Occupations, Retirement, and the Value of Disability Insurance

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Abstract: Occupations vary greatly in physical intensity, and there are, correspondingly, many differences in later-life work disability risk, retirement patterns, and applications for Social Security Disability Insurance (SSDI)—a national program that insures shocks to work productivity due to disability, with about 10 million current beneficiaries in the U.S. In light of its widespread coverage and large differences in utilization across occupations, this paper aims to measure the value of the SSDI program across a broad population and the extent to which it influences the major choice of occupation. Using data from the Health and Retirement Study and O*NET, I estimate a life-cycle equilibrium model of occupational choice, work, savings, and disability at older ages, and find that incorporating occupations and preference heterogeneity is an integral part of understanding work and SSDI application behavior. While SSDI coverage is nearly universal and the premiums from workers are uniform, estimates suggest that the value of the program varies greatly, from being worth 2.1 to 14.5 percent of earned income—depending on preferences and choice of occupation—though for all groups it is welfare improving. I also find that SSDI plays an important role in the choice of occupation for older workers, providing an insurance value that results in over ten percent more people choosing physically intense, blue-collar occupations at older ages. This overall effect, however, masks the underlying selection of less risk-averse individuals into blue-collar jobs, which proves to be necessary for accurately evaluating the impacts of policy on behavior.

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1. Introduction

There is considerable variation in the physical effort required across occupations (Figure 1), and one's labor force participation behavior—most notably in later life—appears to be related to his occupation. In particular, those working in more physically intense, "blue-collar" jobs tend to leave the labor force earlier relative to those whose "white collar" jobs involve fewer physical tasks (Figure 2) and who are more likely to cease working if a disability arises. Indeed, those in blue-collar jobs are more than twice as likely to have applied for Social Security Disability Insurance (SSDI), which is a national program in the U.S. that provides insurance against income lost in the event of work-prohibiting disability. In the context of a life-cycle model, we would expect such later-life differences in productivity and disability risks across occupations—and an insurance program mitigating earnings losses when disability arises—to shape career decisions throughout one's working life.

The goal of this work is to understand the interactions among occupational tasks and choice, and labor force behavior in later life while providing a framework for understanding the mechanisms generating such behavior among adults at older ages. Additionally, motivated by the absolute size of the SSDI program, proposed changes to eligibility criteria, and the clear differences in SSDI utilization across occupations, this paper aims to measure the value of the SSDI policy across a heterogeneous population and the extent to which it influences the types of occupations people choose to work in. To study these effects, I estimate a dynamic, life-cycle model of work, savings, and disability at older ages, following primarily French and Jones (2011),[1] combined with an equilibrium occupational choice component drawing on Card and Lemieux (2001), Lee (2005), and Johnson and Keane (2013). To estimate the parameters of this model, I rely on panel data from the Health and Retirement Study (HRS) and connect it with HRS restricted variables linked to Social Security administrative data, as well as detailed occupation characteristics and requirements from O*NET.[2] I find that incorporating even broadly-defined occupations and preference heterogeneity is a very integral part of understanding work, retirement, and SSDI application behavior.

While there are clear differences in the work and savings patterns observed, participation in SSDI is required for virtually all workers, and the mandatory taxes that contribute to the program are uniform across occupations. Motivated by these factors, I take the estimated model to address a number of questions about the value and effects of SSDI on behavior. The first set of questions are aimed at measuring how much the SSDI program is valued. I find that value of the program varies greatly, from being worth 2.1 to 14.5 percent of earned income—depending on preferences and choice of occupation—though for all groups it is welfare improving. To answer a similar question, Cabral and Cullen (2019) estimate the value of public insurance like SSDI though using demand for private disability insurance. Their findings are that, at least for the population as a whole, the existence of SSDI generates significant welfare gains, and these gains would remain if the program's benefits were expanded. While I find that such an expansion would be beneficial for most types, not all would benefit from expanding the program. Considering this heterogeneity in preferences

[1]Sharing features of models from French (2005) and De Nardi et al. (2010), which similarly address interactions of retirement, health, savings, and insurance.

[2]The HRS is a panel study of Americans over age 50 and their spouses that provides rich data from survey respondents on health, work, finances, and much more, as well as some retrospective information, described below in greater detail.

Figure 1: *Variation in Physical and Psychomotor Requirements of Occupations*

Figure 1: Physical and Psychomotor measures on occupations from O*NET. Each dot represents a three-digit occupation, with select occupations highlighted. Axes are indices of the degree to which physical and psychomotor are skills required in an occupation.

Figure 2: *Male Labor Force Participation by Age and Occupation*

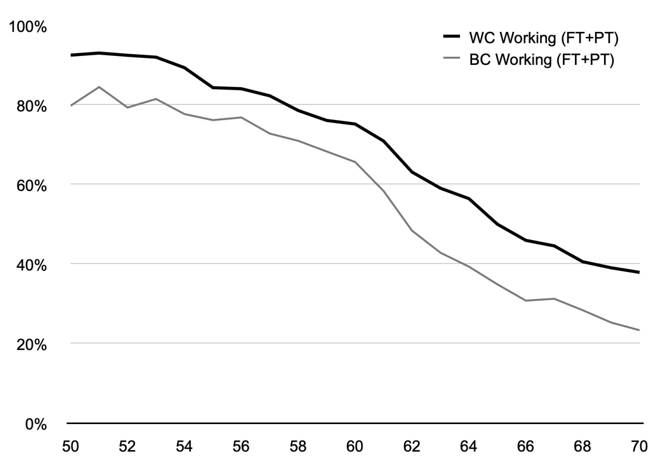


Figure 2: The relative difference in proportion working in WC and BC jobs, while more similar before age 60, increases with age. Participation observations for 22,176 WC and 21,070 BC person-years. Includes all of HRS respondents who have been observed working at least once (and have reported longest occupation held).

and occupations, there could be an element of moral hazard that the program introduces, rendering the valuation of the program more complicated.

