The Labor Supply and Welfare Effects of Early Access to Medicare through Social Security Disability Insurance

Seonghoon Kim*

The Ohio State University

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Abstract

Social Security Disability Insurance (SSDI) beneficiaries receive a cash benefit and become eligible for health insurance from Medicare two years after their enrollment. Disabled workers who leave the labor force typically lose health insurance from their employers, and they face significant medical expenditure risk as a result of their disability. Therefore, access to Medicare makes SSDI an especially attractive alternative to remaining employed for workers with disabilities. My research is the first to analyze the importance of medical expenditure risk and Medicare in analysis of SSDI, and it addresses the following questions: (1) How does access to Medicare via SSDI enrollment affect the incentive to leave employment and to apply for SSDI? (2) What are the welfare effects of access to Medicare via SSDI? (3) How will SSDI policy reforms that change access to Medicare affect labor supply, welfare, and the financial stability of SSDI? To answer these questions, I specify a life-cycle model of labor supply, consumption, and SSDI application decisions. The model incorporates a stochastic process for out-of-pocket medical expenditure as well as the institutional features of Medicare. I estimate the model using data from the Panel Study of Income Dynamics, using the method of Indirect Inference. Counterfactual simulations indicate that availability of Medicare coverage via SSDI enrollment reduces the employment rate of men at ages 23 to 62 by 0.7 percentage points (from 87.7% to 87.0%). Medicare coverage via SSDI improves social welfare even after accounting for the higher taxes required to finance the additional enrollees who are induced to apply. Finally, I find that increasing the Medicare waiting period for SSDI enrollees is a relatively efficient way to reduce the SSDI budget deficit without sacrificing much of social welfare, compared to other alternatives such as making SSDI screening criteria more stringent.

Keywords: Social Security, Disability Insurance, Medicare, Medical Expenditure

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1. Introduction

Social Security Disability Insurance (SSDI) is a major source of income for disabled workers in the U.S. as well as a major component of Federal government expenditure. Over the last four decades, the number of SSDI recipients has increased from 3 million to 10.6 million, and spending for SSDI rose from $18 billion (in 2010 dollars) in 1970 to $129 billion in 2011. Almost 5% of the working age population is currently enrolled in SSDI, and SSDI cash payments accounted for 7.3% of non-defense spending of the U.S. federal government in 2010 (Autor and Duggan, 2011). The number of SSDI beneficiaries is rising so rapidly that the SSDI program will soon be unable to pay full benefits without an increase in the payroll tax that finances the program (Autor and Duggan, 2006).[1]

An important issue that has not been addressed in economic analyses of SSDI is the role of the Medicare coverage provided through SSDI. Since 1973, SSDI recipients have been eligible for health insurance from Medicare two years after enrollment.[2] The two-year Medicare waiting period is intended to reduce fiscal burden by providing health insurance benefits only to those who are not likely to recover from their disability within a short period of time. Access to health insurance from Medicare may be of considerable value to individuals who expect to be out of the labor force and therefore lack access to employer-provided health insurance, but who face significant medical expenditure risk. Medicaid, an alternative source of public health insurance, is generally available only to disabled workers who are quite poor, so it is not a good substitute for Medicare for the typical disabled worker. Other sources of health insurance such as COBRA[3] and state risk pools are often quite expensive. In 2009, average Medicare spending per SSDI recipient was $10,500, more than 80% of the average SSDI cash benefit. (Dahl and

[1] The 2012 Social Security Trustees' report estimates that the SSDI trust fund will be depleted by 2016. Incoming revenue from the SSDI portion of the payroll tax (currently 0.9% of covered earnings for employees) was sufficient to pay only 64% of the SSDI cash payments in 2011.
[2] Medicare coverage includes hospital insurance that helps pay bills for inpatient hospital stays, insurance for office visits, and prescription drug plans.
[3] The Consolidated Omnibus Budget Reconciliation Act (COBRA) of 1985 allows individuals separated from their employers to continue coverage under the employer-provided health insurance plan. Qualified individuals pay the entire premium. The COBRA coverage lasts 18 months in general, but can be extended up to an additional 11 months for disabled workers.

Myerson, 2010).[4] In 2010, SSDI recipients accounted for 18% of all Medicare beneficiaries and 19% of Medicare spending (CMS, 2011).

In this paper, I address the following questions: (1) How does access to Medicare via SSDI enrollment affect the incentive to leave employment and apply for SSDI? (2) What are the welfare effects of access to Medicare via SSDI? (3) How would SSDI policy reforms that change access to Medicare affect labor supply, welfare, and the financial stability of SSDI? The answers to these questions have important implications for understanding the role of Medicare in analysis of SSDI and how to optimally reform the SSDI program.

To answer these questions, I develop and estimate a life-cycle model of labor supply, consumption, and SSDI application decisions. In the model, individuals face a stochastic process for out of pocket medical expenditure, with a mean and variance that depend on type of health insurance coverage, severity of disability, and age. The model incorporates key institutional features of Medicare, such as the two-year waiting period following enrollment in SSDI. The model also incorporates other standard features of life cycle labor supply models, including persistent wage shocks. I estimate the model using data on a sample of men from the Panel Study of Income Dynamics (PSID). The key parameters of the model are structurally estimated via the method of Indirect Inference by minimizing the distance between the life-cycle data profiles observed in the PSID (employment, SSDI enrollment, and consumption expenditure) and the simulated life-cycle profiles generated from my model. The estimated model provides a very good fit to most key features of the data, such as the low labor force participation rate and the high SSDI enrollment among the severely disabled. The parameter estimates indicate that disability is associated with high disutility of work, low marginal utility of consumption, low wages, and high and variable medical expenditure. I also estimate that the probability that an application for SSDI benefits is accepted is increasing in the severity of disability, but is significantly lower than 1 even for the severely disabled.

The estimated model is used to perform counterfactual simulations to analyze the effects of access to Medicare provided through SSDI enrollment. The main findings of this paper are as

[4] Average Medicare spending per capita for the elderly beneficiaries (ages 65 and older) was $9849 in 2009.

follows. First, I find that the provision of Medicare benefits through SSDI has a substantial impact on SSDI application and labor supply decisions. The simulation results indicate that such provision reduces the employment rate of men at ages 23 to 62 by about 0.7 percentage points (from 87.7% to 87.0%) and increases the average SSDI application rate by about 0.5 percentage points per six-month period (from 3.6% to 4.1%, a 13% increase) compared to a counterfactual world in which Medicare is not available to SSDI beneficiaries. I also find that the employment and SSDI application responses are more elastic for the moderately disabled than for the severely disabled because moderately disabled workers are closest to the margin of indifference between SSDI application and working. Second, my results indicate that the provision of Medicare coverage to SSDI beneficiaries improves *ex ante* welfare of the population as a whole even after accounting for the higher taxes required to finance the additional enrollees induced to apply. I find that individuals would be willing to pay up to 0.5% of lifetime consumption to retain Medicare coverage through SSDI. This is because individuals who face disability risk, but do not know whether or when they will become disabled, value the availability of health insurance (Medicare coverage) in addition to the income insurance (cash payments) feature of SSDI. Medicare coverage accounts for almost half of the total welfare gain from the SSDI program. An important implication of these findings is that policy options to reduce the financial imbalance of the SSDI program should include changes in Medicare availability as well as changes in SSDI benefits and eligibility. For example, if the goal of a policy maker is to eliminate the SSDI budget deficit even at the cost of reduced *ex ante* social welfare, my simulation results indicate that reducing the value of the insurance coverage provided by Medicare (by increasing the Medicare waiting period) is a less costly approach compared to other options such as increasing the stringency of SSDI screening. My estimates indicate that the SSDI program rejects about 20% of applications from severely disabled workers, and a further increase in the rejection rate would impose a significant reduction in the value of SSDI, compared to a delay in Medicare eligibility.

My analysis is most closely related to that of Low and Pistaferri (2011). In their model, the key trade-off faced by workers is the loss of earnings and risk of rejection when applying for SSDI versus the prospect of a cash benefit if the application is accepted. My model incorporates this feature and adds another key tradeoff faced by potential SSDI applicants: because an SSDI applicant must leave employment to apply, employer-provided health insurance is sacrificed along with earnings. The benefit of applying for SSDI includes the possibility of Medicare coverage as well as the prospect of a cash benefit. This is a favorable trade for individuals who are severely disabled, since the disutility of work is very high for them. But, the prospect of Medicare coverage may attract low-productivity non-disabled or moderately disabled applicants as well, just as the prospect of the cash benefit is attractive to such workers.

My work is also related to reduced-form studies on the work disincentive effects of SSDI. This literature estimates the treatment effect of SSDI on employment (Parsons, 1980; Bound, 1989; Autor and Duggan, 2003; Chen and van der Klaauw, 2008; von Watcher et al. 2011; Maestas et al.,2012; French and Song, 2012). Because of their reduced-form nature, these studies cannot separately identify the employment effects of the cash benefit and Medicare benefit features of SSDI. Moreover, the reduced-form approach of these studies limits their ability to address the effects of policy reforms, which is my focus. Finally, my research is related to the effect of health insurance on labor supply. Among much research in this literature, my work is closely related to that of Blau and Gilleskie (2006, 2008) and French and Jones (2011). These studies model the labor supply and Social Security retirement benefit claiming decisions of older workers and study the effect of health insurance (e.g., employer-provided health insurance, retiree health insurance, changing Medicare eligibility age) on the retirement decision. However, they do not focus on health insurance benefits in the context of SSDI.

The remainder of the paper is structured as follows. Section 2 presents the life-cycle model. The data used to estimate the model are described in Section 3. Section 4 discusses the identification strategy and the estimation results. In section 5, I discuss the labor supply and welfare effects of early access to Medicare through SSDI enrollment. In Section 6, I analyze a version of the model without health insurance and medical expenditure and perform a sensitivity analysis. Section 7 concludes.

2. Model

A. Individual Problem

I specify a model where individuals choose how much to consume, whether to participate in the labor force, and whether to apply for SSDI each period so as to maximize the expected present discounted value (EPDV) of remaining lifetime utility. These decisions require evaluating the benefits and costs of leaving employment to apply for SSDI. The focus of my research is to investigate the effects of access to Medicare through SSDI, so the model features health insurance available through SSDI enrollment or employment, as well as the distribution of out-of-pocket medical expenditure that individuals face. The model also incorporates other public programs, because they can reduce the opportunity cost of applying for SSDI by providing temporary income or health insurance coverage during the application period. The model is in discrete time and the length of a period is six months.[5]

Individual *i*'s decision problem at time *t* takes the following form:

$$(1) \qquad \underset{c_{it}, P_{it}, DI_{it}^{App}}{Max} \; U(c_{it}, P_{it}; L_{it}) + E_t\left[\sum_{s=t+1}^{T+1} \beta^{s-t} \psi(s,t;L_{is-1}) U(c_{is}, P_{is}; L_{is})\right]$$

where c_{it} is consumption expenditure net of out-of-pocket medical expenditure, P_{it} is a binary variable equal to one if employed, DI_{it}^{App} is a binary indicator equal to one if applying for SSDI, *L* is a categorical indicator of disability status, β is the time discount rate, and $\psi(s,t,L_{is})$ is the probability of being alive in period *s* conditional on disability status in period *s*-1. L_{it} =0 if the agent does not have any disability, L_{it} =1 if he has a moderate disability, and L_{it} =2 if he has a severe disability.[6]

Individuals enter the labor force at age 23. If a worker was employed in *t*-1, employment is a choice variable in period *t* as long as his job is not destroyed at the beginning of period *t*. The job is destroyed (i.e., he is laid off) with probability ϕ_1 each period. If a person was not employed in period *t*-1 or is laid off at the beginning of period *t*, he receives a job offer with probability ϕ_2.

[5] Low and Pistaferri (2011) use a quarter while Benitez-Silva et al. (2011) and Bound et al. (2010) use a year as the unit of time. I choose a 6-month period as the time unit because there is a 5-month waiting period for the SSDI application at the onset of disability and I can reduce computational burden compared to a quarterly time unit. My notation is mainly the same as in Low and Pistaferri (2011) to facilitate comparison.

[6] Disability status follows an exogenous first-order Markov process that depends only on a quadratic in age.

If he does not receive a job offer, employment is not an option in period t. An individual can apply for SSDI in period t only if he was not employed in t-1, chooses not to work in period t, and meets a work history requirement.[7] The non-employment requirement when applying for SSDI implies that the labor market frictions influence SSDI application behavior because a lack of employment opportunities would provide an incentive to apply for SSDI (Black, Daniel, and Sanders, 2002). In the model, working is not an option if the individual is enrolled in SSDI.[8] Individuals must retire by age T^{R} , which I assume to be age 65. I impose this assumption because Medicare is available to everyone at age 65, and workers are eligible to apply for SSDI until the full retirement age (FRA).[9] The date of death is uncertain, and the last age to which an individual can survive is T. T is assumed to be age 90. It is important to model uncertainty in the date of death because mortality risk is quite high for the severely disabled. There is no bequest motive. Shocks are realized at the beginning of each period before the period's choices are made.

