or congenital deformity)
5. Paralysis (including from polio)
6. Hernias; hiatal hernia
7. Other problems; lupus; osteoporosis; pinched nerve; carpal tunnel syndrome; fibrositis

Heart, circulatory and blood conditions

1. Heart problems: heart attack (coronary) or failure; arteriosclerosis; aneurysms; heart deformities; angina; congestive heart disease
2. High blood pressure (hypertension)
3. Stroke; cerebral hemorrhage or accident
4. Blood disorders: anemia; hemophilia; polycythemia; toxemia
5. Other problems; phlebitis, clots, embolisms; varicose veins; hemorrhoids; low blood pressure

Respiratory system conditions

1. Allergies; hay fever; sinusitis; tonsillitis
2. Asthma
3. Bronchitis; pneumonia; “acute upper respiratory problems”
4. Emphysema
5. Other problems; tuberculosis

Neurological and sensory conditions

1. Blindness or vision problems: glaucoma; cataracts; detached retina
2. Deafness, hearing loss or other ear conditions
3. Multiple sclerosis; cerebral palsy; epilepsy; Parkinson's; ALS; "seizures"; neuropathy
4. Speech conditions; congenital speech defects; stuttering
5. Mental retardation; learning disabilities; Down syndrome
6. Other problems; sciatica; meningitis; "memory loss"

B Robustness of Spousal Labor Supply Responses to Husbands' Disability

This section provides additional analysis regarding wives' labor supply responses to their husbands' disability. Table 14 reports event study regression coefficients where the estimation equation is 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) controls for the wives' health status by including dummy variables for wives' disability status as well as the interactions of husbands' disability onset and wives' disability status as follows:

$$y_{it} = \alpha_i + \gamma_t + X_{it}'\beta + \sum_{k=-4}^{5} \delta_k \cdot I_{itk} + \sum_{s} \left(A_{it}^s + \sum_{k=-4}^{5} \delta_k^s \cdot I_{itk} \cdot A_{it}^s \right) + \epsilon_{it} \tag{19}$$

where A_{it}^s is an indicator for the wife in household i being disabled with severity $s \in \{\text{moderate, severe}\}$ at period t. Columns (1) and (2) indicate that although correlated disability status partially affects wives' labor supply responses, the baseline result of small added worker effects still persists.

Next, I explore whether the small spousal labor supply responses are driven by households whose husbands are receiving SSI/DI benefits. This is done by including the interaction of post-onset dummies and the dummy for whether the husband is receiving SSI/DI or not. These results are reported in column (3). Note that these are not causal estimates of the effect of SSI/DI receipt since applying for disability benefits is an endogenous choice. The coefficients in column (3) imply that indeed wives with husbands who are on 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 among non-SSI/DI receiving households. Although wives whose husbands are not receiving

Table 14: Robustness - Wives' Weekly Hours Worked in the Event of Husbands' Disability

	(1) Wives' Hours	(2) Wives' Hours	(3) Wives' Hours	(4) Wives' Hours
Year = -4, -3	0.318	0.800	0.810	-0.373
	(0.751)	(0.825)	(0.826)	(1.266)
Year = -2, -1	-1.171	-0.858	-0.827	-3.885**
	(0.996)	(1.083)	(1.085)	(1.818)
Year = 0, 1	-1.861	-0.707	-0.538	-1.391
	(1.157)	(1.273)	(1.323)	(2.121)
Year = 0, 1 × Receiving SSI/DI			-1.648 (3.203)	
Year = 2, 3	-0.955	1.041	1.515	-1.252
	(1.322)	(1.412)	(1.519)	(1.968)
Year = 2, 3 × Receiving SSI/DI			-3.232 (2.801)	
Controls for wives' disability status	No	Yes	Yes	Yes
Cause of husbands' disability	All	All	All	Accident / acute conditions*
Observations	16,365	16,327	16,327	16,327
R-sq	0.091	0.112	0.113	0.114

Notes: Results are based on a sample of married households where both spouses are under age 65 in the HRS Core survey (1992-2014). Standard errors in parentheses, clustered at the household level. ** indicates statistical significance at the 5 percent level.

* Acute conditions include paralysis, heart problems, and stroke.

disability benefits increase their weekly working hours by 1.5 hours by the second and third year of their husbands' disability onset, again these estimates are imprecise.