This moral hazard consideration motivates a second set of questions: By insuring an event that is more likely to transpire in blue-collar occupations, to what extent might SSDI generate more selection into these occupations? Through counterfactual analysis I find that the program plays an important role in the choice of occupation for older workers, with the insurance value SSDI provides resulting in over five percentage points more (from 47 to 52 percent) more people choosing to work in physically intense, blue-collar occupations at older ages. This aspect of the results aligns well with Michaud and Wiczer (2018), who in a calibrated macroeconomic GE model that measures the reallocation of occupations when disability insurance like SSDI is introduced. While our contexts and approaches differ, we both find evidence of comparable degrees of moral hazard through selection into "riskier" occupations due to SSDI. I also find, in a similar vein, that blue-collar jobs are partially subsidized by social disability insurance: To maintain the current composition of occupations without SSDI, earnings in blue-collar jobs would need to be nearly 9 percent greater to compensate for greater risk of being unable to work due to disability in those jobs. In addition to its effects on older-age occupation decisions, retirement timing and savings decisions are two other aspects of retirement and savings behavior that are affected by the presence of SSDI. Through additional counterfactual analyses, I find, as might be expected, that SSDI results in what could be categorized as lower precautionary savings or self-insurance against disability.[3] As time passes, however, for those who do not experience work disability, this savings is treated more as retirement savings so that, in the presence of SSDI, due to this lower retirement savings, people stopping work by about 1.5 years later than they would if there were no SSDI.

A final aspect of this paper emphasizes the effects that selection into occupations based on risk aversion levels has on the overall findings. The results here suggest that less risk-averse individuals—who, all else equal, value insurance less—select into blue-collar jobs at a greater rate, where they are more likely to face the risk that SSDI partially insures. This particular pattern of selection mitigates the effects that SSDI has on occupation choices, so that *not* accounting for this would lead us to overestimate the moral hazard introduced by SSDI and to underestimate the value of SSDI benefits. More generally, as in van der Klaauw and Wolpin (2008) and De Nardi et al. (2010), for example, this aspect highlights the importance of accounting for preference heterogeneity when measuring the value of policy and predicting its influences on behavior.

I will proceed with describing patterns in retirement, disability, and occupations from the HRS data, as well as the SSDI program in Section 2. Following that, in Section 3 I will develop a model of occupational choice, retirement, and savings that incorporates the SSDI program and equilibrium effects on earnings. Section 4 describes the two-stage Method of Simulated Moments estimation procedure followed by results in Section 5. In Section 6, I present the results from counterfactual analyses to measure the value and impact of SSDI on job choice, followed by a concluding discussion of the results and policy implications in Section 7.

[3] Especially for the less risk-averse and patient agents. This effect on savings is demonstrated in Hall (1978) and Kimball (1990) and applied to injury and disability in both Kantor and Fishback (1996) and Chandra and Samwick (2009).

2. Retirement and Disability Patterns Across Occupations

In this study I account for several aspects of the Social Security system and model behavior on work, savings, and the overall SSDI process, while uniquely focusing on the role of occupations. The labor force participation patterns by occupation (Figure 2) suggest that the relationship between work and aging depends on the tasks an occupation requires. As aging and disability processes are not independent, we might expect the patterns and effects of SSDI across occupations to differ as well. Indeed, there are strong connections between disability, work, and occupations. In this section I will give background on the SSDI program and how it relates to work characteristics, using some descriptive statistics from the HRS data.

Social Security Disability Insurance. The SSDI program is part of the Old-Age, Survivors, and Disability Insurance (OASDI) program, which is administered federally under the U.S. Social Security Administration (SSA). The Old-Age component refers to retirement benefits—commonly known as "Social Security"—while Survivors Insurance provides benefits to spouses surviving the insured deceased. Coverage is nearly universal, and the program is funded through general revenues and a 12.4 percent tax on earnings, with 1.8 percent dedicated to funding SSDI, regardless of occupation.[4] The SSDI program alone is substantial, with 9.9 million beneficiaries receiving payments, and total costs of about $148 billion in 2019.

The programs under OASDI are closely linked—especially as SSDI benefits are based on Old-Age benefits—and I incorporate both programs in the behavioral estimation and analysis here. If approved for SSDI benefits, the beneficiary will receive a monthly payment equivalent to what he would have received if claiming at his Full-Retirement Age (FRA). Once he reaches this age, SSDI benefits cease and are converted to Old-Age retirement benefits for the remainder of his life. The Old-Age retirement monthly benefits levels are a function of taxed earnings history and the age at which one chooses to claim benefits relative to his FRA, which, for the HRS sample I use, is between ages 65–66. Claiming benefits can occur from ages 62 to 70; claiming before the FRA reduces monthly benefits, while claiming later increases benefits. The average monthly retirement benefits for current Old-Age retirement beneficiaries of any claiming age is about $1,500, while for former workers receiving SSDI, who on average have lower earnings histories, the monthly benefit is under $1,200. For reference, someone who earned, on average, $48K over his entire working life would be entitled to about $1,840 in benefits per month claiming benefits at his FRA.[5] In addition to monthly cash benefits, SSDI beneficiaries may also receive Medicare coverage. Medicare is a national health insurance program that covers people ages 65 and over *as well as* SSDI beneficiaries, who become eligible for Medicare within two years of the onset of disability, and some immediately for particular qualifying disabilities. The value of Medicare is modeled here through lower out-of-pocket medical expenses, and for many is a very important aspect of the program.

An individual may qualify to receive Social Security Disability Insurance (SSDI) if he is "unable

[4] Participation is automatic for nearly any person employed in the U.S., with over 90 percent of all workers paying the Federal Insurance Contribution Act (FICA) or Self-Employed Contributions Act (SECA) flat tax on income up to $106K in 2010 (and currently $137K). Half of the 12.4 percent tax is paid directly by the employee, and the other half by the employer. Paying this tax translates to participation in and goes towards funding the program. Additionally, another 2.9 percent of tax on earnings is paid to the Medicare trust fund.