The period budget constraint before retirement is:[10]

$$(2) \qquad A_{it+1} = R\begin{bmatrix} A_{it} + w_{it}hP_{it} + (DI_{it}E_{it}^{DI} + SSI_{it} + UI_{it})(1-P_{it}) \\ +SN_{it} - c_{it} - M_{it} - \tau_{it} + sp_{it} \end{bmatrix}, A_{it+1} \geq 0$$

where A_{it} is assets, R is the gross interest rate, w_{it} is the hourly wage, h is hours of work if employed (set at 1000 hours per six month period), E_{it}^{DI} is an indicator variable for receiving a cash benefit from SSDI, and DI_{it} is the monetary value of the SSDI cash benefit, determined as a function of past earnings history. There is a liquidity constraint, $A_{it} \geq 0 \ \forall t$, which prevents workers from borrowing against uncertain future income. The model incorporates two income-tested welfare programs: (i) Supplemental Nutritional Assistance Program (SNAP, formerly known as Food Stamps) and (ii) Supplemental Security Income (SSI), a welfare program for the elderly and the disabled. SSI_{it} is the SSI benefit, and SN_{it} is the SNAP benefit (treated as

[7] In general, eligibility requires having worked at least 5 of the last 10 years before the onset of disability.
[8] In reality, SSDI beneficiaries can earn up to $1010 per month, but most SSDI beneficiaries do not work.
[9] The FRA was 65 for people born before 1938. The FRA gradually increases for those born in 1938 and after, until it reaches 67 for people born after 1959.
[10] The specification of the budget constraint follows Low and Pistaferri (2011) with the addition of out-of-pocket medical expenditure, the minimum consumption floor, and spousal income.

equivalent to cash). UI_{it} is unemployment insurance (UI) benefit payments.[11] As stated above, it is important to incorporate UI and SNAP because they can bridge the income gap between the onset of disability and the receipt of SSDI benefits (Rutledge, 2011; Low and Pistaferri, 2011). In effect, the UI and SNAP benefits reduce the cost of being out of labor force while applying for SSDI. M_{it} is out-of-pocket medical care expenditure. It is a random variable drawn from a distribution that is conditional on the type of health insurance, age, and disability status. The choice of health insurance type and the out-of-pocket medical expenditure process are described in detail below.

It is possible that cash on hand (after-tax income plus assets net of medical expenditure) can become negative due to a large medical expenditure shock. In this case, the individual is eligible for Medicaid (public health insurance for the poor). Rather than modeling Medicaid directly, which is difficult given the complexity of the program, I assume that there is a consumption floor, $\bar{C} > 0$. If the agent's cash on hand for a given employment and SSDI application decision is below the consumption floor, the government provides cash to make up the difference. $\bar{C}$ is set at the maximum level of the SNAP benefit payments. I explain the details of how enrollment and benefits for means-tested programs are determined in Section A of the Appendix. The variable sp_{it} is income from the spouse. I treat income contributed to the household by the wife as determined by an exogenous stochastic process.[12] The variable τ_{it} is the sum of income and payroll taxes, the details of which are described in Section B of the Appendix.

B. SSDI screening process

[11] The benefit level is set at 80% of the previous earnings. Laid-off workers are assumed to be eligible for UI for one period following the layoff.

[12] The wife may provide health insurance to her husband if she chooses to work. Thus, I may overestimate the value of access to Medicare coverage through SSDI for married household heads. However, the wife's labor supply response following the husband's disability onset (so called *the added worker effect*) observed in recent studies using U.S data is negligible (Gallipoli and Turner, 2012). Thus, I conjecture that the size of overestimation would be small. Also, Blau and Gilleskie (2006) estimate a model of married couples in which they make decisions jointly, but the effects of health insurance on labor supply were similar when they estimate a similar model without modeling the spouse's decisions (Blau and Gilleskie, 2008).

In the model, SSDI applications made in period t are approved or disapproved at the end of the period. If approved, the applicant begins to receive the benefit in period t+1. If the application is denied, the applicant can work in period t+1 if he receives a job offer at the beginning of t+1. The criteria for approval of an application by the SSA are known in general, but from the applicant's perspective approval is uncertain because true disability status is not perfectly observable to SSA examiners.[13] In the model, I approximate the screening process using a simple approach. I characterize the acceptance probability as a linear function of age with parameters that depend on disability status:[14]

$$(3)\ \Pr\left(E_{it}^{DI}=1\,|\,DI_{it}^{App}=1, L_{it}, t\right)=\pi_0^L+\pi_0^L\times t,\ L=0,\ 1,\ 2$$

Once enrolled in SSDI, the beneficiary is reassessed at random intervals, reflecting the so called Continuing Disability Review (CDR). The probability of reassessment is given by P^{CDR}, a constant, in the model. The probability that a beneficiary will remain eligible for SSDI benefits conditional on reassessment is also determined by equation (3). The parameters of equation (3), together with P^{CDR}, determine the efficiency of the SSDI program in enrolling its intended recipients while screening out the less-severely disabled. The details of eligibility rules for SSDI application and the benefit formula are described in Section C of the Appendix.[15]

C. Out-of-pocket Medical Expenditure

I assume that out-of-pocket medical expenditure depends on health insurance type, disability status, age, and the previous period's medical expenditure shock. I allow two types of health insurance: employer-provided health insurance and Medicare. An individual is assumed to

[13] The criterion for SSDI eligibility is "*inability to engage in any substantial gainful activity by reason of any medically determinable physical or mental impairment, which can be expected to result in death, or which has lasted, or can be expected to last, for a continuous period of at least 12 months* (SSA, 2012)."
[14] Chen and van der Klauuw (2008) provide indirect evidence that the acceptance probabilities can be well represented by a linear function of age (Figure 2, p.771).
[15] I do not model the appeal process because of the difficulty of identifying the impact of the various appeals mechanisms without access to administrative data. This is not a serious limitation in terms of studying the life-cycle behavior to the extent that a rejected applicant can apply again following the reject of the application in the model, although reapplication and appeal are not exactly the same.

have employer-provided health insurance if he works.[16] If he has received an SSDI cash benefit for more than two years (four periods in the model), he receives health insurance from Medicare. Otherwise, he does not have any health insurance coverage until he retires at age 65 and enrolls in Medicare. I do not allow individuals to gain coverage by buying coverage from a private insurance plan.[17] These assumptions about health insurance, combined with the assumption of exogenous disability status, imply that out-of-pocket medical expenditure is exogenous, conditional on employment and SSDI status.[18] I allow both the mean and variance of out-of-pocket medical expenditure to depend on health insurance type, disability status, and age. Following French and Jones (2011), I specify the out-of-pocket medical expenditure equation as follows:

$$\ln M_{it} = m(t, HI_{it}, L_{it}) + \sigma(HI_{it}, L_{it}, t) \times \zeta^{m}_{it} \qquad (4)$$

where HI_{it} is a categorical indicator of the health insurance plan type that individual *i* holds in period *t* (*HI*=none, employer-provided, Medicare), $m(.)$ is a deterministic component, and $\sigma(HI_{it}, L_{it}, t)$ is the standard deviation of out-of-pocket medical expenditure.[19] ζ^{m}_{it} follows a stationary AR(1) process: $\zeta^{m}_{it} = f^{m}_{i} + \upsilon^{m}_{it} + \omega^{m}_{it}$, $\upsilon^{m}_{it} = \rho_m \upsilon^{m}_{i,t-1} + \varepsilon^{m}_{it}$, $\varepsilon^{m}_{it} \sim N(0, \sigma^2_{\varepsilon,m})$, $\omega^{m}_{it} \sim N(0, \sigma^2_{\omega,m})$, $f^{m}_{i} \sim N(0, \sigma^2_{f,m})$, $|\rho_m| < 1$

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[16] I impose this assumption to avoid modeling the choice of jobs with different health insurance coverage. This assumption is reasonable because about 80% of the (full-time) employed individuals in my sample have employer-provided health insurance coverage. My model would underestimate the value of Medicare benefits in SSDI for workers without employer-provided health insurance coverage.

[17] I do not think that this is a very restrictive assumption because the lion's share of health insurance is determined by employment and SSDI receipt or means-tested welfare programs. Only 5% of individuals in my sample directly purchased private health insurance. Compared to a model in which individuals have the option to buy private health insurance, my model will overestimate the value of SSDI because those who would buy private health insurance, if it were available, are more likely to apply for SSDI in the model.

[18] This assumption is common in the literature, but it could result in misleading inferences to the extent that "individuals are willing and able to substitute between medical care and other consumption" (Blau and Gilleskie, 2008, p. 477). However, most estimates of the price elasticity of demand for medical care are small, generally about -0.2 (Liu and Chollet, 2006). The estimates of income elasticity of demand for medical care found in the literature are also inelastic, generally less than 0.2 (Ringel et al. 2002). Blau and Gilleskie (2008) estimate a model of retirement in which medical expenditure is a choice variable, and they found that the results are quite similar to the results of their previous paper (Blau and Gilleskie, 2006) in which medical expenditure is exogenously given.

[19] I standardize the variance of ζ^{m}_{it} to be one, so the group-specific variance of out-of-pocket medical expenditure is determined by $\sigma(HI_{it}, L_{it}, t)$.

where f_i^m is the time-invariant person-specific component, υ_{it}^m is the persistent component, ρ_m is the degree of persistence, ω_{it}^m is an innovation to the persistent component, and ε_{it}^m is the transitory component of the medical expenditure shock. I choose this specification because it is parsimonious and particularly useful when the sample is classified into several groups (age, types of health insurance, and disability status). Furthermore, the sum of a white noise process and an AR(1) process has been shown to capture the key features of the log of medical care costs (French and Jones, 2004). Identification of the variances and the AR(1) parameter is discussed in Section D of the Appendix.

D. Earnings

I assume that the log hourly wage offer in period *t* for individual *i* is:

(5) $$\ln w_{it} = \alpha_1 I(L_{it}=1) + \alpha_2 I(L_{it}=2) + X_{it}^{'}\alpha_X + \varepsilon_{it}^w + \omega_{it}^w$$

where X is a vector of observables including age, age squared, and marital status, and ε_{it}^w is a persistent productivity shock, assumed to follow a random walk process with innovation g: $\varepsilon_{it}^w = \varepsilon_{it-1}^w + g_{it}$, $g_{it} \sim N(0,\sigma_g^2)$. ω_{it}^w is a transitory productivity shock: $\omega_{it}^w \sim N(0,\sigma_{\omega,W}^2)$. These productivity shocks are independent of disability shocks. For example, a productivity shock might be caused by changes in technology or trade policies. A worker who receives a negative permanent productivity shock has a low opportunity cost of applying for SSDI even if he is not disabled. Details of the specification and identification of the wage (and spouse income) processes are in Section E of the Appendix.

E. Preferences

Utility in period *t* depends on consumption, labor supply and disability status:

(6) $$u(c_{it}, P_{it}; L_{it}) = \frac{(c_{it}\exp(\sum_{j=1}^{2}\theta_j I(L_{it}=j) + \eta P_{it}))^{1-\gamma}}{1-\gamma} + P_{it}(\sum_{j=0}^{2}\kappa_j I(L_{it}=j))$$

The functional form is non-separable between consumption and labor market participation with coefficient of relative risk aversion γ. η captures the effect of labor market participation on the utility from consumption. θ_1 and θ_2 capture the effects of moderate and severe disability on the utility of consumption respectively. κ_0, κ_1, and κ_2 are the additive part of the utility cost of labor market participation for the non-disabled, moderately disabled, and severely disabled respectively. I allow a flexible specification of preferences where marginal utility of consumption and the utility cost of work depend on the degree of disability, so the incentive to participate in the labor force or to apply for SSDI is also related to the changes in preferences due to disability.

G. Model Solution

The model is solved numerically by backward recursion starting from period T. Between ages T^R and T, the only choice variable is consumption. Prior to T^R, the individual chooses employment and SSDI application each period in addition to consumption. To solve the model, I use an approximation method developed by Keane and Wolpin (1994). The details of the model solution are described in Section F of the Appendix.

3. Data

A. PSID

I use the 1986-2009 waves of the Panel Study of Income Dynamics (PSID) to conduct my empirical analysis. The PSID began in 1968 with about 5,000 households and has tracked these families and their split-offs until now.[20] The PSID has several advantages over other longitudinal data sets for this study: (1) It includes individuals aged 50 and under, a growing part of the SSDI rolls. (2) Recent survey years of the PSID (since 1999) include a thorough set of consumption expenditure items, which I use to estimate the model. (3) The PSID has very rich information on disability status, labor market activities, and receipt of social insurance and welfare over long periods of time.

[20] A split-off family is a person or a group of persons who moved out of the original household due to marriage, working in another place, etc.

Following Low and Pistaferri (2011), I use a sample of low-educated male heads of household aged between 23 and 62 to estimate this model. However, I include individuals over age 62 to estimate survival risk, disability transitions, and out-of-pocket medical expenditure. Low education is defined as a highest completed grade of 12 or below. The schooling limitation is reasonable because SSDI receipt is much more common for low-educated workers due to their relatively high incidence of disability, the high risk of a negative permanent productivity shock, and the higher probability of acceptance of a SSDI application, relative to college attendees and graduates. I exclude the Latino sub-sample, the self-employed, and those with missing information on key variables such as education, disability status, and state of residence.[21]

Disability status and SSDI receipt

I create a three-state categorical measure of disability status using the following questions in the PSID: (1) “Do you have any physical or nervous condition that limits the type of work or the amount of work that you do?” (2) “Does this condition keep you from doing some type of work?” (3) “For work you can do, how much does it limit the amount of work you can do?”[22] A person is assigned to the severe disability category if he answers “[can] not [work] at all” to the third question or “can do nothing” to the second question. He is assigned to the moderate disability category if he answers “yes” to the first question and “somewhat” or “just a little” to the third question. Otherwise, he is treated as non-disabled. A common criticism of self-reported disability status is that individuals may exaggerate their disability status to justify their SSDI enrollment or non-participation in the labor force. However, Benitez-Silva et al. (2004) present evidence that self-reported disability status is an unbiased estimate of the implicit disability status inferred by the SSA during the SSDI review process. Meyer and Mok (2009) and Low and Pistaferri (2011) show that the measure of disability I use here is correlated with objective measures of health status (e.g., days of hospital stay).

[21] In the PSID, 2000 Latino households were added in 1990 but they were dropped after 1995, and they were not asked about Social Security income type.

[22] The first question is asked to all respondents. The second question is asked to those who answer “yes” to the first one and the answers can be “yes”, “no,” “can do nothing.” The third question is asked to those who answer “yes” or “no” to the second question and the answers can be “a lot”, “somewhat”, “just a little”, or “[can] not [work] at all.”