Finally, column (4) documents responses in wives' working hours based on alternative definitions of husbands' disabilities. I employ the same estimation model as equation (1) but distinguish whether the disability is due to accidents and/or certain acute conditions (paralysis, heart problems, and stroke). Arguably, these disabilities are less likely to be expected and therefore more likely to be regarded as an unexpected shock. Formally, the estimation model is as follows:

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

where g indicates the disability group (whether or not the disability is due to accidents/acute conditions). Column (4) reports δ_k^g for the disability group in which the disability was due to accidents and/or acute conditions. Again, added worker effects are not observed even when conditioning on certain disabilities that are more likely to be unexpected. This implies that although there may be 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.

C 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:

$$y_{t_b} = \frac{\sum_{t=t_0}^{t_b} e_t^*}{35} \tag{21}$$

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

$$e_t^* \quad = \quad \min\{w_{ht}h_{ht}, e^{max}\} \tag{22}$$

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.

$$AIME \quad = \quad \frac{y_{t_b}}{12} \tag{23}$$

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 (23) 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.

$$\begin{aligned} PIA \quad = \quad & 0.90 \times \min\{AIME, b_1\} + 0.32 \times \min\Big\{\max\{AIME - b_1, 0\}, b_2 - b_1\Big\} \\ & + 0.15 \times \max\{AIME - b_2, 0\} \end{aligned} \tag{24}$$

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.

$$b_t(y_{t_b}, DI_t = 1) \quad = \quad 12 \times PIA \tag{25}$$

Household retirement benefits are computed as the sum of both spouses' retirement benefits based on the husband's average lifetime earnings.[52] I use the fact that wives are eligible for 50% of their husbands' PIA and that the total amount of benefits payable to a family is capped at a maximum family benefit amount (PIA^{fmax}). PIA^{fmax} is computed

[52]See footnote 23 regarding the use of the husband's average lifetime earnings to compute the wife's retirement benefits.

based on the husband's PIA as follows.

$$\begin{aligned} PIA^{fmax} &= 1.5 \times \min\{PIA, b_1^f\} + 2.72 \times \min\Big\{\max\{PIA - b_1^f, 0\}, b_2^f - b_1^f\Big\} \\ &\quad + 1.34 \times \min\Big\{\max\{PIA - b_2^f, 0\}, b_3^f - b_2^f\Big\} + 1.75 \times \max\{PIA - b_3^f, 0\} \end{aligned} \tag{26}$$

The bend points (b_1^f, b_2^f, b_3^f) are set as b_1^f= \$1,056, b_2^f = \$1,524, and b_3^f = \$1,987 based on the Social Security formula in 2015.

Finally, household retirement benefits are calculated as below.

$$b_t(y, DI_t = 0) = 12 \times \min\{1.5 \times PIA, PIA^{fmax}\} \tag{27}$$

D Taxes

Household taxes $\tau(A_t, w_{ht}h_{ht}, w_{wt}h_{wt})$ are computed as the sum of payroll taxes of both spouses and federal income tax.

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 τ_{jt}^P is specified as follows.

$$\tau_{jt}^P = 0.062 \times \min\{w_{jt}h_{jt}, e^{max}\} + 0.0145 \times w_{jt}h_{jt}, \quad j \in \{h, w\} \tag{28}$$

Federal income tax – Federal income tax is a progressive tax on labor and non-labor income. Define the taxable household income as follows

$$I_t = \max\{rA_t + w_{ht}h_{ht} + w_{wt}h_{wt} - d, 0\} \tag{29}$$

where d denotes the amount of household deduction. I set d as d = \$12,600 based on the standard deduction for married households filing jointly in 2015.

Similar to the PIA computation formula, the federal income tax has seven progressive tax rates that are applied to seven taxable income brackets. Table 15 reports the amount of federal income tax τ_t^F that the household pays based on taxable household income I_t. I use the 2015 income tax brackets for married households filing jointly.

Table 15: Federal Tax by Taxable Income Brackets (in $)

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

Note: All values are in 2015 dollars.