[5] From the 2020 Annual Report of the Board of Trustees, accessed at: `www.ssa.gov/oact/TR/2020/tr2020.pdf` and monthly snapshot figures at: `https://www.ssa.gov/policy/docs/quickfacts/stat_snapshot`.

to work because of a medical condition that is expected to last at least 12 months or result in death" and has not yet reached his FRA for Old-Age benefits.[6] Whether one will meet this criteria and qualify for SSDI benefits is determined through a known, structured evaluation process, though qualification is somewhat less than deterministic in the sense that it depends on one's qualifying disability, age, training, and type of work performed in the past. Of those who apply, a bit over 70 percent are ultimately approved.[7]

There is variation in both the number of SSDI applications and approval rates across time and geography, and a wide literature showing that application rates increase in economic downturns, and approval rates decrease as somewhat more "marginal" cases are reviewed. While not a primary feature, in this model economic conditions do appear broadly through year fixed effects in earnings, where layoffs and reduced hours affect annual earnings estimates. There are also studies exploiting the widespread variation in the award rates of administrative law judges assigned to cases. For example, French and Song (2014) and Maestas et al. (2013) use variation in administrative law judges' award rates and their random assignment to applicants to identify the effects of SSDI application approval and rejection on labor supply. In this paper, policy variation time or location, and factors such as reviewer assignment are not explicitly accounted for for two reasons. First, it is not feasible to explicitly incorporate all such aspects into life-cycle structural such as this. This comes at the expense of there being more noise, but with the benefit of addressing questions that could not be addressed without these methods. The second factor is that one of the primary decisions studied here, choice of occupation at older ages, is a decision spanning long periods of time as opposed to being contemporaneous with any policy variation.

Disability Application, Work, and Occupations. Table 1 introduces some of the ways in which the relationship between disability and SSDI application vary by occupation for the HRS sample of men that will be described in Section 4.1. Here we have both the share within each occupation of those who say they have a "health problem that limits work" and, within each response category, whether they have ever applied for SSDI. Among blue-collar workers, it is somewhat more common to have a health problem that limits work, 31.9 percent versus 26.6 percent for white-collar workers. Within either category, the share who at the time of responding—which includes those only in their early 50s—have ever applied for SSDI is very different, with the likelihood of SSDI application far greater for those in blue-collar occupations. Overall, those in blue-collar occupations are about twice as likely to have applied for SSDI than those in white-collar occupations (20.5 versus 10.1 percent).

Additionally, those who do say that they have a health problem limiting work are also more likely to be working despite that problem if in white-collar jobs, 47.8 percent, compared to those

[6]As described by the Social Security Administration: `https://www.ssa.gov/benefits/disability/`. It is important to note the difference between SSDI and state-run Workers' Compensation programs, which, unlike SSDI, insure short-term injuries that occurred while working, where the vast majority of SSDI claims are not due to a work-related event.

[7]More details about the SSDI application and determination process are included in Appendix A.2. Several studies model multiple stages of the SSDI application and appeals processes, where this and more granular timing are of central focus. Rust et al. (2001), develop a structural model monthly decisions, including centrally SSDI decisions, the appeals process, and interactions between SSDI with a number of public programs. Additionally, Burkhauser et al. (2004), develop and estimate a structural model of the timing of SSDI application, and emphasize that while health conditions are precursors to application, timing is affected greatly by SSDI benefits relative to work income. Low and Pistaferri (2015) emphasize the aspect of false-negative rejection risk involved when one is required to not work in order for an application for SSDI benefits not to be summarily rejected.

Table 1: *Differences Work-Limiting Health Problems and SSDI Application:*

		Ever Applied for SSDI?
White-Collar Occupations		
Health Problem...	Limits Work (26.6%)	28.0%
	Does Not Limit Work (73.4%)	3.7
	All	10.1
Blue-Collar Occupations		
Health Problem...	Limits Work (31.9%)	46.6%
	Does Not Limit Work (68.1%)	8.5
	All	20.5

Note: HRS sample, 9,204 person-years.

in blue-collar jobs, where only about 34 percent are working, for people ages 50-59 (not shown in the table). While there are some differences in the features of blue- and white-collar workers, many of these differences seem to be attributable to work characteristics as they remain even controlling for these differences in worker features like education and income. Despite such patterns, the effect of occupations on retirement has not been a prominent feature in most studies of retirement (with exceptions such as Helppie McFall et al. (2015), Moore and Hayward (1990), and this paper).

Types of Health and Disability. The modeling component of this paper emphasizes physical health and disability, however people may be limited in their capacity to work due to mental health problems or cognitive decline. Indeed, a large and growing share of SSDI beneficiaries have mental health as their qualifying disability. In the HRS sample here, however, I find that composite CES-D scores—a measurement of experience with symptoms associated with depression—differ only very slightly for people in blue- versus white-collar occupations when controlling for health and education. For example, among those ages 55–59, who have a high school education and are in good health, 45.7 percent of those in blue-collar occupations expressed no difficulties with any of the mental health concerns listed, which compares closely to the 43.0 percent for those in white-collar occupations. So while a large share have mental health as the qualifying disability in SSDI application, because there does not seem to be a relationship between CES-D measures and occupation, I do not model this aspect explicitly—though such types of disability are captured broadly through self-reported health, parameters, and channels that are shared across individuals.

As for the cognitive aspect of health, the HRS has several excellent measures of cognition. However, while these measures are particularly appropriate for studying severe decline or predicting dementia, they are less appropriate for this study for two reasons. The first is that, controlling for other demographic factors for the HRS sample, these cognitive measures do not seem to be connected with retirement or SSDI application by occupation. Measures of physical health in the HRS, on the other hand, do vary at these younger ages and differ in their relationship with work by occupation. The second, related reason cognitive measures are not introduced here is that many of the changes in a respondent's cognitive measures occur at somewhat older ages, past when many exit the labor force and past the Full Retirement Age where the SSDI program is relevant.