Enrollment in SSDI is identified by two questions in the PSID. First, individuals are asked about the amount of Social Security payments. Then, they are asked whether the Social Security payment is due to disability, retirement, survivor's benefits, or other reasons (e.g., dependent). Using this information, I can identify whether the household head is receiving SSDI benefits. Unfortunately, the PSID does not ask about SSDI application.[23]

Out-of-pocket medical care expenditure

The PSID has asked several questions about health insurance and health care costs since 1999. The items that I use to estimate equation (4) are (a) whether a respondent is covered by any health insurance plan, (b) type of health insurance plan, (c) amount of health insurance premium paid, and (d) out-of-pocket expenditure for nursing home, hospital bills, doctor visits, outpatient surgery, dental bills, prescriptions, and in-home medical care. The PSID asks about household-level medical expenditure (including children and other residents in addition to the wife), not person-specific. Therefore, I focus on household medical expenditure risk. Also, the reference period of the medical care expenditure items in PSID is two years, while the unit of time is a six-month period in the model. I estimate the six-month variance and persistence of out-of-pocket medical expenditure from the variance of the two-year sum of out-of-pocket medical expenditure using the variance correction method described in Section G of the Appendix.

Consumption expenditure

Consumption expenditure data are taken from the 2005, 2007, and 2009 survey waves. The expenditure categories include food, health care, housing, transportation, education, child care, home repairs and maintenance, household furnishing and equipment, clothing and apparel, trips and vacations, recreation and entertainment, and telecommunication. Li et al. (2010) find that PSID total consumption expenditure is about 1% higher than the Consumption Expenditure Survey (CEX) total consumption expenditure for comparable categories. Consumption expenditure that I use in the paper includes non-durable goods and service. I do not include

[23] The approach to identify SSDI policy parameters in the absence of SSDI application information is described below.

durables because they can function like assets and it is difficult to measure the flow of consumption services in the durables.

B. Sample statistics

Table 1 reports summary statistics of the sample. 9.4% of sample individuals report severe disability, and 10.6% report moderate disability. In general, individuals with severe disability are older, less likely to work, work fewer hours, earn less if they work, and are much more likely to be enrolled in SSDI than individuals with no disability. [24] There is a big difference between the moderately disabled and the severely disabled. Individuals with moderate disability are about 3.3 times more likely to work and 4 times less likely to be on SSDI than those with severe disability.

4. Estimation results

I describe three groups of parameters, according to how they are estimated.

1. The first group of parameters is estimated non-structurally (first-stage estimation). They include parameters of (i) the mortality hazard function, (ii) the disability transition probabilities, (iii) the log out-of-pocket medical expenditure equation, (iv) the log wage offer equation, and (v) the log spouse income equation. These parameters are not jointly estimated with the preference and policy parameters, nor jointly across the above five sets of parameters. The assumption that justifies this approach is that these processes are exogenously given. An important implication of imposing this assumption is that I do not allow individuals to differ in some permanent features that are unobserved to a researcher. For example, I rule out an endogenous disability transition process, i.e., a risk-loving person who chooses to work in a dangerous plant would have a higher probability of becoming severely disabled. This is a potentially important limitation imposed for computational feasibility, which I further discuss in

[24] As stated above, I use different survey waves (but the same sample selection rule) for the log consumption regression and the log out-of-pocket medical expenditure regression due to data availability. The implicit assumption that I make here is that the relationship among key variables is stable over time.

the conclusion.[25] The estimates of the first group of parameters are taken as given in the second stage Indirect Inference estimation.

2. The second group of parameters is set to arbitrary values commonly used in the literature. They include (i) the CRRA parameter (γ), (ii) the time discount rate (β), (iii) the job offer rate (ϕ_1), (iv) the gross interest rate (R), (v) the maximum benefit level of SNAP $(\bar{T}_{SN})$ and SSI $(\bar{T}_{SSI})$, (vi) the income replacement rate for UI, and (vii) the standard deduction for calculating net income (d) and the income threshold $(\underline{y})$ for means-tested welfare programs. (i)-(iii) are not key parameters of interest, and it is computationally costly to estimate them structurally. (iv)-(vii) are observable so I set these parameters to representative observed values. The second group of parameters is summarized in Table 2.

3. The third group of parameters is structurally estimated by Indirect Inference as described below. This group includes (i) utility function parameters, (ii) acceptance probabilities of SSDI application, (iii) the re-assessment probability of SSDI status, and (iv) the layoff probability.

A. Profiles for exogenous state variables and first stage estimates

In this subsection, I briefly summarize the profiles for exogenous state variables and the first-stage estimation results. (i) Figure 1 plots predicted disability transition rates. It shows that the probability of becoming disabled is increasing with age and that disability is highly persistent. (ii) Table 3 shows that both the mean and variance of medical expenditure rise with age regardless of health insurance type, and those in the no health insurance group have the

[25] There could be various possible biases induced by unobserved heterogeneity, but I think that the most plausible case is an upward bias in the effect of access to Medicare via SSDI on labor supply and welfare. If risk aversion varies in the population conditional on disability status, then individuals who are risk-loving are more likely to become disabled and to incur high medical expenditures as a result of disabilities so they value the Medicare provision via SSDI. Thus, they are *ex ante* more likely not to work in order to apply for SSDI. If a person is risk-averse, then he would expect to be less likely to be disabled so he would not value the Medicare provision through SSDI much and he will continue to be employed. Thus, some of the association between access to Medicare via SSDI and labor supply and welfare would be driven by the difference in risk aversion. In this case, my model overestimates the effect of access to Medicare via SSDI. However, French and Jones (2011) find a similar effect of health insurance on labor supply, regardless of whether they estimate the same model with preference heterogeneity or not.

highest average medical expenses and standard deviation at any given age. Table 4 reports the variances of permanent, persistent, and transitory components of the log medical expenditure shock. These variances imply that the majority of the innovation (73%) comes from the non-transitory component, as French and Jones (2011) also found.[26] (iii) Table 5 reports estimates of the log wage offer equation. In order to account for selection into work, I use Heckman's two-step estimation method, with UI generosity and household income transfer as exclusion restrictions following Low and Pistaferri (2011). Severe disability reduces the offered wage by 32 percentage points while moderate disability reduces it by 16 percentage points. Table 6 reports the estimated variances of the permanent and transitory productivity shocks. The estimates are similar to those reported in other papers using the PSID data (Meghir and Pistaferri, 2004; Low et al., 2010). The other details on the first-stage estimation results are in Section H of the Appendix.[27]

B. Parameters estimated by Indirect Inference

I use the method of Indirect Inference to estimate the utility function, lay off probability, and SSDI policy parameters. Indirect Inference is useful when the likelihood function does not have an analytical form, because it does not require evaluation of the likelihood function. This is the case for my model, in which I have both continuous and discrete choice variables. Another useful property of Indirect Inference is that it does not require a researcher to observe choice variables as long as he can observe other variables that are closely governed by the choice variables. The PSID does not have data on the SSDI application choice, but it has information on SSDI enrollment status. Since SSDI status is primarily determined by previous SSDI application choice, I can use information on SSDI status to *indirectly infer* parameters that determine the SSDI application decision. Details of Indirect Inference estimation are described in Section I of the Appendix.[28]

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[26] The other parameter estimates of the log out-of-pocket medical expenditure process are reported in Section H of the Appendix.
[27] The predicted conditional probability of death by disability status and age, and the distribution of disability status by age are shown in the Figures A1-2 of the Appendix (page 61).
[28] I choose the estimation method and the set of auxiliary moments following Low and Pistaferri (2011). However, I allow more flexible specifications in preferences and SSDI policy parameters.

B.1. Auxiliary Moments

I use four sets of auxiliary moments to estimate the parameters of interest. (1) The SSDI enrollment rate by disability status and age group; (2) The composition of SSDI beneficiaries by disability status and age group; (3) The employment rate by disability status and age group; (4) The coefficient estimates from the log consumption regression. The SSDI enrollment rate and the composition of SSDI beneficiaries are used to identify SSDI policy parameters because these moments are determined by the acceptance probability (conditional on SSDI application) and the SSDI reassessment probability. The employment rate is related to utility costs of working and the layoff probability. Finally, the coefficient estimates from the log consumption regression are used to identify other preference parameters. I discuss the rationale for the identification of the structural parameters in Section J of the Appendix in more detail.

B.2. Indirect Inference parameter estimates

Parameter estimates from the Indirect Inference estimation are reported in Table 7. Working induces a 31% loss of utility measured in terms of consumption. A moderate disability induces a 9.6% loss of utility while a severe disability induces 38.6% loss of utility. I estimate that the layoff probability is 9.8% per six-month period. The estimated layoff probability seems higher than conventional estimates but the sample is low-educated workers, whose layoff probability tends to be relatively high. The signs and magnitudes of the estimated additive utility cost of working conditional on disability status are as expected: 1) all signs are negative, and 2) severe disability is associated with the highest utility cost of working (-0.79) while no disability is associated with the lowest utility cost of working (-0.025).

The SSDI application acceptance probability increases with age and the severity of disability. For those with no disability, I estimate that the acceptance probability is almost zero, i.e., the SSDI program successfully screenins out applicants who are capable of work. The acceptance probability for moderately disabled workers is virtually constant at 27% at age 23. I estimate that the acceptance probability for the severely disabled is 47% at age 23 and rises by 0.5 percentage points each six-month period, reaching 87% at age 62. The probability of reassessment per six-month period is estimated at 17.3%. This value suggests that a review of SSDI status will be performed about every three years on average.[29]

C. Model Fit

Table 8 shows the moments matched by Indirect Inference. Each of the four panels corresponds to one set of auxiliary moments. In most cases, the model closely replicates the patterns of the observed data moments. The main exception is that the coefficient on the receipt of SSDI (for the non-disabled) in the log consumption equation is much larger in absolute value in the model (-.30) than in the data (-.03).[30] A detailed discussion of the model fit is in Section J of the Appendix.

5. Counterfactual Policy Analysis

In this section, I use the estimated model to perform counterfactual policy simulations to study the effects of access to Medicare through SSDI on behavior and welfare, and the welfare implications of alternative approaches to eliminating the financial imbalance of SSDI.[31] I evaluate the implications for welfare and behavior holding the government budget constant across the counterfactual policy simulations through the adjustment of a universal lump sum tax or transfer.[32] I measure welfare effects by willingness to pay (WTP) computed as the proportion of lifetime consumption an individual would be willing to give up in order to avoid a harmful policy change. The formula to compute WTP is described in Section K of the Appendix. In a future draft, standard error estimates for the simulations will be reported, using repeated draws from the joint distribution of the Indirect Inference parameter estimates to generate a distribution of simulation results.

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[29] The frequency of the review seems a little high at first glance. However, given that most reassessments are conducted approximately every 3 years, the estimated reassessment probability is reasonable.
[30] This could stem from the failure of the model to account for sources of consumption support other than SSDI and welfare programs, such as part-time work, and income transfer from parents/siblings/relatives.
[31] The model is simulated for 50,000 hypothetical agents whose distribution of initial state variables is matched to the distribution of the same state variables of individuals at age 23 observed in the PSID.
[32] If a policy change results in a decrease (increase) in government net spending, *every* household receives (pays) a cash transfer of the size required to hold the government budget constant. Low and Pistaferri (2011) imposed government budget neutrality through payroll tax rate adjustment, but my approach is different because Medicaid and other means-tested welfare programs are not funded by the payroll tax. In Low and Pistaferri (2011), the payroll tax income is the sole source of the government expenditure for social insurance and welfare programs.

A. Value of Access to Medicare via SSDI

To isolate the effects of health insurance through Medicare, I simulate a counterfactual regime in which SSDI recipients are not eligible for Medicare, and compare the results with simulations of the baseline model (i.e. the actual policy regime). Note that this is an extreme case; in reality SSDI recipients might seek other sources of health insurance rather than going uninsured as assumed in the counterfactual simulation. Also, note that *Medicaid* remains available in this scenario, in an implicit form via the consumption floor.

In Table 9, I find that eliminating access to Medicare via SSDI reduces *ex ante* welfare, that is, expected lifetime utility of an individual at age 23 who does not know whether or when he will become disabled. Individuals are willing to pay up to 0.5% of their lifetime consumption to maintain Medicare coverage through SSDI enrollment (the first row of the second column). The reported welfare effect of Medicare eligibility through SSDI seems small at first. But, the share of the population on SSDI affected by this policy change is also small (about 5%). The magnitude of the welfare effect of Medicare coverage is higher when a higher level of risk aversion is assumed (recall that the CRRA is set to 1.5), but the fit of the model becomes considerably worse with a higher degree of risk aversion. Also, as noted above, after exhausting most of their cash on hand, individuals are eligible for Medicaid. Another way to rationalize the modest magnitude of the welfare effect is to look at the cost of financing Medicare benefits for SSDI recipients. Workers pay 1.45% of their earnings to fund Medicare, and about one fifth of Medicare spending goes to SSDI beneficiaries. This implies that the SSDI share of the Medicare payroll tax rate is about 0.3% of earnings. Thus, WTP for access to Medicare via SSDI enrollment of 0.5% of lifetime consumption seems reasonable.

As with any type of health insurance, the value of Medicare benefits provided through SSDI comes from two sources: 1) reduced average out-of-pocket medical expenditure and 2) reduced volatility of out-of-pocket medical expenditure. In order to evaluate the independent contribution of each source to the value of Medicare benefits, I re-compute WTP for Medicare benefits in SSDI after setting the variance of out-of-pocket medical expenditure to zero in both the baseline and counterfactual specification. I find that WTP for Medicare benefits in SSDI drops by about 40% when there is no volatility in the out-of-pocket medical expenditure process.

This finding implies that about 60% of the value of Medicare coverage in SSDI comes from reduced mean medical expenditure and the other 40% comes from reduced volatility (not shown in the table).