E Estimating the Wage Offer Process

The husband and wife's model of employment is specified as equations (30) and (31), respectively.

$$P^*_{iht} = X'_{it}\beta_h + \sum_{s=1}^{s} \vartheta_s \cdot \mathbf{1}(s_{iht} = s) + Z'_{iht}\beta_{Z_h} + \epsilon_{iht} \tag{30}$$

$$P^*_{iwt} = X'_{it}\beta_w + Z'_{iwt}\beta_{Z_w} + \epsilon_{iwt} \tag{31}$$

P^*_{ijt} denotes the utility from working and the econometrician observes the indicator for whether an individual is employed or not: $P_{ijt} = \mathbf{1}(P^*_{ijt} > 0)$. Z_{ijt} is the vector of exclusion restrictions that affect the individual's probability of working but are plausibly exogenous to wages (conditional on X_{it} and disability status s_{iht}).

For females, I use potential UI and SNAP benefits, and SSI/DI award probabilities as exclusion restrictions. For males, I use the same exclusion restrictions as females but also add their interaction terms with dummy variables that indicate disability severity. The interaction with disability severity accounts for the possibility of differences in the effect of the exclusion restriction variables by health status.

Potential UI and SNAP benefits affect one's likelihood of working through an income effect but are plausibly exogenous to wages. Unlike actual benefits which is the result of both the individual's decision to apply for benefits as well as other endogenous variables that affect the amount of benefits, potential benefits are those that a "representative" individual would have received if one took up the benefits for certain.[53] Therefore, the variation only comes

[53] The individual is "representative" in terms of the endogenous variables (e.g., earnings, liquid assets) that enter into the computation of benefits.

from exogenous characteristics such as state of residence, year, and certain demographics. I use federal and state legislative formulae for each calendar year from 1992 to 2014 where UI benefits vary by state and year and SNAP benefits vary by year and family size.

SSI/DI award probabilities affect whether an individual chooses to work or not since higher likelihood of being awarded benefits would incentivize (marginal) individuals to work less and apply for disability benefits . I use a "residualized" version of SSI/DI award probabilities since although there is wide state-year variation in award rates, part of this may be due to certain state level characteristics that are also correlated with wages. First, I define SSI/DI award rates as the percentage of disability claims (SSDI and SSI applications) that were approved of benefits in the initial determination stage and calculate this for each state and fiscal year. This is done by using the SSA State Agency Fiscal Year Workload Data[54] for years 2001 and beyond as well as using data from 1992 to 2000 obtained directly from the SSA through the Freedom of Information Act. Next, I compute state-year level demographic characteristics that may partly account for the variation in disability benefit award rates. I use the CPS March Annual Supplement to compute each state's unemployment rate and per capita income. Also, for each state, I compute the percentage of working-age individuals who are male, have low educational attainment, employed in industries with high injury/illness rates, disabled, and below 150% of the federal poverty line, respectively. The residualized SSI/DI award rate is the residual of the regression of disability award rates on the aforementioned state-year level characteristics and year fixed effects.

F Computing Standard Errors of the Second Stage Model Parameters

Recall that some model parameters ($\boldsymbol{\theta_f}$) are calibrated or estimated without explicitly using the model in the first stage and the remaining model parameters ($\boldsymbol{\theta_s}$) are estimated in the second stage using indirect inference. The second stage estimate $\hat{\boldsymbol{\theta}}_{\boldsymbol{s}}$ is chosen such that it minimizes the weighted distance between the vector of data moments $\boldsymbol{m_d}$ and the vector of simulated moments $\boldsymbol{m_s}(\hat{\boldsymbol{\theta}}_{\boldsymbol{f}}, \boldsymbol{\theta_s})$ where the weight is specified by the matrix $\hat{W}$:

$$\hat{\boldsymbol{\theta}}_{\boldsymbol{s}} = \arg\min_{\boldsymbol{\theta_s}} \left(\boldsymbol{m_d} - \boldsymbol{m_s}(\hat{\boldsymbol{\theta}}_{\boldsymbol{f}}, \boldsymbol{\theta_s})\right)' \hat{W} \left(\boldsymbol{m_d} - \boldsymbol{m_s}(\hat{\boldsymbol{\theta}}_{\boldsymbol{f}}, \boldsymbol{\theta_s})\right) \tag{32}$$

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

[54]This data is publicly available at https://www.ssa.gov/disability/data/ssa-sa-fywl.htm.

$$var(\hat{\boldsymbol{\theta}}_{\boldsymbol{s}}) \quad = \quad \left(1+\frac{1}{H}\right)(J'\hat{W}J)^{-1}(J'\hat{W}S\hat{W}J)(J'\hat{W}J)^{-1} \tag{33}$$

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