Employer Accommodation. When a health limitation arises, whether that limitation translates to a work disability depends on the person's jobs requirements, though in some circumstances an employer may be able to accommodate an employee's health problems. Several studies have focused on the role of employer accommodation when health limitations arise. Burkhauser et al. (1999) demonstrate that employer accommodation pushes back the timing of SSDI application and, furthermore, Hill et al. (2016) find that while employer accommodation delays disability, it does not make eventual disability insurance claiming. People do face slightly different prospects for employer accommodation depending on occupation. The HRS includes several questions about employer accommodation. In my sample, when asked whether the respondent would be able to reduce working hours, 33.5% of blue-collar versus 40.8% of white-collar workers said that their employers would accommodate a request for reduced hours. When respondents were asked whether they could move to a less demanding job if necessary, 33.7% of blue-collar workers responded that their employer would be willing to move a worker to a less demanding job if needed, versus a similar 36.7% for white-collar workers As with mental and cognitive health, the employer accommodation process is not a separate feature in modeling here as it does not vary across occupations to nearly as significant an extent that physical aspects of health do. Instead, it enters though mechanisms in the model that are common across occupations.

3. A Model of Work, Savings, and Disability Application

The model here builds on approaches from French (2005) and French and Jones (2011) in analyzing retirement, health, health insurance, and saving behavior at older ages, while additionally incorporating choice of occupation in equilibrium, occupation-dependent productivity and disability, and the SSDI application process. The goal of this model is to find the parameters that replicate a number of patterns in the data in order to understand the mechanisms generating various aspects of behavior, analyze behavior under counterfactual scenarios, and measure value and effects of SSDI.

In this life-cycle model, each person makes annual decisions about work status, savings, applying for SSDI, and claiming Old-Age Social Security benefits. These choices are made facing uncertainty about—but knowing the distributions over—health, medical expenses, and mortality; SSDI application approval; and earnings from work. Each person chooses an occupation within a general-sector labor market and proceeds to maximize current and future expected discounted utility—a function of consumption and leisure—for the remainder of his life, expressed as

$$u(c_t, L_t) + E\left[\sum_{j=t+1}^{T+1} \beta^{j-t}\left(\prod_{k=t}^{j-1} s_k\right)\Big[s_j u(c_j, L_j) + (1-s_j)B(A_j)\Big]\right], \tag{1}$$

subject to the constraints and information available to him outlined below. Time t corresponds to the person's age, future utility is discounted at β, the probability of surviving to age t conditional on having survived to age $t-1$ is s_t. In the event of death at age t or past terminal age T, he leaves assets A_t as bequests.[8]

Preferences. An individual's utility over consumption and leisure in time t is modeled to exhibit

[8] While this model is of behavior from age 50 on, in Appendix **??**, I describe the effects from a model that also includes decisions over occupation and savings at younger ages.

constant relative risk aversion (CRRA) and is specified by

$$u(c_t, L_t) = \frac{1}{1-\eta} \left(c_t^{\alpha_c} L_t^{1-\alpha_c} \right)^{1-\eta} . \tag{2}$$

The utility weight on consumption relative to leisure is represented by α_c, and the coefficient of relative risk aversion η measures the degree of curvature of the function from which we obtain measures of risk aversion and labor supply elasticity. The utility costs of work, applying for SSDI, and performing work while in poor health all come through the leisure component of utility, with

$$\begin{aligned} L_t = L - N_t - \varphi_{P,\,t} P_t - \varphi_{\mathrm{DI},\,t} \mathrm{DI}_t^{app} - \varphi_{\mathrm{SW},\,t} \mathbb{1}_{\{occ_y \neq occ_o\}} \\ - (\varphi_{\mathrm{BC}} + \varphi_{\mathrm{BC}^H} H_t) \cdot \mathrm{BC} - \varphi_{\mathrm{WC}^H} H_t \cdot \mathrm{WC} \end{aligned} \tag{3}$$

and is measured in hours. It enters utility as a function of total hours available, L, minus both time-varying and fixed utility cost parameters. The number of hours worked if working is N_t, and the psychic fixed costs—or possible benefits—of working ($\varphi_{P,\,t}$) at time t when participation $P_t = 1$. Applying for disability insurance benefits has utility cost ($\varphi_{\mathrm{DI},\,t}$) at time t when $\mathrm{DI}_t^{app} = 1$, working in a blue-collar job (φ_{BC}), working in a blue-collar job while in poor health (φ_{BC^H}), and working in a white-collar job while in poor health (φ_{WC^H}). BC and WC are indicators for working in either a blue- or white-collar occupation, and H_t is an indicator for being in poor health. The term $\varphi_{\mathrm{SW},\,t}$ captures the cost of switching occupations and $\mathbb{1}_{\{occ_y \neq occ_o\}}$ is an indicator for the occupations at young and older ages being different.[9]

If the individual does not survive time from period $t-1$ to t, or if he arrives at the model's terminal age T, he leaves assets A_t through bequests that give utility

$$B(A_t) = \frac{\alpha_B (A_t + K_0)^{(1-\eta)\alpha_c}}{1-\eta} , \tag{4}$$

which is the functional form from De Nardi (2004). Here, α_B represents the relative utility weight on bequests and K_0 gives the extent to which bequests are a luxury good.[10]

The estimation of the model will allow for preference heterogeneity across people along three dimensions: patience through discount factor β, the degree of risk aversion η, and the utility cost of performing blue-collar relative to white-collar work, φ_{BC}.

Health, Disability, and Mortality Risks. Individuals face future uncertainty in overall health H_t, disability due to the presence of functional limitations d_t, and a survival probability $s_t < 1$. These transition processes all depend on prior status and age, and the health and disability processes additionally differ by past younger-age and current older-age occupations, with $\mathbf{occ} = (occ_y, occ_o)$.[11]

[9] This utility cost of switching occupations is distinct from the potential monetary cost, which will enter through earnings offers that will be described in equation (16). This reflects the potential loss of occupation-specific human capital not transferred from past work in another occupation as in Kambourov and Manovskii (2009).