Column (3) of Table 9 shows behavioral responses to elimination of Medicare coverage from SSDI. When access to Medicare via SSDI enrollment is eliminated, SSDI application as an alternative to remaining employed becomes less attractive. Thus, the average SSDI application rate drops from 4.1% to 3.6% per period, and this decline in the SSDI application rate leads to an increase in the employment rate. The fraction of the population working increases from 87.0% to 87.7% (fourth row). What is more interesting is that the behavioral responses are more elastic for the moderately disabled than for the severely disabled. The employment rate for the severely disabled increases by 0.9 percentage points (from 20.6% to 21.5% per period) while the employment rate for the moderately disabled increases by 2.5 percentage points (from 73.7% to 76.2%). This is because the moderately disabled are closest to the margin of indifference between SSDI application and working. This is consistent with my finding that eliminating access to Medicare coverage causes the fraction of moderately disabled workers among newly accepted SSDI beneficiaries to decrease from 17.8% to 15.8% (last row).

In order to further understand how medical expenditure risk affects the value of Medicare, I conduct additional simulations in which 1) everybody is required to purchase health insurance, and 2) employer-provided health insurance is not available. I discuss the welfare implications of these policy experiments below. See section L of the Appendix for other results from these simulations.

The first setting is roughly similar to the environment that will exist when the Affordable Care Act (ACA) is fully implemented in 2014. In this experiment, an individual without health insurance is required to purchase a health insurance plan that provides the same coverage at the same cost as the employer-provided health insurance plan in the model (i.e., those without health insurance now face the same out-of-pocket medical expenditure distribution as those with employer-provided health insurance). In this scenario, SSDI enrollees during the two-year waiting period will have access to health insurance through the ACA and then they will be covered by Medicare after the waiting period. Thus, SSDI beneficiaries will always have access to health insurance even when Medicare coverage is not available, implying that the value of Medicare in SSDI should be smaller than in the baseline specification. Compared to the baseline case when individuals are willing to give up 0.5 percent of their lifetime consumption for the provision of Medicare coverage via SSDI, willingness to pay declines to about 0.4 percent. The welfare effect of Medicare is smaller but still positive because Medicare is much less costly than employer-provided health insurance in terms of out-of-pocket medical expenditure to individuals.

The next experiment eliminates employer-provided health insurance (but retains Medicare eligibility at age 65). This is an extreme case but it is useful to study the value of Medicare in SSDI when *uninsured* medical expenditure risk becomes larger. Willingness to pay increases to 0.73 percent of lifetime consumption. This is because access to health insurance prior to age 65 is only possible through enrollment in SSDI. Since Medicare through SSDI is the only source of health insurance prior to age 65, the behavioral effects of Medicare coverage in SSDI are larger compared to the baseline specification or the alternative specification with mandatory health insurance purchase.

B. Policy reforms aimed at restoring financial stability of the SSDI program

According to the 2012 Social Security Trustees report, the SSDI trust fund will be exhausted by 2016. Once depleted, SSDI will use trust fund income (i.e., payroll taxes plus interest) that is supposed to go to Social Security Old-Age Survivor Insurance (OASI). Without any reforms to curb soaring SSDI spending, this would increase the financial problem of the Social Security program as a whole. Fortunately, SSDI is relatively easier to fix than OASI because OASI entry is largely determined by demography while SSDI entry is more sensitive to economic incentives. However, a previous SSDI reform in 1983 intended to slow down the growth of the SSDI rolls failed because the more stringent screening criteria and reassessment process it imposed caused public backlash, leading to repeal of the reform (Burkhauser and Daly, 2011).[33] This historical lesson implies that it is important to design and implement a reform that not only reduces the program spending but also minimizes the welfare cost.

Thus, I explore policy alternatives that equate SSDI spending to payroll tax income (i.e., no SSDI budget deficit), and compare the welfare costs of those policy alternatives.[34] Specifically, I consider varying the following SSDI policy parameters: 1) lowering the acceptance probability of an SSDI application, 2) increasing the payroll tax rate, 3) reducing the SSDI cash benefit, and 4) delaying access to Medicare (i.e., increasing the Medicare waiting period).[35]

Column (1) of Table 10 shows that the SSDI budget deficit can be eliminated through either 1) lowering the acceptance probability by 28%, 2) raising the payroll tax rate by 8.1%, 3) cutting the SSDI cash benefit by 23%, or 4) increasing the waiting period for Medicare benefits by 9 years (from 2 years to 11 years).

Lowering the SSDI acceptance probability is most successful at reducing the program population. It reduces the fraction of SSDI beneficiaries by 12% (from 5.2% to 4.1%). However, this is the most costly policy option in terms of *ex ante* welfare. The population as a whole is willing to pay 0.8% of lifetime consumption to avoid this policy, even accounting for the lower tax associated with a smaller program size. About 40% of those who are severely disabled are denied SSDI benefits under this policy, compared to about 20% in the baseline. Those who are denied SSDI benefits either have to work despite a high work disutility or receive the minimum consumption from the government if they do not work and are very poor.

Increasing the payroll tax rate that funds SSDI (and Medicare for SSDI beneficiaries) is an alternative way to restore fiscal stability of the program, but incurs a welfare cost almost as

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[33] In 1984, the Congress reversed the previous reform of the SSDI screening process and further liberalized acceptance of SSDI applications from those suffering from back/muscle pain and mental illness. Since these disabilities have relatively low mortality, the average duration of SSDI spells and the program population have increased.

[34] In the baseline model, SSDI spending is about 30% more than its income from the disability insurance share of Social Security payroll tax income. In reality, SSDI spending exceeded its income by a little less than one quarter in 2011 (SSA, 2012).

[35] There are other alternatives that can reduce the SSDI budget deficit, such as an increase in the re-assessment probability or an increase in the required period of non-employment before applying for SSDI (currently one period in the model). I will consider these alternatives in a future draft.

high as the previous policy intervention. Increasing the payroll tax raises deadweight loss in the labor market and so reduces *ex ante* welfare of society by 0.7% of lifetime consumption. Row 3 shows that as the net-of-tax wage rate goes down due to the increased payroll tax burden, slightly fewer people choose to work, and more people apply for SSDI.[36]

The most efficient solutions that eliminate the SSDI budget deficit are the policies that cut benefits. In the fourth row of Table 10, I find that a 23% cash benefit cut eliminates the SSDI budget deficit at a welfare cost of 0.19% of lifetime consumption. In contrast to reducing the acceptance probability, this policy does not prevent severely disabled workers from entering SSDI. Since the SSDI application decision of severely disabled workers is inelastic with respect to the level of the SSDI cash benefit (the elasticity is 0.13), reducing the benefit is less costly in terms of welfare compared to making SSDI entry more stringent. WTP to avoid a 23% cash benefit cut is only one quarter of the magnitude of WTP to avoid the above two policy alternatives.

Increasing the Medicare waiting period by 9 years (from 2 years to 11 years) is also a less costly approach to eliminating the SSDI deficit. WTP to avoid this policy is also small at 0.20% because this policy does not block severely disabled workers from entering SSDI and some SSDI beneficiaries who exhaust their savings will be eligible for Medicaid (through the minimum consumption floor in the model) during the extended waiting period. According to an SSA actuarial study, a disabled worker who is accepted to the SSDI program at age 50, which is the average age of new SSDI entrants in 2011, is expected to live an additional 17.6 years (Zayatz, 2011). Thus, a 9-year waiting period makes him expect to receive Medicare coverage for 6.6 years, equivalent to approximately a 60% decrease in the time eligible for Medicare coverage through SSDI.

Through the policy simulations in this subsection, I show that policies that achieve the same fiscal goal can have very different welfare implications. These results have direct relevance for the ongoing debate over how to reduce the cost of SSDI.

C. Value of Medicare to SSDI applicants

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[36] This additional payroll tax is only used to fund SSDI and Medicare for SSDI beneficiaries.

In this subsection, I explore how welfare and behavior of individuals at relatively high risk of applying for SSDI are affected by policy interventions. Given that the majority of workers never become severely disabled, it is important to understand behavior and welfare of workers who are at relatively high risk of applying for SSDI. To implement this, I treat simulated individuals who ever applied for SSDI in the baseline specification as individuals who are at high risk of applying for SSDI. If a person applying for SSDI at age 40 in the baseline specification chooses not to apply for SSDI at age 40 in a counterfactual policy simulation, I can attribute this change solely to the changed SSDI policy because there is no other change in the model.

Table 11 reports changes in welfare, employment rates, and the proportion of SSDI recipients in the "high-risk" group.[37] As expected, the welfare and behavioral responses to a policy change are larger for this group. The first row shows that the possibility of eligibility for Medicare via SSDI enrollment increases the EPDV of lifetime welfare by 1.7%. This welfare gain for individuals at high risk of applying for SSDI is about twice as large as the welfare gain for the total population (see the last row).

6. Alternative Specifications

A. No health insurance and medical expenditure process

I argued above that ignoring medical expenditure and health insurance would result in underestimating the value of SSDI. In this subsection, I eliminate medical expenditure and health insurance and re-estimate the model to study this issue. The results reported in Table 12 show that WTP for SSDI coverage drops from 1.1% to 0.7% of lifetime consumption when health insurance and medical expenditure are eliminated.[38] Columns (1) and (2) of the first and second rows reveal that fewer workers apply for SSDI and eventually enroll in SSDI in this scenario. This in turn leads to a modest increase in the fraction of individuals employed.

[37] In this exercise, I use expected present discount value (EPDV) of lifetime welfare in the first period (before any shocks are realized) instead of WTP because I analyze a subset of the total population.
[38] The parameter estimates behind these simulations are shown in Section M of the Appendix.

Since this version of the model is similar to that of Low and Pistaferri (2011), I implement an additional simulation to see whether I can reproduce their results. Specifically, I simulate the effects of a 10% increase in SSDI cash benefits, using the model estimated without incorporating health insurance and medical expenditure. Low and Pistaferri (2011) show that a 10% rise in SSDI cash payments worsens *ex ante* welfare of society as a whole by about 0.13% of their lifetime consumption (p.30). But, I find that the same 10% increase improves welfare by 0.05%. Although the sign is different, the quantitative difference is small. Also, my finding is consistent with Meyer and Mok (2008) who find that the current SSDI cash benefit is lower than the optimal level.

B. Robustness of results to changes in calibrated parameters

In this subsection, I report the results from a robustness analysis in which the model is re-estimated using alternative values of parameters that were not estimated. The results are summarized in Table 12. First, I consider changes in the degree of risk aversion, which determines the value of insurance. Column (4) of the third and fourth rows shows that the WTP for Medicare benefits in SSDI and behavior are quite sensitive to changes in the CRRA parameter γ. WTP changes from 0.1% of lifetime consumption to 1.6% when I increase the value of γ from 1 to 2. However, as noted above, the overall model fit becomes much worse when using these values. Second, I consider changes in the consumption floor. If the government provides more generous consumption support, a worker will value Medicare coverage in SSDI less. The results are consistent with this intuition, but the welfare effects are small in quantitative terms. WTP for Medicare coverage via SSDI drops by 0.04 percent when I raise the consumption floor from the baseline value of $3,000 to $4,000 per six-month period. Finally, I consider changes in the time discount rate. I find that WTP goes up by 0.3 percent when people become more patient (β=1.0), while WTP drops by 0.2 percent when they become more impatient (β=0.95).[39]

7. Concluding Remarks

[39] Lockwood (2012) also shows that the demand for insurance increases when people become more patient.

Using a life-cycle model of SSDI application, labor supply, and consumption decisions that incorporates the distribution of out-of-pocket medical expenditure and the institutional features of Medicare, I have highlighted the importance of Medicare in economic analysis of SSDI. I show that Medicare coverage via SSDI enrollment, which accounts for about one fifth of total Medicare spending, induces workers to leave the labor force to apply for SSDI. I also show that access to Medicare coverage via SSDI improves social welfare, accounting for close to half of the total welfare gain from cash and Medicare benefits through SSDI. Thus, ignoring the Medicare benefit available through SSDI leads to underestimation of the value of SSDI. The findings of this paper imply that policymakers should incorporate Medicare when considering how optimally to reform the SSDI program.

The approach used in this paper is also useful to understand how a change in the health insurance market, e.g., the Affordable Care Act (ACA), would affect the incentive to leave employment and to apply for SSDI. The mandatory health insurance purchase clause of the ACA makes health insurance coverage available independent of employment, and thus eliminates a disincentive to apply for SSDI benefits by those who fear the loss of health insurance coverage during the two-year Medicare waiting period after being accepted into the SSDI program. However, the finding of my study shows that the ACA reduces the value of health insurance benefits available through SSDI. This implies that the ACA may discourage SSDI applications by individuals who are most likely to be affected by the Act. [40]

There are limitations of my study that should be addressed in future research. First, I assume that individuals retire at age 65. By relaxing this assumption and additionally modeling the OASI claiming decision, future research should study the role of Medicare benefits provided through SSDI in the retirement decision. [41] Jointly modeling SSDI application and OASI claiming decisions is important for understanding the implications of future Medicare reforms

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[40] This is consistent with the finding of Coe et al. (2012). They show that states adopting policies that expand health care access are associated with lower SSDI application rates (after controlling for state- and year- fixed effects).

[41] In the current model, workers before age 65 cannot receive the OASI benefits. In reality, some of older workers apply for SSDI before age 65 as an alternative pathway to retirement and receiving full OASI benefits. Duggan et al. (2007) find that increasing the OASI benefit's full retirement age from 65 to 67 and increasing the penalty for claiming benefits at the early retirement age of 62 led to an additional 0.6% of men and 0.9% of women between the ages of 45 and 64 receiving SSDI benefits in 2005.

(such as changing Medicare eligibility from age 65 to 67 or increasing the Medicare payroll tax rate) for SSDI application and retirement decisions and welfare of both disabled and older workers. This is a key policy issue because Medicare is in serious financial trouble as well.[42] Second, I do not allow for unobserved permanent preference heterogeneity in the model. It is possible that individuals with different preference types for leisure or risk aversion may make different decisions (e.g., selection into applying for SSDI by an individual with a relatively high disutility of work, or a higher probability of becoming disabled by a risk-loving worker). To address potential biases due to unobserved heterogeneity, future work should incorporate an approach such as that of van der Klaauw and Wolpin (2008), which allows individuals to differ by a finite number of discrete preference types.

[42] A 2012 Medicare trustees report predicts that the Medicare trust fund will be exhausted by 2024.

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Figure 1 Fitted six-month disability transition rates (L=0 if no disability, L=2 if severe disability)

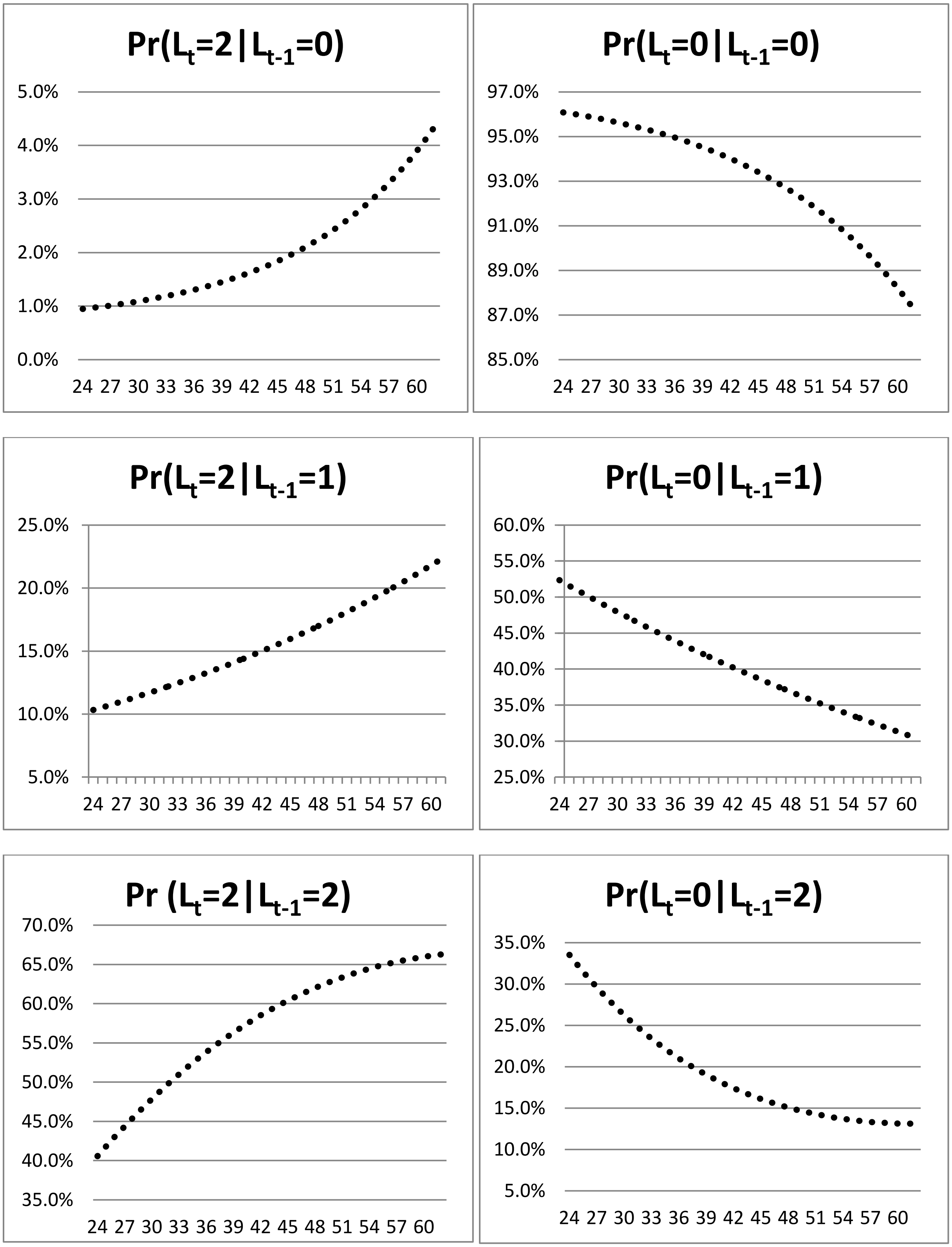

Table 1 Sample means by disability status

Variable	No disability	Moderate disability	Severe disability
Age	40.2	45.0	47.7
Married	0.72	0.75	0.62
Family size	2.96	3.04	2.54
Worked > 6 months last year	0.93	0.70	0.21
Hourly wage| hours> 0	19.4	18.7	16.6
Family income	59501	52879	33917
Hours of work| hours> 0	2074	1828	1372
Income from transfers	2272	6074	8685
SSDI recipient	0.006	0.10	0.45
Number of individuals	2757	260	211
Number of person-year observations	17270	1598	1275

Note: monetary values are in 2006$; all statistics are calculated with longitudinal weights.

Table 2 Calibrated parameters

Parameter	Estimate
Coefficient of Relative Risk Aversion (γ)	1.5
(annualized) Time discount rate (β)	0.97
Job offer probability per six-month period (ϕ_1)	0.75
(annualized) Gross interest rate (R)	1.03
Income replacement rate for UI benefit	0.8
Maximum SNAP monthly benefit ($\overline{T}_{SN}$)	\$500
Maximum SSI monthly benefit ($\overline{T}_{SSI}$)	\$600
Standard deduction in net income calculation for SNAP and SSI (d)	\$140
Monthly income threshold for the SNAP and SSI ($\underline{y}$)	\$1500

Note: $\overline{T}_{SN}, \overline{T}_{SSI}, d,$ and $\underline{y}$ are parameters used to calculate program benefit amounts. The benefit formula for each program is described in Section A of the Appendix.

Table 3 Two-year sum of out of pocket medical care expenditure by age and health insurance

Age group	Statistics	Employer-provided HI	Medicare	None
23-44	Mean (SD)	\$5086 (\$5880)	\$3010 (\$5395)	\$4150 (\$6629)
45-64	Mean (SD)	\$6174 (\$6623)	\$5129 (\$7164)	\$8398 (\$9815)
65 and above	Mean (SD)	\$6643 (\$8695)	\$6787 (\$8290)	\$10051 (\$13920)

Note: monetary values are in 2006$; SD denotes standard deviation.

Table 4 Variance and persistence of the residual component of (six-month) log medical expenditure

Parameter	Estimate	Standard Error
Variance of permanent person-specific component $(\sigma^2_{f,m})$	0.636	0. 022
Variance of persistent component $(\sigma^2_{\omega,m})$	0.647	0. 037
Variance of transitory component $(\sigma^2_{v,m})$	0.472	0. 049
Autocorrelation of persistent component (ρ_m)	0.557	0.047

Note: The share of the non-transitory component $\left(\frac{\sigma^2_{f,m}+\sigma^2_{\omega,m}}{\sigma^2_{f,m}+\sigma^2_{v,m}+\sigma^2_{\omega,m}}\right) = 0.731$

Table 5 Log wage offer regression results

	participation	log hourly wage without selection	log hourly wage with selection
Moderate	-0.220 (0.015)	-0.101 (0.019)	-0.158 (0.024)
Severe	-0.682 (0.018)	-0.104 (0.067)	-0.318 (0.090)
Mills Ratio			0.188 (0.048)
State-level UI generosity	-0.000258 (0.000198)		
Income transfer/100	-0.00420 (0.00197)		
N	19596	17227	17227

Note: other controls include age, age squared, whether married, and year dummies; standard errors are in parentheses.

Table 6 Variances of log wage offer

Parameter	Estimate
Permanent shock (σ_η^2)	0.020 (0.002)
Measurement error (σ_ω^2)	0.033 (0.001)

Note: standard errors are in parentheses.

Table 7 Parameters estimated by Indirect Inference

Parameter	Estimate
Non-separable utility cost of working (η)	-0.310 (0.0025)
Utility cost of moderate disability (θ_1)	-0.096 (0.088)
Utility cost of severe disability (θ_2)	-0.386 (0.015)
Layoff probability (ϕ_1)	0.098 (0.001)
Utility cost of labor force participation | L=0 (κ_0)	-0.025 (0.0014)
Utility cost of labor force participation | L=1 (κ_1)	-0.220 (0.0033)
Utility cost of labor force participation | L=2 (κ_2)	-0.791 (0.0048)
SSDI acceptance probability (per six month) | L=0	0.0007 +0.00003*t (0.0014) (0.00045)
SSDI acceptance probability | L=1	0.27 + 0.0001*t (0.0048) (0.0078)
SSDI acceptance probability | L=2	0.47 + 0.005*t (0.0054) (0.0017)
SSDI reassessment probability (P^{CDR})	0.173 (0.0036)

Note: standard errors are in parentheses. *L* is 0 if no disability, 1 if moderate disability, 2 if severe disability.

Table 8 Model Fit

A. Labor market participation by age group and disability status

Age group	No disability		Moderate disability		Severe disability	
	Observed	Predicted	Observed	Predicted	Observed	Predicted
23-32	0.95	0.95	0.81	0.89	0.49	0.50
33-42	0.96	0.96	0.80	0.85	0.30	0.30
43-52	0.96	0.96	0.78	0.79	0.25	0.25
53-62	0.85	0.82	0.58	0.53	0.14	0.13

B. Share of SSDI recipients by age and disability status (in %)

% of SSDI recipients	Observed	Predicted
$E_{it}^{DI}=1 \mid L_{it}=2, t<45$	33.7	33.9
$E_{it}^{DI}=1 \mid L_{it}=2, t\geq 45$	58.6	56.0
$E_{it}^{DI}=1 \mid L_{it}=1, t<45$	5.6	5.4
$E_{it}^{DI}=1 \mid L_{it}=1, t\geq 45$	14.2	14.2
$E_{it}^{DI}=1 \mid L_{it}=0, t<45$	0.29	0.25
$E_{it}^{DI}=1 \mid L_{it}=0, t\geq 45$	1.03	1.06

Note: t denotes age, L_{it} denotes work-limiting disability status (0 for no disability, 1 for moderate disability, and 2 for severe disability); E_{it}^{DI} is 1if enrolled in SSDI, 0 otherwise).

C. Composition of SSDI beneficiaries by age and disability status (in %)

% of disability status	Observed	Predicted
$L_{it}=2 \mid E_{it}^{DI}=1, t<45$	67.2	67.9
$L_{it}=2 \mid E_{it}^{DI}=1, t\geq 45$	71.9	70.0
$L_{it}=1 \mid E_{it}^{DI}=1, t<45$	19.6	19.8
$L_{it}=1 \mid E_{it}^{DI}=1, t\geq 45$	19.6	20.7
$L_{it}=0 \mid E_{it}^{DI}=1, t<45$	13.2	12.3
$L_{it}=0 \mid E_{it}^{DI}=1, t\geq 45$	8.4	9.3

D. Log consumption regression

Coefficient estimates	Observed	Predicted
Moderate disability	-0.04	-0.03
Moderate*On SSDI	0.09	0.09
Severe disability	-0.11	-0.04
Severe disability*On SSDI	0.19	0.14
On SSDI	-0.03	-0.30
Employed	0.12	0.11

Notes: controls include age, age square, and transfer income

Table 9 Effects of access to Medicare benefits provided through SSDI enrollment

	(1) Baseline (Medicare is available via SSDI)	(2) No Medicare via SSDI	(3) % difference
Willingness to pay	0.00%	-0.50%	n/a
$FR(DI^{App}=1)$	4.07%	3.57%	-13.0%
$FR(working)$	87.0%	87.7%	0.8%
FR(working | L=1)	73.7%	76.2%	3.3%
FR(working | L=2)	20.6%	21.5%	4.5%
FR(*DI*=1 | L=1)	12.2%	11.6%	-5.3%
FR(*DI*=1 | L=2)	53.7%	53.6%	-0.2%
$FR(L=1 \| DI^{App}=1, DI=1)$	17.8%	15.8%	-11.9%

Note: In all specifications, Medicare coverage for individuals over age 65 is available. FR(A|B) denotes the fraction of the population satisfying A conditional on B. L is 1 if moderate disability, and 2 if severe disability. % Difference is calculated at the mid-point.

Table 10 Policy alternatives that equate SSDI spending to payroll tax income

	(1) Changes in policy parameter	(2) Willingness to pay	(3) $FR(DI=1)$	(4) $FR(DI^{App}=1)$	(5) $FR(working)$
Baseline	n/a	n/a	5.24%	3.57%	87.0%
Lowering acceptance probability	27.80%↓	-0.82%	4.12%	3.33%	88.7%
Increasing payroll tax	8.1% ↑ (from 7.65% to 8.27%)	-0.70%	5.29%	3.61%	86.9%
Reducing SSDI cash benefit	22.80% ↓	-0.19%	5.14%	3.47%	87.4%
Increasing Medicare waiting period	9 years ↑ (from 2 years to 11 years)	-0.20%	5.16%	3.51%	87.5%

Note: *FR*(A) denotes the fraction of the population satisfying A.

Table 11 Value of Medicare to SSDI applicants

	(1) Baseline (Medicare is available via SSDI)	(2) No Medicare via SSDI	(3) % Difference	(4) Mandatory HI purchase (Medicare is available via SSDI)	(5) Mandatory HI purchase + No Medicare via SSDI	(6) % Difference
EPDV of lifetime welfare	-24.23	-24.65	-1.7%	-20.4	-20.86	-2.2%
$FR(working)$	84.7%	85.6%	1.03%	85.6%	86.4%	0.98%
$FR(DI^{App}=1)$	4.4%	3.8%	-14.12%	3.9%	3.5%	-11.47%
$FR(DI=1)$	6.44%	6.41%	-0.51%	6.4%	6.2%	-3.15%
EPDV of lifetime welfare (for the population as a whole)	-24.09	-24.32	-0.9%	-17.95	-17.68	-1.5%

Note: *FR*(A) denotes the fraction of the population satisfying A.