[10] Without K_0, it is difficult to distinguish bequest motives from precautionary savings; De Nardi et al. (2010) describe K_0 as the level of wealth at which savings can be interpreted as bequest motives as opposed to precautionary savings.

[11] It is worth noting here that disability d_t is not synonymous with receiving SSDI or being unable to work, though it is predictive—especially so in blue-collar occupations as incorporated in this model. Also, the health and disability transition processes, perhaps surprisingly, do not differ greatly by occupation over the ages studied here, as will be show in subsection 4.2. This has not been found to be the case, however, over younger ages (Fletcher et al., 2011)

A person's health H_t may be "good" ($H_t = 1$) or "bad" ($H_t = 0$) and the probability of being in health $H_t = j$ is

$$\pi_{ij}^{H}(t) = \Pr(H_t = j | H_{t-1} = i, \mathbf{occ}, t) \quad \text{with} \quad i, j \in \{0, 1\} \,. \tag{5}$$

The disability transition process works similarly, where one may have a functional limitation ($d_t = 1$) or not ($d_t = 0$).[12] The probability of disability status $d_t = j$ is:

$$\pi_{ij}^{d}(t) = \Pr(d_t = j | d_{t-1} = i, \mathbf{occ}, t) \quad \text{with} \quad i, j \in \{0, 1\} \,. \tag{6}$$

The probability that someone alive at age $t-1$ will survive to age t depends on both age and health status, so that survival probability $s_t = s(H_{t-1}, t)$, which allows for mortality to increase with age and poor health.

Disability Application and Insurance. An individual can apply for SSDI at any point before his Social Security Normal Retirement Age but cannot work during that period ($P_t = 0$), reflecting the program requirement of no "substantial gainful employment." Utility coefficient φ_{DI} in equation (3) captures the costs—due to high "hassle" or possible stigma—of going through the application process. The probability $\mathit{\Delta}_t$ of an SSDI application being approved for those who apply ($\mathrm{DI}_t^{app} = 1$) depends on health H_t, presence of functional limitations d_t, and occupation **occ**, so that $\mathit{\Delta}_t = \mathit{\Delta}(H_t, d_t, \mathbf{occ}, t)$. These aspects are designed to reflect the Disability Insurance system described in section 2 as closely as possible, while at the same time keeping the process general enough to be estimated in the model. If his application is approved, $\mathrm{DI}_t^{rec} = 1$, and he immediately receives amount $\mathbf{ssdi}_t$ and annually thereafter, which is equal to the Social Security old-age benefits he would receive by claiming at his Normal Retirement Age.

Wealth, Income, and the Budget Constraint. Every year, the individual agent carries forward wealth through assets A_t and has income Y_t and transfer payments $\mathbf{tr}_t$ that finance "out-of-pocket" medical expenses M_t and consumption c_t. Wealth includes any financial assets and retirement savings accounts, as well as non-financial assets—primarily housing. Assets are accumulated so that

$$A_{t+1} = A_t + Y_t + \mathbf{tr}_t - M_t - c_t \,. \tag{7}$$

Consumption c_t must satisfy the following budget constraint, where in each period savings may occur but additional borrowing may not[13]:

$$A_t + Y_t + \mathrm{tr}_t - c_t \geq 0 \,. \tag{8}$$

Specific sources of income include returns on assets r, own and spousal income, $y_t + y_t^{\mathrm{SP}}$, and any

[12] A functional limitation, as described further in subsection 4.2, exists when someone has difficulty with one or more Activities of Daily Living (ADL)—e.g. walking up a flight of stairs—or Instrumental Activities of Daily Living (IADL)—e.g. preparing a meal.

[13] Following French and Jones (2011) and Hubbard et al. (1995), outside transfers tr_t—which may come from government, charity, or family—provide a consumption floor so that $c_t \geq \underline{c} > 0$, with

$$\mathrm{tr}_t = \max\{0,\ \underline{c} + M_t - (A_t + Y_t)\} \,.$$

Consumption floor $\underline{c}$ is important for the identification of estimated risk aversion levels. The exclusion of M_t from budget constraint (8) allows for medical debt to be acquired but not the accumulation of further debt for non-medical expenses, which to a large degree reflects the data.

Social Security old-age benefits or disability insurance, $\mathbf{ss}_t + \mathbf{ssdi}_t$, so that

$$Y_t = Y(rA_t + y_t + y_t^{\text{sp}} + \mathbf{ss}_t + \mathbf{ssdi}_t,\, \tau)\,, \tag{9}$$

with τ reflecting the income tax structure. The agent's own income from work is a function of his age, health and functional limitations, hours worked, past earnings, and current older-age occupation and longest occupation held at younger ages with shock ω_t:

$$y_t = y_t(H_t, d_t, N_t, y_{t-1}, \mathbf{occ}, t) + \omega_t\,. \tag{10}$$

For those married with working spouses when entering the model, spousal income depends on the agent's earning history and age. Out-of-pocket medical expenses M_t depend on health, income Y_t, whether one receives Medicare insurance coverage, indicated by $\mathbf{med}_t = 1$ if so, and age with error ξ_t:

$$M_t = M_t(H_t, Y_t, \mathbf{med}_t, t) + \xi_t\,. \tag{11}$$

To be covered by Medicare one must be at least age 65 or, with few exceptions, receiving SSDI for two years—that Medicare decreases medical expenses is a feature that is highly relevant for understanding the value of SSDI and application behavior. Details of the functional form assumptions for estimating y_t, y_t^{sp}, M_t, and shocks $\boldsymbol{\epsilon_t} = (\omega_t, \xi_{t-1}, \cdot)$ are described in subsection 4.2.