Table 12 Alternative specifications

	(1)	(2)	(3)	(4)	(5)
	$FR(DI=1)$	$FR(DI^{App}=1)$	$FR(working)$	WTP for Medicare benefits via SSDI	WTP for SSDI (including both cash and Medicare benefits)
Baseline	5.24%	3.57%	87.0%	0.5%	1.1%
No health insurance and medical expenditure process	4.85%	3.12%	87.1%	-	0.7%
Less risk-averse $(\gamma=1)$	1.33%	1.58%	93.9%	0.1%	-
More risk-averse $(\gamma=2)$	4.51%	4.11%	60.0%	1.6%	-
Consumption floor ($2,000)	4.70%	3.19%	88.0%	0.5%	-
Consumption floor ($4,000)	5.75%	4.00%	85.7%	0.4%	-
More patient $(\beta=1.00)$	3.73%	2.79%	89.4%	0.8%	-
Less patient $(\beta=0.95)$	6.06%	3.94%	85.5%	0.3%	-

Note: The baseline specification is as follows: CRRA (γ) = 1.5; time discount rate (β) = 0.98; consumption floor = $3,000; For the specification without health insurance and medical expenditure process, WTP for SSDI refers to WTP for SSDI cash benefits. FR(A) denotes the fraction of the population satisfying A.

Appendix

A. Means-tested Welfare Programs

Supplemental Nutritional Assistance Program (SNAP). The SNAP program (formerly and still commonly known as the Food Stamp program) is a means-tested welfare program that provides benefits to needy families. Due to computational complexity, I do not model actual SNAP benefit schedules for all states. Instead, I assume that 1) there is a single SNAP benefit scheme for all states; 2) only income is considered for means-testing (i.e., assets are ignored)[43]; 3) there is no take-up decision: individuals enroll in SNAP if they are eligible. Following Low and Pistaferri (2011), net income to be considered for means-testing is defined to be:

$$y_{it}^{net} = w_{it} h P_{it} + DI_{it} E_{it}^{DI} (1 - P_{it}) - \tau_{it} - d \qquad \text{(A1)}$$

where d is the standard deduction in calculating net income for the SNAP benefit calculation. The SNAP benefit is given by

$$SN_{it} = \begin{Bmatrix} \bar{T}_{SN} - 0.3 \times y_{it}^{net} & if \ E_{it}^{SN} = 1 \\ 0 & otherwise \end{Bmatrix} \qquad \text{(A2)}$$

where $\bar{T}_{SN}$ is the maximum level of the SNAP payment and E_{it}^{SN} is the eligibility indicator for SNAP. $E_{it}^{SN} = 1$ if $y_{it}^{net} \leq \underline{y}$ where $\underline{y}$ is the income threshold for SNAP.

Supplemental Security Income (SSI). SSI program is a means-tested program available to disabled or aged low income individuals. As of December 2009, 16.3% of SSDI recipients were also receiving an SSI benefit because their SSDI benefit plus other income was below the SSI threshold (SSA, 2010). The definition of disability and the screening process in the SSI program are similar to that of the SSDI program, and criteria for means-testing $\underline{y}$ are similar to those of the SNAP. Thus, I assume that an individual receives an SSI cash benefit if $E_{it}^{SN} E_{it}^{DI} = 1$, and that the value of the SSI cash benefit is given by

[43] In reality, most households do not face an asset test (www.fns.usda.gov/snap/applicant_recipients/eligibility.htm). Even if a household is subject to an asset test, only liquid wealth is counted as assets. However, I do not distinguish between liquid and non-liquid assets in my model. For example, housing wealth and cash savings are treated as the same. Thus, it is difficult to model an asset test in the current framework.

(A3) $$SSI_{it} = \begin{cases} \bar{T}_{SSI} - y_{it}^{net} & if\ E_{it}^{SSI} = 1 \\ 0 & otherwise \end{cases}$$

where $\bar{T}_{SSI}$ is the maximum level of the SSI payment for a couple. The indicator for receiving SSI before retirement at retirement age is E_{it}^{SSI} where $E_{it}^{SSI} = E_{it}^{DI} E_{it}^{SN}$. That is, an individual (before retirement age) can receive SSI benefit only when he receives SSDI and qualifies for a means-tested program.

B. Computation of taxes

SSDI benefits are taxable income. Also, there are state and federal income taxes, too. I account for the tax on SSDI cash benefit and other income taxes because the payroll tax as well as the tax on SSDI cash benefit affects the incentive to apply for SSDI. Incomes from SNAP and SSI are not subject to tax. It is important to Social Security Disability Insurance (SSDI) benefit and unemployment insurance benefit because the taxation on those cash benefits can affect their life-cycle behavior, too. In the previous research, e.g., Low and Pistaferri (2010), only labor income was taxed. I define pre-tax income as $Y_{it}^{T} = w_t h + DI_{it} + (R-1)A_{it}$. I assume that individuals are subject to the same tax rule. Regarding the tax rule, I use the tax function used in French and Jones (2011). In their calculation, Rhode Island is chosen as a representative state. For the computation of federal taxes, they use the standard deduction, and the tax tables for the head of household as of 1998. The amounts of taxes, τ, is determined as $\tau = Y^{T} - Y^{P}$. The following is the table of post-tax income by pre-tax income:

Table A1: Post-tax income

Pre-tax income (Y^T)	Post-tax income (Y^P)	Marginal tax rate
[0, 6250)	$0.9235Y^T$	0.0765
[6250, 40200)	5771.88+0.7384(Y^T -6250)	0.2616
[40200, 68400)	30840.56+0.5881(Y^T -40200)	0.4119
[68400, 93950)	47424.98+0.6501(Y^T -68400)	0.3499
[93950, 148250)	64035.03+0.6166(Y^T -93950)	0.3834
[148250, 284700)	97515.41+0.5640(Y^T -148250)	0.4360
284700 and above	174474.21+0.5239(Y^T -284700)	0.4761

Source: French and Jones (2011)

C. Social Security Disability Insurance

Eligibility In the model, a worker is eligible to apply for SSDI when he satisfies two conditions: (1) he must be out of the labor force for one six-month period before applying; (2) he must have worked for at least 10 periods (20 quarters) if he is age 31 or older; if he is age 30 or younger, he must have worked half the time between age 21 and the age of disability. For example, if he is disabled at age 27, he must have worked 6 periods (12 quarters).

Cash benefit The SSDI benefit is determined by the same formula that is used to calculate Social Security retirement benefits (Old-Age and Survivors Insurance, OASI), but there is no penalty for early retirement in the SSDI program. The SSDI benefit is a function of an inflation-adjusted lifetime earning measure, called Average Indexed Monthly Earnings (AIME). The level of cash benefit is a major determinant of SSDI application in the model, so it is important to calculate AIME accurately. In the model, I calculate updated AIME using the worker's earnings history. The formula for the monthly SSDI cash benefit is as follows:

$$(A4)\ DI_{it} = \begin{cases} 0.9\times AIME_{it} & if\ \ AIME_{it} \le a_1 \\ 0.9\times a_1 + 0.32\times(AIME_{it} - a_1) & if\ \ a_1 < AIME_{it} \le a_2 \\ 0.9\times a_1 + 0.32\times(a_2 - a_1) + 0.15\times(AIME_{it} - a_2) & if\ \ a_2 < AIME_{it} \end{cases}$$

where $AIME_{it}$ is average indexed monthly earnings, and benefit bend points a_1 and a_2 are scaled to reflect average nominal wage growth each year. In 2006, the monthly value of a_1 is \$656, and the value of a_2 is \$3,955. Regarding the calculation of AIME, I use the following formula for workers before retirement age:

$$(A5)\ \begin{cases} AIME_t = \{AIME_{t-1}\times(t-1) + \min(a_{\max}, w_t h_t)\}/t,\ \ \mathrm{t}\in[1,70] \\ AIME_t = \max\{AIME_{t-1}, \{AIME_{t-1}\times(t-1) + \min(a_{\max}, w_t h_t)\}/t\},\ \ \mathrm{t}\in[71,84] \end{cases}$$

where $a_{\max}$ is the maximum taxable earnings. $a_{\max}$ for a year-period is \$94,200 in 2006. The cut-off point at age 58 is to take into account that AIME is calculated based on the highest 35 years of earnings. If a worker is retired, there is no change in AIME: $AIME_t = AIME_{t-1}$

<u>The termination of SSDI status</u> Individuals can leave the SSDI program for three reasons: (1) a recipient decides to go back to work and continues to earn more than the SGA limit after a trial work period; (2) he is rejected on reassessment; (3) he dies. A person who left the program for the first two reasons can always re-apply again as long as he satisfies the application requirements.

D. The identification of the variances and AR(1) parameter of log out-of-pocket medical expenditure

I estimate the variances and the AR(1) parameter using the following moments:

$$(A7)\quad \begin{aligned} &Var(\zeta_{it}^m) = \sigma_{f,m}^2 + \sigma_{v,m}^2 + \sigma_{\omega,m}^2\ \ \forall t \\ &Cov(\zeta_{it}^m, \zeta_{it+1}^m) = \sigma_{f,m}^2 + \rho_m \sigma_{v,m}^2\ \ \forall t \\ &Cov(\zeta_{it}^m, \zeta_{it+k}^m) = \sigma_{f,m}^2 + {\rho_m}^k \sigma_{v,m}^2\ \ \forall t,\ \mathrm{k}>1 \end{aligned}$$

Note that I do not allow the variances $(\sigma_{f,m}^2, \sigma_{v,m}^2, \sigma_{\omega,m}^2)$ and the autocorrelation parameter (ρ_m) in equation (4) to be different within health insurance-disability-age groups. I standardize the variance of ζ_{it}^{m} to be one, so the group-specific variance of out-of-pocket medical expenditure is determined by $\sigma(HI_{it}, L_{it}, t)$. This approach is parsimonious and particularly useful when the sample is classified into several groups.

E. Log wage offer process

To account for selection into the labor force, I use Heckman's two-stage estimation method. The selection equation is specified as a probit model:

$$\text{(A8)} \quad S_{it}^{*} = X_{it}^{'} s_1 + s_2 L_{it}^{1} + s_3 L_{it}^{2} + R_{it}^{'} s_4 + \varpi_{it}$$

where R_{it} is a vector of variables assumed to affect labor force participation but not wages, and ϖ_{it} is the residual. $g_{it} (= \varepsilon_{it}^{W} - \varepsilon_{it-1}^{W})$ is the innovation to the persistent component of unobserved productivity found in equation (5).

Following Low et al. (2010), the productivity risk will be estimated using the residual of the second-stage regression. I use the following moment conditions:

$$\text{(A9)} \quad \begin{aligned} & E(g_{it} \mid P_{it} = 1, P_{it-1} = 1) = \rho \sigma_{\zeta} \lambda(s_{it}) \\ & E(g_{it}^{2} \mid P_{it} = 1, P_{it-1} = 1) = \sigma_{\zeta}^{2} (1 - \rho^{2} s_{it} \lambda(s_{it})) + 2\sigma_{\omega}^{2} \\ & -E(g_{it} g_{it+1} \mid P_{it} = 1, P_{it-1} = 1) = \sigma_{\omega}^{2} \end{aligned}$$

where σ_{ζ}^{2} is the variance of permanent productivity shock, and σ_{ω}^{2} is the variance of measurement error. For more details about the identification of permanent productivity shock, see Low et al. (2010).

Spouse Income. To reduce computational burden, I model a simple exogenous spousal income process: $\ln sp_{it} = \beta_0^{sp} + \beta_1^{sp} t + \beta_2^{sp} t^2 + \varepsilon_{it}^{sp}$ where ε_{it}^{sp} is an *i.i.d.* error term assumed to be distributed as $\varepsilon_{it}^{sp} \sim N(0, \sigma_{sp}^{2})$. I use the FE approach to control for individual-specific unobserved heterogeneity.

F. Solution method

I present the solution method prior to retirement. The Bellman equation can be written as follows:

$$\text{(A10)} \quad \max_{C_{it}, DI_{it}^{App}, P_{it}} \left\{ V_{it}(S_{it}) = U(c_{it}, P_{it}; L_{it}) + \beta\psi(t+1, L_{it}) E_t \left[V_{it+1}(S_{it+1}) \right] \right\}$$

The period *t* state space after the realization of shocks and before choices are made is:

$$\text{(A11)} \qquad S_{it} = (A_{it}, L_{it}, P_{it-1}, q_{it}^{DI}, Dur_{it}^{DI}, AIME_{t-1}, \varepsilon_{it}^{w}, \varepsilon_{it}^{m})$$

where q_{it}^{DI} is the length of work experience, which is used to determine eligibility for SSDI, Dur_{it}^{DI} is the duration of time receiving cash SSDI benefit, which determines eligibility for Medicare and the likelihood of SSDI reassessment, and ε_{it}^{m} is a stochastic component of out-of-pocket medical expenditure. To solve the model, I first calculate $E_t V_{t+1}$ over a randomly selected subset of state points by *Monte Carlo* integration, and run a polynomial regression of $E_t V_{t+1}$ on the state variables. Then I approximate $E_t V_{t+1}$ for all other state space points using the estimated regression parameters. The approximated expected value of the next period's value function is typically denoted by *Emax*. By substituting the *Emax* function for $E_t V_{t+1}$ in equation (A10), I can obtain the optimal choices at age *t*. Repeating the procedure of calculating the *Emax* function and obtaining optimal choices using the *Emax* function for each age gives the solution to the lifetime utility maximization problem in equation (1).

G. Variance correction for out-of-pocket medical expenditure

In the PSID data, we only observe the sum of out-of-medical expenditure for two calendar years. But, the unit of time in my model is a six-month period. I account for the difference in the reference period by the procedure that I describe below. For the convenience of explanation, I treat the two-year measure to be one-year sum of four quarterly medical expenditures below and I suppress a subscript for an individual.

I define P_i to be the observed sum of out-of-medical expenditure for four consecutive calendar quarters in *i* th wave, and Q_{ij} for the unobserved out-of-pocket medical expenditure for quarter *j* in *i* th wave: $P_i = \sum_{j=1}^{4} Q_{ij}$

Ignoring the deterministic component, quarterly out-of-pocket medical expenditure consists of persistent component, *a*, and transitory component, ω.

$$\mathrm{Q}_{ij} = a_{ij} + \varepsilon_{ij} \ \ \forall \mathrm{j} \in \{1,2,3,4\} \text{ where } a_{ij} = \rho a_{ij-1} + \omega_j ;\ \varepsilon_{ij} \sim N(0,\sigma_\varepsilon^2);\ \omega_{ij} \sim N(0,\sigma_\omega^2); 0 < \rho < 1$$

Then the variance of out-of-pocket medical expenditure for a six-month period can be written as follows:

(A12) $V(Q_{i1}) = V(Q_{i2}) = V(Q_{i3}) = V(Q_{i4}) = (\sigma_a^2 + \sigma_\varepsilon^2)$ where the variance of persistent component can be also expressed as $\sigma_a^2 = \dfrac{\sigma_\varpi^2}{1-\rho^2}$. As it is obviously shown in the above equation, an underlying assumption is that the quarterly variance of out-of-pocket medical expenditure is constant within wave *i*. Using the above expression of the variance of quarterly out-of-pocket medical expenditure, we can express the variance of the observed sum of out-of-pocket medical expenditure in the following way:

$$\text{(A13)} V(P_i) = V(Q_{i1} + Q_{i2} + Q_{i3} + Q_{i4}) = \{\sum_{j=1}^{4} V(Q_{ij}) + \sum_{j \neq k} COV(Q_{ij}, Q_{ik})\} = 4(\sigma_a^2 + \sigma_\varepsilon^2) + 2\sigma_a^2\{\rho^3 + 2\rho^2 + 3\rho\}$$

By re-arranging the above equation, we can express the variance of *unobserved* quarterly out-of-pocket medical expenditure in the following way:

$$\text{(A14) } V(Q_{ij}) = (\sigma_a^2 + \sigma_\varepsilon^2) = \frac{1}{4}V(P_1) - \frac{1}{2}(\rho^3 + 2\rho^2 + 3\rho)\sigma_a^2 \quad \forall \mathrm{j} \in \{1,2,3,4\}$$

Also, I construct covariance of *observed* out-of-pocket medical expenditures between different waves. For example, covariance between *wave 1* and *wave 2* and between *wave 1* and *wave 3* can be written as follows:

(A15) $$\begin{cases} COV(P_1,P_2)=COV(Q_{11}+Q_{12}+Q_{13}+Q_{14},Q_{21}+Q_{22}+Q_{23}+Q_{24}) \\ =\sum_{j=1}^{4}\sum_{k=1}^{4}COV(Q_{1j},Q_{2k})=(\rho^7+2\rho^6+3\rho^5+4\rho^4+3\rho^3+2\rho^2+\rho)\sigma_a^2 \\ COV(P_1,P_3)=COV(Q_{11}+Q_{12}+Q_{13}+Q_{14},Q_{31}+Q_{32}+Q_{33}+Q_{34}) \\ =\sum_{j=1}^{4}\sum_{k=1}^{4}COV(Q_{1j},Q_{3k})=(\rho^{11}+2\rho^{10}+3\rho^9+4\rho^8+3\rho^7+2\rho^6+\rho^5)\sigma_a^2 \end{cases}$$

I omit the expressions of covariance between other waves to save space but they can be expressed in a similar way. By matching above variance and covariance of out-of-pocket medical expenditure observed in the data, I estimate σ_a^2, σ_ε^2, and ρ. The estimation results are reported in Table 3. Alternatively, De Nardi et al.(2010) who use the AHEAD data, where medical expenditures are reported as a two-year average, multiply 1.424 to the residual variance of the log medical expenditure regression to correct for the two-year frequency variance.

H. First-Stage Estimation Results

H.1. Survival risk

Figure A1 plots the death probability conditional on the previous period's disability status. In all disability types, death probabilities increase exponentially with age. Individuals with severe disability status have a considerably higher probability of death in the next period. The calculation of death probability is as follows.

The probability of being alive in period *t* depends on disability status in period *t-1*and age. The survival function (from period t-1 to period t) can be written as:

(A16) $$\psi(t \mid L_{it-1}) = 1 - \Pr(death_{it} \mid L_{it-1}, t)$$

I do not directly compute the probability of death conditional on the last period's disability status because the PSID data considerably underestimates mortality risk in old ages and has few observations over age 80 (French, 2005; Fonseca et al. 2009). I calculate equation (A16) using standard life tables in conjunction with Bayes' rule following the approach of French (2005). I use the Bayes' rule for two reasons: 1) the PSID underestimates death probability by 25% compared to National Center for Health Statistics (NCHS). 2) Some cells have too few observations to directly calculate survival probability by age, disability status, and education group. Conditional death probability using Bayes' rule in Eq (7) can be written as follows:

$$\text{(A17)}\ \Pr(death_{it} \mid L_{it-1}, t) = \Pr(death_{it}) \times \frac{\Pr(L_{it-1} \mid death_{it})}{\Pr(L_{it-1})}$$

Note that all elements in the above equation are calculated separately by education group but the notation is omitted because only the low-educated group is used in the paper.

I first describe how I calculate $\Pr(death_{it})$ by education group. I assume that death probability (unconditional on education and health) is given by $\Pr(death_t) = \%higheduc_t \times \Pr(death_t \mid higheduc_t) + \%loweduc_t \times \Pr(death_t \mid loweduc_t)$ where *%higheduc* and *%loweduc* denote the share of high education group and the share of low education group among individuals with age *t*. Then education-specific death probability can be calculated as follows:

$$\left(\text{A18}\right)\Pr(death_t \mid higheduc_t) = \frac{\%loweduc_t \times \Pr(death_t \mid loweduc_t) - \Pr(death_t)}{\%higheduc_t}$$

$$= \frac{\%loweduc_t \times \Pr(death_t \mid higheduct_t) \times A_t - \Pr(death_t)}{\%higheduc_t}$$

$$\Rightarrow \Pr(death_t \mid higheduc_t) = \frac{\Pr(death_t)}{\%loweduc \times A_t - \%higheduc_t}$$

where $A_t = \dfrac{\Pr(death_t \mid higheduc_t)}{\Pr(death_t \mid loweduc_t)}$, and $\%higheduc_t$ and $\%\ loweduc_t$ are the shares of high education and low education for each age *t* respectively. I use this approach because I do not have A_t for every age. Otherwise, I do not need to calculate education-specific death probability this way. The NCHS reports education-specific number of deaths per 1,000 by four age groups in 2007 (Xu et al., 2010).[44] Assuming that A_t is relatively stable and linear, I linearly estimate A_t for each age using A_t for four age groups available in the NCHS report. The shares of each education group are obtained using the American Community Survey 2007 by each age. $\Pr(L_{it-1} \mid death_{it})$

[44] Micro-level death certificate data which contains education information is not publicly available yet.

and $\Pr(L_{it-1})$ are estimated from the PSID data and I specify $\Pr(L_{it-1} \mid death_{it})$ as multinomial logits.

H.2. Disability risk

Figure 2 plots predicted disability transition rates based on estimates of the following equation:[45]

$$(A19)\ \Pr(L_{it} = j \mid L_{it-1} = k) = \frac{\exp(\beta^L_{0,j,k} + \beta^L_{1,j,k}t + \beta^L_{2,j,k}t^2)}{\sum_{s=0}^{2}\exp(\beta^L_{0,s,k} + \beta^L_{1,s,k}t + \beta^L_{2,s,k}t^2)},\ j \in \{0,1,2\}, k \in \{0,1,2\}$$

The top left panel shows the probability of becoming severely disabled, given no disability at *t*-1. The probability of becoming disabled is increasing with age. The top right panel shows that the probability of remaining in the no disability state given no disability at *t*-1 is decreasing in age. The bottom panels show disability dynamics conditional on being severely disabled in the last period. The bottom left panel shows that the probability of remaining in the severe disability state is higher as a person becomes older. Similarly, the probability of returning to the no disability state is decreasing in age.

H.3. Out-of-pocket medical expenditure risk

Average medical expenditure rises with age regardless of health insurance type, and those in the no health insurance group have the highest average medical expenses at any given age. An important part of the value of health insurance comes from reduced volatility of medical expenditure so I also report the standard deviation of out-of-pocket medical expenditure in Table 3. The standard deviation rises with age and the no health insurance group has the highest standard deviation at any give age.

I fit the medical expenditure data using equation (4). I use a person-fixed effect approach to estimate the within-person variation of medical expenditure. In equation (4), the deterministic component of out-of-pocket medical expenditure is a function of disability status, health

[45] Figure A2 in the Appendix plots the distribution of work-limiting disability status by age, *not* conditional on the last period's disability status.

insurance type, and age. The equation for the deterministic component of out-of-pocket medical expenditure is given by:

$$\text{(A20)}\quad m(t, HI_{it}, L_{it}) = \mu_0 + \mu_1 t + \mu_2 t^2 + \mu_3 I(L_{it} = 1) + \mu_4 I(L_{it} = 2) + \sum_{HI} \sum_{a \in \{t<65, t\geq 65\}} \mu_{HI,a}$$

where *HI* is a categorical variable where $HI \in$ {employer-provided health insurance, Medicare} . None is an omitted health insurance category. *a* is a binary indicator to differentiate the effects of Medicare on medical expenditure on the disabled and the elderly. The variance shifter σ(t, HI_{it}, L_{it}) has the same specification. I fit equation (4) in two stages. First, I estimate equation (A18) using person-specific FE and then estimate the variance shifter using the residual of the first stage estimation.

Table A2. Coefficients of Log out-of-pocket medical expenditure regression

Variable	Level *m(t,HI,L)*	Variance σ*(t,HI,L)*
Employer-provided health insurance	0.32	-2.27
Medicare	-0. 57	-1.58
Moderate disability	0. 04	0. 46
Severe disability	0.20	0. 96

Note: controls include age and age square, a dummy variable for age 65 and above, and interaction terms of the dummy variable for age 65 and health insurance type dummies; EPI denotes employer-provided health insurance.

H.4 Wage Offer Process

Table 5 reports estimates of the log wage offer equation, accounting using Heckman's two-stage estimation method. The first column shows estimates of marginal effects from the participation probit. The exclusion restrictions are cash unemployment insurance (UI) payments and unearned income. The coefficients on the exclusion restriction variables and the Mills ratio are all significantly different from zero, and the signs are as expected. More generous UI benefits and higher income transfers reduce employment. The second and third columns show the log hourly wage offer estimates, with and without accounting for selection. Severe disability reduces the offered wage by 32 percentage points (column 3) while moderate disability reduces it by 16 percentage points, accounting for selection.

Table 6 reports the estimated variances of the permanent and transitory productivity shocks.[46] These variances are calculated from the residuals of the log wage offer regression and account for selection into labor market participation.

The estimation results for the log spouse income process are reported in the following:

Table A3. Coefficients of Log (annual) spousal income process

Variable	Coefficient
Age	0.258
Age square/100	-0.360
Constant	1.374

Note: the regression result includes person-fixed effects.

I. Indirect Inference

In Indirect Inference, the auxiliary model does not produce consistent estimates of the parameters of interest, Θ. Instead, estimating the auxiliary model yields consistent estimates of auxiliary parameters, $\beta(\Theta_0)$, so called a pseudo-true value, where Θ_0 is the true value of Θ. If a given set of structural parameters of interest can produce the auxiliary moments computed from simulated data capable of closely resembling auxiliary moments obtained from real data, this implies that the chosen set of parameter estimates are close to the true value of structural parameters of interest. The requirement for the auxiliary models is that they should be able to represent the key relationships in the data. The goal of Indirect Inference is to find the value of Θ which minimizes the weighted distance between the auxiliary parameters estimated on the simulated data and the auxiliary parameters estimated on the actual data:

[46] The variances are calculated from hourly wage data where the reference period is a year. To account for the six-month time period in the model, I assume that a person receives a productivity shock with a probability of 0.5, following the approach of Low et al. (2010).

$$\text{(A20)} \qquad \min_{\Theta}\left(\hat{\beta}^D - S^{-1}\sum_{s=1}^{S}\hat{\beta}^S(\Theta)\right)'\Lambda\left(\hat{\beta}^D - S^{-1}\sum_{s=1}^{S}\hat{\beta}^S(\Theta)\right)$$

where $\hat{\beta}^D$ is a vector of auxiliary moments estimated from the actual data and $\hat{\beta}^S(\Theta)$ is the corresponding set of moments in the simulated data. S is the number of simulations. The optimal weighting matrix, denoted by Λ, is the inverse of the covariance matrix of the data moments, i.e., $\Lambda = \text{var}(\hat{\beta}^D)^{-1}$. To minimize the objective function, I use a variant of the Nelder-Mead simplex algorithm developed by Lee and Wiswall (2007).[47]

J. Auxiliary moments

There are four sets of auxiliary moments to identify utility function and SSDI policy parameters. The following arguments for identification are largely borrowed from Low and Pistaferri (2011).

1. Proportion of SSDI beneficiaries by disability status and age group (23-44,45-62)

The proportion of SSDI beneficiaries by disability status is determined by the acceptance probability, conditional on SSDI application. For example, a very high proportion of SSDI beneficiaries among young workers with severe work-limiting disability status implies that there must be a high probability of acceptance of SSDI application for those workers.

2. Composition of SSDI beneficiaries by disability status age group (23-44, 45-62)

These moments are related to the utility cost of labor market participation as a function of disability status and to the reassessment probability of SSDI status. First, the share of each disability status among the total SSDI recipients reflects the incentive to apply for SSDI conditional on not being disabled. If non-disabled individuals have a high disutility of working, then there would be many SSDI applicants who are not disabled. Second, the share of non-disabled and moderately disabled workers among SSDI recipients reflects the frequency of SSDI status review. If the SSDI beneficiary pool is largely composed of severely disabled workers, this implies that the SSDI review probability is high.