Timing of Choices and Information. At the beginning of the model, the individual chooses a broad blue- or white-collar occupation, occ^o, to work in for the remainder of his working years. At this time he is plausibly quite familiar with his own preferences over work as well as, broadly, the Social Security retirement and disability programs. Thereafter he makes decisions annually about how much to save and consume, c_t, whether to work, P_t, and if so how much. The individual can costlessly begin claiming Social Security old-age (OASI) benefits, decision SS_t, beginning at age 62 and up to age 70. The annual benefit amount, $\mathbf{ss}_t$, is received immediately at time t when applying and is an increasing function of current and past earnings, "average indexed monthly income" or AIME_t, and age of claiming. At any point prior to his Normal Retirement Age, he may apply for Social Security disability insurance (SSDI) benefits, DI_t^{app}. If approved, he immediately receives benefit amount $\mathbf{ssdi}_t$ annually, which are equal to the level of OASI benefits he would have received if claiming at Normal Retirement Age.[14] Vector $\mathbf{OASDI}_t = (\text{DI}_{t-1}^{rec}, \text{SS}_{t-1}\text{AIME}_t)$ represents the Social Security OASDI program parameters for the individual entering into time t—whether he is receiving SSDI benefits after applying, whether he has claimed and received old-age Social Security benefits, and the earnings history that would determine any Social Security benefits.

Solution to the Individual's Problem. Each agent chooses an occupation to work in at older ages $occ_o = \mathbf{o}$ over occupation $\mathbf{o}'$ if $V_t^{\mathbf{o}}(\mathcal{S}_t) > V_t^{\mathbf{o}'}(\mathcal{S}_t)$, where

$$V_t^{\mathbf{o}}(\mathcal{S}_t) = \max_{\mathcal{D}_t} \Big\{ u(c_t, L_t) + \beta\big[(1 - s_{t+1})B(A_{t+1}) + s_{t+1} EV_{t+1}^{\mathbf{o}}(\mathcal{S}_{t+1})\big] \Big\}\,, \tag{12}$$

with

$$EV^{\mathbf{o}}(\mathcal{S}_{t+1}) = \max_{\mathcal{D}_{t+1}} \int V^{\mathbf{o}}(\mathcal{S}_{t+1})\, dF(\mathcal{S}_{t+1} \,|\, \mathcal{S}_t, \mathcal{D}_t, t)\,. \tag{13}$$

[14] While a potentially lengthy process, those whose SSDI application is approved receive retroactive benefits; SSDI benefits automatically convert to OASI benefits upon reaching one's Normal Retirement Age.

Following the one-time decision of occupation for work at older ages, he makes a series of decisions at each time t, represented by $\mathcal{D}_t = (c_t, P_t, \mathrm{SS}_t, \mathrm{DI}_t^{app})$, subject to budget constraint equation (8). After this, decisions are made annually knowing the state space $\mathcal{S}_t = (A_t, H_t, d_t, P_{t-1}, \mathbf{OASDI}_t, \mathbf{occ}, \boldsymbol{\epsilon_t})$ with uncertainty over, but knowing the distribution of uncertain outcomes, $F(\mathcal{S}_{t+1} \,|\, \mathcal{S}_t, \mathcal{D}_t, t)$, conditional on current state variables and the transition processes given current survival, health, and disability, equations (5)-(6), earnings (10), medical expenses (11), and probability of SSDI application approval $\varDelta_t$.[15] In practice, I solve (12) numerically over the state space, for a given set of preference parameters, through backwards induction from maximum age T.

Details on state space discretization and interpolation are in Appendix A.4.

4. Estimating Parameters through Method of Simulated Moments

The parameters of the model are estimated through the method of simulated moments (MSM), a minimum-distance estimation method that can be applied for discrete choice models such as this, which do not have closed-form solutions.[16] This estimation is performed here through a two-stage procedure, as first demonstrated for life-cycle models in Gourinchas and Parker (2002) and Cagetti (2003), and applied in the older-age, life-cycle models that are the basis for this model, French (2005), French and Jones (2011), and De Nardi et al. (2010). In the first stage, the parameters determined outside of the modeled process are determined. These include health, disability, and survival transition processes; conditional SSDI approval rates; medical spending; and (partial-equilibrium) earnings processes. First-stage estimates then enter into the model in the second stage, which involves finding that parameters that generate simulated behavior closest, in the generalized method of moments (GMM) sense, to the behavior in the data. These second-stage parameters include preference parameters, coefficients on an equation predicting preference types, and the equilibrium effects on wages, with this wage component being based on methods from Card and Lemieux (2001), Lee (2005), and Johnson and Keane (2013).

4.1. Data from the HRS and O*NET

The primary data set I rely on comes from the Health and Retirement Study (HRS), a rich panel study of Americans age 50 and their spouses. The HRS survey began in 1992 and is conducted biennially, offering extensive data on health, family, work, finances, and much more. My sample includes 2,507 men born between 1931–47 who have a high school education or some college, and I study responses from 1996 through 2014, for a total of ten waves.To categorize jobs as blue-collar or white-collar, I turn to occupational characteristics in O*NET, which are offered for all three-digit occupations. I sort occupations into "blue-collar" or "white-collar" depending on the degree to which psychomotor and physical skills are required by three-digit occupation, seen visually in Figure 1, where the cluster of occupations with higher (lower) physical requirements are categorized as blue-collar (white-collar). More details on sample selection are provided in Appendix A.1

[15]These do not all appear explicitly as state variables since some state variables are functions of these outcomes.
[16]This method was developed in McFadden (1989) and Duffie and Singleton (1993).

Table 2: *Some Characteristics of the HRS Sample* confirm up-to-date

Education				
Less than High School, High School		59.1%		
Some College, College		40.9		
Percent in Occupation	Older Ages		Younger Ages	
Blue-Collar	52.6		56.4	
White-Collar	47.4		43.6	
	Median Permanent Income by Quantile[2]			
	Centile:	25$^{\text{th}}$	50$^{\text{th}}$	75$^{\text{th}}$
High School:				
Blue-Collar (67.1%)		$ 31,014	44,495	59,596
White-Collar (32.9%)		31,131	49,372	67,367
Some College:				
Blue-Collar (42.8%)		$ 33,318	45,237	62,500
White-Collar (57.2%)		38,644	61,025	87,398

[1]The proportion in all education categories in the HRS for these birth years is (a) *less than HS*, 23.4%, (b) *GED*, 5.8%, (c) *high school graduate*, 28.9%, (d) *some college*, 20.0%, (e) *college and above*, 22.0%.
[2]Corresponds to AIME within birth year cohort, 2010$.

4.2. First-Stage Parameter Computation

The agents' beliefs over uncertain future health, functional limitations, survival, spousal income and medical costs are measured in this stage and are incorporated as fixed parameters of the model in the second stage of estimation.

Functional Limitations, Health Risks, and Survival. While there are a number of ways to capture physical ability in the HRS data, I use a measure of *functional limitation*—that will be proxy for physical ability—as well as the *self-reported health* measure, which is a popular choice in many studies using HRS data and will be useful here as well, especially in forming mortality expectations. Both the functional limitation and health transition probabilities are estimated separately by occupation, and a snapshot of the estimates are shown in Table 3. While they do not differ greatly by occupation, the initial distribution of health is somewhat worse for those in blue-collar jobs. How the transition processes are applied computationally in practice is that for each t the simulated agent receives a shock, and the transition probabilities determine cutoffs for that value translating to a particular outcome.[17]

Survival probability s_t is a function of health and age so that $s_t = s(H_t, t)$. I follow French (2005) in computing conditional survival probabilities using Bayes' Rule, with

$$s(H_t, t) = \Pr(\text{Survive}_t \,|\, t_{t-1} = h) = \frac{\Pr(H_{t-1} = H \,|\, \text{Survive}_t)}{P(H_{t-1} = H)} \times \Pr(\text{Survive}_t)$$

[17]Because the HRS gives us two-year state transitions, I estimate the one-year state transition processes following De Nardi et al. (2010) for health, functional limitations, and survival. The two-year state transition probabilities, where s is generically health, functional limitation, and survival with outcomes in set $\mathbf{S}$ conditional on individual status vector $x_{i,t}$ is $\Pr(s_{t+2} = \ell \,|\, s_t = j) = \sum_{k \in \mathbf{S}} \Pr(s_{t+2} = \ell \,|\, s_{t+1} = k) \cdot \Pr(s_{t+1} = k \,|\, s_t = j) = \sum_{k \in \mathbf{S}} \pi_{k\ell,t+1} \pi_{ik,t}$ where $\pi_{ik,t} = \frac{\exp(\mathbf{x}'_{i,t}\boldsymbol{\beta}_k)}{\sum_{m \in \mathbf{S}} \exp(\mathbf{x}'_{i,t}\boldsymbol{\beta}_m)}$. Coefficient $\boldsymbol{\beta}_k$ is estimated using maximum likelihood and used to approximate the corresponding figures in the transition matrices.

Table 3: *Select Functional Limitation and Health Transition Probabilities:*

	Probability of Good Health $t+1$		Probability of No Functional Limitation $t+1$	
	White-Collar	*Blue-Collar*	*White-Collar*	*Blue-Collar*
Good Health or No Limitation in t, age:				
50-54	.88	.87	.80	.78
60-64	.84	.84	.73	.70
Poor Health or Limitation in t, age:				
50-54	.79	.81	.89	.90
60-64	.88	.89	.94	.93

for $H \in \{\text{good, bad}\}$. In estimation I assume that the final $T = 90$ regardless of health status.[18]

Probability of SSDI Approval. The probability Δ_t of an SSDI application being approved for those who apply ($\text{DI}_t^{app} = 1$) depends on health H_t, presence of functional limitations d_t, and occupation **occ**, so that $\Delta_t = \Delta(H_t, d_t, \mathbf{occ}, t)$. I take a logistic regression of approval for those who applied in the model on these factors. The probability of approval is higher for those in bad health, with functional limitations, in blue-collar occupations, and who are older. For illustration, a person who is age 55 in bad health, has a functional limitation, and is in a blue-collar occupation has about an 82 percent chance of being approved if he applies, where if he were in a white-collar occupation his likelihood of approval would be 75 percent. Not having a functional limitation reduces both probabilities by fifteen percent. The overall rate of at which an SSDI application is ultimately approved in the HRS is 76 percent. This is somewhat higher than the national average, likely owing to this sample being older than the national population.

Medical Expenses, Return on Assets, and Spousal Earnings This first stage includes basic estimates of log out-of-pocket medical expenses M_t depend on state variables health, income Y_t, age, and whether one receives Medicare insurance coverage, indicated by $\mathbf{med}_t = 1$. As discussed in Section 3, very high medical expenses do not carry over as debt for more than one period but do drive consumption down to consumption floor $\underline{c}$. Medical expenses are higher for those in worse health, older, and have higher levels of income. Medicare coverage, however, is associated with medical expenses that are about 23 percent lower for those in bad health and covered by Medicare, making it a potentially valuable aspect of receiving SSDI. Lower medical expenses with lower income Y_t may be due to some combination of lower demand for health and medical care, greater charity care, and receipt of means-tested Medicaid benefits. Return on assets is assumed to be $r = 0.03$, common in many studies of savings behavior over the same time period. Log income from spousal earnings, y^{sp} depends on respondent's work status and permanent income level, asset level, and respondent's age, which are all state variables of the model.

[18] Survival probabilities are obtained from the U.S. Social Security Administration's *Office of the Chief Actuary* reports: Actuarial Study 120, "Life Tables for the United States Social Security Area 1900-2100" by Felicitie C. Bell and Michael L. Miller. Available at `www.ssa.gov/oact/NOTES/as120/LOT.html`. These give one-year survival probabilities at age t by sex and birth year cohort, conditional on survival up to age t. I use the 1945 birth year cohort.