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[47] I thank Donghoon Lee for sharing his simplex routine for MPI.

3. Proportion employed classified by disability status and age group (23-32, 33-42, 43-52, 53-62)

These moments are closely related to the utility costs of working across different states of disability and a layoff probability. For example, a lower labor force participation rate among severely disabled workers implies that disutility of labor participation given severe disability is high. Also, if a young worker, who is less likely to quit due to low savings, is not working, it may be due to a high layoff probability.

4. Coefficient estimates from the log consumption regression

The following regression is used to identify the non-separable utility costs of disability and work, η and θ:[48]

$$\text{(A20)}\qquad \begin{aligned} \ln c_{it} &= \alpha_0 + \alpha_1 L_{it}^1 + \alpha_2 E_{it}^{DI} L_{it}^1 + \alpha_3 L_{it}^2 + \alpha_4 E_{it}^{DI} L_{it}^1 + \alpha_5 E_{it}^{DI} + \alpha_6 P_{it} \\ &+ \alpha_7 t + \alpha_8 t^2 + \alpha_9 TransferIncome + \varepsilon_{cit} \end{aligned}$$

First, the effect of working on consumption is captured by α_6. This coefficient helps to pin down the non-separable utility cost of working because working has a direct effect on the marginal utility of consumption. Second, coefficients α_1 through α_4 are related to the non-separable utility costs of disability, θ_1 and θ_2. The parameter α_3(or α_1) captures the effect of disability on consumption. Disability is not only related to the loss of labor income, but also related to a decrease in the marginal utility of consumption. α_4(or α_2) is the effect of disability on consumption when labor income is insured by the SSDI benefit. Thus, comparing α_3(or α_1) with $\alpha_3 + \alpha_4$ (or $\alpha_1 + \alpha_2$) helps to isolate the non-separable utility cost of severe (moderate) disability. In the regression, I use a person-fixed effect approach to estimate the within-person variation of consumption expenditure.

5. More discussion of the model fit

[48] The PSID asks consumption expenditure at the household level and thus c_{it} is adjusted by the number of adult-equivalent family members using OECD equivalent scale.

Panel A reports employment rates by age and disability. The model replicates both the decline in participation with the degree of disability and with age. Particularly, the simulated moments match the observed moments for the severely disabled very well. However, the simulated employment rates of moderately and non- disabled workers aged between 53 and 62 are 3-5 percentage points lower than the actual, and the simulated moments for moderately disabled workers aged between 23-42 are over-predicted by 5-8 percentage points.

Panel B shows SSDI enrollment by disability status and age. The share of SSDI recipients rapidly increases with the degree of disability and age. About two thirds of older workers with severe disability are on the SSDI program, and about one third of younger workers with severe disability are on the SSDI program. Among the non-disabled, only 3 out of 1,000 workers under age 45 are currently covered by SSDI, and 1 out of 100 workers aged 45 and over are on the SSDI. The model replicates the pattern of SSDI receipt by disability status and age quite well.

Panel C shows the composition of SSDI recipients by disability status and age group. The data moments show that more than two thirds of SSDI recipients are severely disabled. However, the data also reveals that a non-negligible share of SSDI recipients have no work-limiting disability (8-13%). Given the very low acceptance probability of SSDI application by the non-disabled workers, these non-disabled SSDI recipients must have recovered from their disability after entry to SSDI. The simulated moments capture the composition of SSDI recipients by disability status and age group very well.

Panel D shows moments obtained from estimating the auxiliary log consumption equation. The data moments show that disability is associated with a drop in consumption expenditure, but the receipt of SSDI benefits prevents consumption expenditure from falling. The model generally replicates the signs and the magnitude of the coefficients, but the coefficient on the receipt of SSDI (for the non-disabled) is over-predicted in magnitude.

K. Calculation of Willingness To Pay (WTP)

Following Low et al. (2010), I use WTP instead of compensating variation (CV) wealth as a measure of welfare changes because the initial level of median assets for individuals at age

23 (the beginning period in the model) is only about \$3,000. For example, if CV for a certain policy intervention exceeds the initial level of assets, e.g., \$100,000, this implies that individuals start their life cycle with the debt of \$97,000. However, the model incorporates the liquidity constraint (A>0) and the consumption floor which cancels any debt. Thus, it is difficult to interpret the implications of having CV exceeding the initial wealth level. Denote *ex ante* expected remaining lifetime utility in the baseline model as follows:

$$E_t U_{baselise} = E_t \sum_{s=t}^{T} \beta^{s-t} U(c_s, DI_s^{App}, P_s; L_s)$$

Then WTP, the proportion of consumption an individual is willing to pay to equate *ex ante* expected lifetime utility of the baseline model and that of a counterfactual regime is defined as follows:

$$E_t U_{counterfacutal} |_{\pi} \equiv E_t \sum_{s=t}^{T} \beta^{s-t} U((1-WTP)c_s, DI_s^{App}, P_s; L_s) = E_t U_{baselise}$$

L. Effects of Medicare benefits provided through SSDI

Table A4.

	(1) Baseline (Medicare is available via SSDI)	(2) No Medicare via SSDI	(3) % Difference (not *%p* difference)	(4) Mandatory HI purchase (Medicare is available via SSDI)	(5) Mandatory HI purchase + No Medicare in SSDI	(6) % Difference	(7) No employer-provided HI (Medicare is available via SSDI)	(8) No EPHI + No Medicare in SSDI	(9) % Difference
Willingness to pay	0.00%	-0.50%	n/a	0.00%	-0.38%	n/a	0.00%	-0.73%	n/a
$FR(DI^{App}=1 \mid L=1)$	7.53%	6.14%	-20.3%	6.55%	5.84%	-11.5%	9.79%	7.10%	-31.0%
$FR(DI^{App}=1 \mid L=2)$	19.7%	18.6%	-5.7%	18.7%	18.4%	-1.5%	21.6%	19.2%	-12.1%
$FR(working)$	87.0%	87.7%	0.8%	87.8%	88.4%	0.6%	85.2%	86.7%	7.8%
FR(working |L=1)	73.7%	76.2%	3.3%	75.7%	78.4%	3.5%	68.1%	73.2%	7.2%
FR(working |L=2)	20.6%	21.5%	4.5%	21.0%	21.6%	2.8%	17.0%	18.7%	9.5%
FR(*DI*=1 |L=1)	12.2%	11.6%	-5.3%	12. 0%	10.1%	-7.9%	15.7%	13.7%	-13.8%
FR(*DI*=1 |L=2)	53.7%	53.6%	-0.2%	54.3%	53.7%	-0.9%	57.6%	57.4%	-0.3%
$FR(L=1 \mid DI^{App}=1, DI=1)$	17.8%	15.8%	-11.9%	16.7%	14.4%	-14.7%	20.8%	17.4%	-17.8%

Note: Columns (1), (4), and (7) include Medicare coverage after two years on SSDI. Columns (2), (5), and (8) show the simulation results when eliminating Medicare coverage in SSDI. In all specifications, Medicare coverage for individuals over age 65 is available. FR(A|B) denotes the fraction of the population satisfying A conditional on B. L is 1 if moderate disability, and 2 if severe disability. % Difference is calculated at the mid-point.

M. Indirect Inference estimates and simulated moments for the alternative specification without health insurance and medical expenditure process

Table A5. Parameters estimated by Indirect Inference for the specifications with and without medical expenditure process.

Parameter	Estimate from baseline specification	Estimate from no medical expenditure specification
Non-separable utility cost of working (η)	-0.310	-0.404
Utility cost of moderate disability (θ_1)	-0.096	-0.206
Utility cost of severe disability (θ_2)	-0.386	-0.500
Layoff probability (ϕ_1)	0.098	0.112
Utility cost of labor force participation | L=0 (κ_0)	-0.025	-0.161
Utility cost of labor force participation | L=1 (κ_1)	-0.220	-0.359
Utility cost of labor force participation | L=2 (κ_2)	-0.791	-1.171
SSDI acceptance probability | L=0	0.0007+0.00003*t	0.0008+0.0000*t
SSDI acceptance probability L=1	0.27+0.0001*t	0.30+0.0016*t
SSDI acceptance probability | L=2	0.47+0.005*t	0.43+0.0041*t
SSDI reassessment probability (P^{CDR})	0.173	0.176

Figure A1 Fitted conditional probability of death by the previous period's disability status

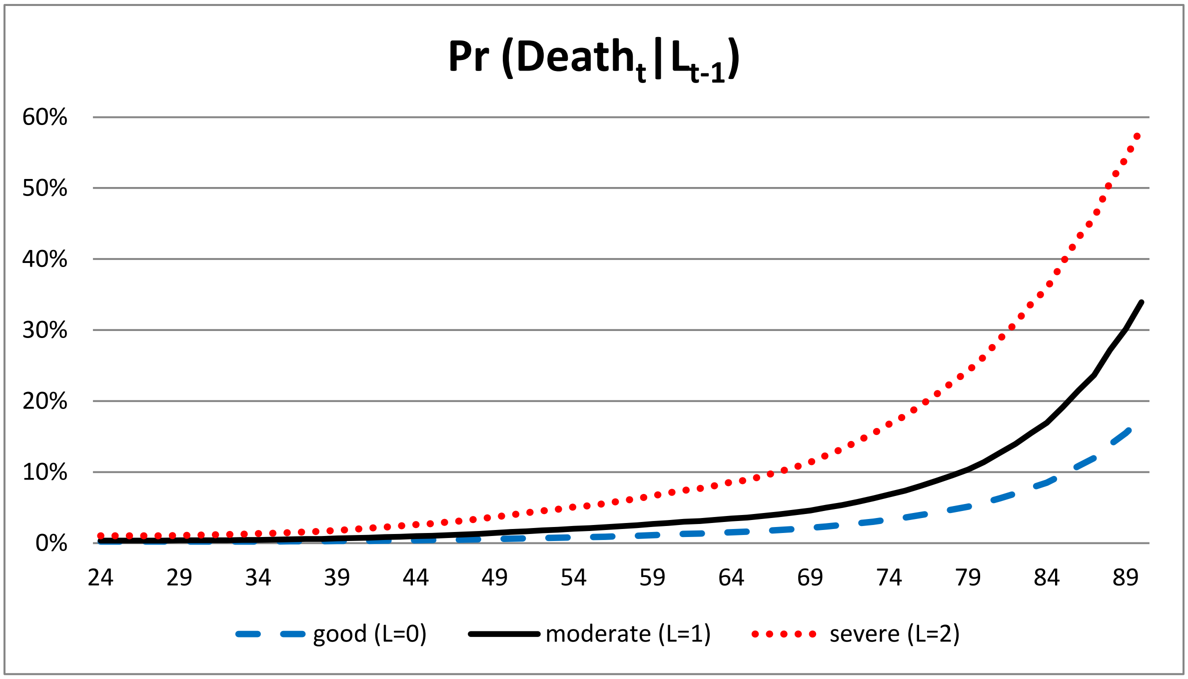
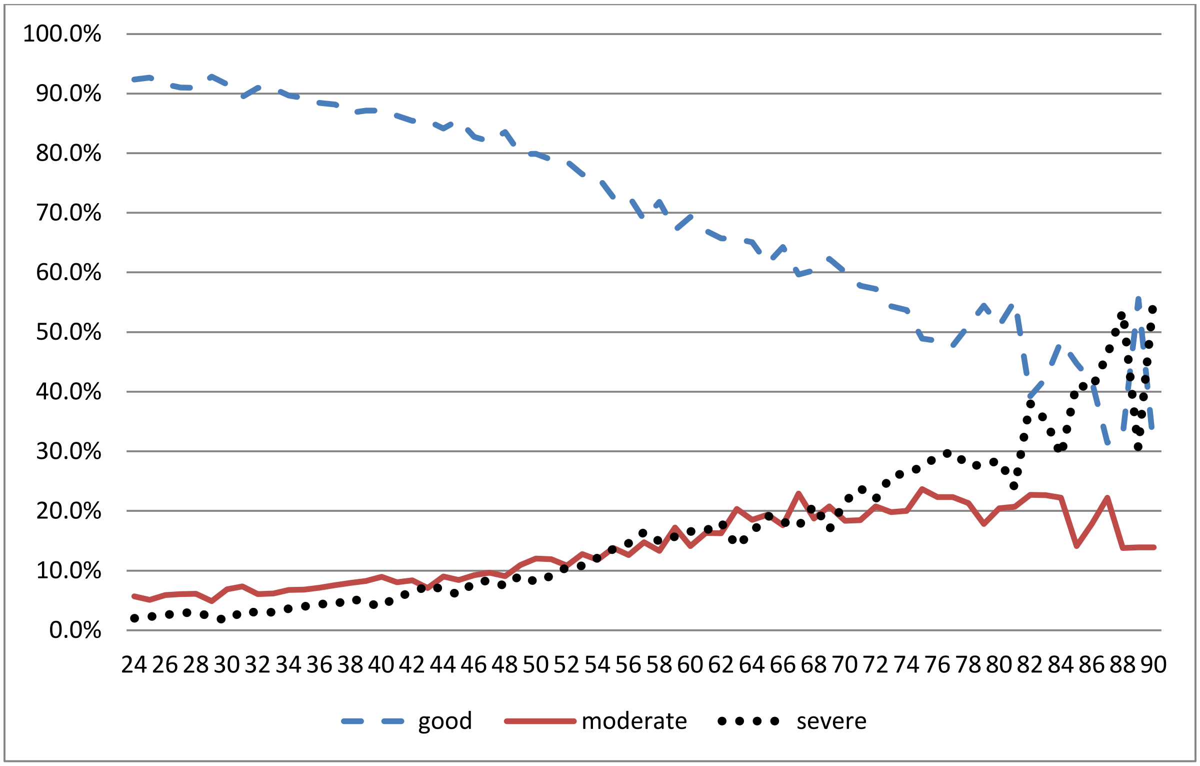


Figure A2 Distribution of disability status by age



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