4.3. Second-Stage Parameter Estimation

In this stage, we take estimates determined in the first stage and, through MSM, solve for the preference parameters of heterogeneous agents and parameters determining the equilibrium relative wage in both blue- and white-collar occupations. Analytically, letting the parameters estimated in the first stage be represented by $\widehat{\chi}$ and θ denote the vector of parameters estimated in the second stage—including parameters of the utility function, fixed costs of work, and type prediction—the estimator $\widehat{\theta}$ is given by

$$\widehat{\theta} = \underset{\theta}{\operatorname{argmin}}\ \widehat{\boldsymbol{\phi}}\,(\theta, \widehat{\chi})'\ \varOmega\ \widehat{\boldsymbol{\phi}}\,(\theta, \widehat{\chi}) \tag{14}$$

where $\widehat{\boldsymbol{\phi}}$ denotes the vector of moment conditions described below from the HRS data and simulated behavior for a given set of parameters. The weighting matrix $\varOmega$ contains the inverse of the estimated variance-covariance matrix of the estimates of the sample moments along and off the diagonal.

4.3.1. Second-Stage Moments and Associated Parameters

The moment conditions identifying the parameters of the model consist of the HRS and simulated data on choice of occupation, SSDI application and health, work and retirement, and savings. Specifically:

- *Share in Occupations, Switching.* To identify the utility cost of BC work (φ_{BC}) and cost of switching occupations (φ_{SW}), I match moments on (i) the share in blue-collar and white collar occupations at older ages and the share in blue-collar jobs at older ages for those who worked in (ii) blue-collar jobs and (iii) white-collar jobs at younger ages. (*3 moments.*)
- *Disability Application and Approval.* The stigma or hassle utility cost of going through the SSDI application process by age, $\varphi_{\text{DI},t}$, comes from moments on (i) SSDI application by age 55 by regular income quartile and occupation and (ii) disability application ever (for this model, after age 50) by regular income quartile and occupation. (*8 + 8 = 16 moments.*)
- *Work and Retirement Timing.* This set includes a number of moments by two-year age groups for ages 51 to 72 ($T = 11$ groups). These are (i) the proportion working full-time, part-time, and not working by occupation, and age (ii) the proportion working (either full- or part-time) by health status, occupation, and age. Together these help to identify time-varying fixed cost of work ($\varphi_{P,t}$), disutility of working while in bad health (φ_{BC^H} and φ_{WC^H}), disutility of working in blue collar jobs (φ_{BC}), and relative utility weight on consumption (α_c). (*4T + 4T = 88 moments.*)
- *Assets and Savings.* These moments include (i) median total assets by five age group,[19], tertile of regular permanent income (corresponding to AIME and occupation and (ii) the ratio of assets at the 75th/25th percentiles by age group, occupation. These identify risk aversion (η) and patience (β), weight on consumption α_c, bequest parameters K_0 and α_B, consumption floor $\underline{c}$. (*30 + 10 = 40 moments.*)

[19] The moments are by age group as opposed to age due to the small cell sizes for some categories combined with the high variance in wealth holdings.

4.3.2. Heterogeneous Preference Types

The assignment of preference types depends on the initial characteristics of individuals and is made alongside the estimation of preference parameters and the equilibrium component of earnings in the second stage.[20] I include four possible preference profile types, which can differ in degree of risk aversion, η, patience, β, and (dis)taste for blue collar work, φ_{BC}. Though η is sometimes determined outside of the model in similar studies, I estimate this in the second stage and allow it to differ by type given that, as we will see, this parameter plays a significant role in determining the cost of health and disability risks and, consequently, the value of disability insurance.[21] Heterogeneity in φ_{BC} allows for realistic variation in preferences that influence choice of occupation, which is a central decision in this model. To predict the types, I estimate the coefficients of a multinomial logistic regression within the second MSM stage, where the probability of individual i being *Type* $n \in \{\text{I}, \text{II}, \text{III}, \text{IV}\}$ is

$$\Pr(i{=}\textit{Type } n) = \frac{\exp(\boldsymbol{b}_n \boldsymbol{X}_i)}{1 + \sum_{k \neq n} \exp(\boldsymbol{b}_k \mathbf{X}_i)} \tag{15}$$

where

$$\begin{aligned}\boldsymbol{b}_n \mathbf{X}_i =& b_{n,0} + b_{n,1}(\text{Asset/Income})_i + b_{n,2}(\text{Education})_i \\ &+ b_{n,3}(\text{Physical Activity})_i + b_{n,4}(\text{Income Gamble})_i \,,\end{aligned}$$

so that the probability of having one of four combinations of β, η, and φ_{BC} is predicted by an HRS respondent's assets relative to permanent income at age 50, education, physical activity enjoyment question, and responses to an income gamble question about earnings choice for a hypothetical job intended to capture risk aversion.

4.3.3. Earnings and Computing Labor Market Equilibrium

The equilibrium component of earnings is also calculated as part of the second stage, and is affected by the proportion of simulated individuals choosing each occupation. To compute the equilibrium component, I rely on methods described below from Card and Lemieux (2001), Lee (2005), Johnson and Keane (2013) while making some modifications to comport with the model here. In addition to the equilibrium component of relative earnings between high- and low-skilled blue- and white-collar workers, earnings also depend on age, health, and functional limitations interacted with occupation. Specifically,

$$\begin{aligned}\ln y_t = \quad & EQ^*_{j,e} + \gamma_0 + \gamma_1 N_t + \gamma_2 \text{Age}_t + \gamma_3 \text{Age}^2 + \gamma_4 \mathbb{1}_{\{\text{BC},\textit{poor H}\}} \\ & + \gamma_5 \mathbb{1}_{\{occ_y \neq occ_o\}} + \gamma_6 \mathbb{1}_{\{\text{WC},\textit{poor H}\}} \\ & + \gamma_7 \mathbb{1}_{\{\text{BC}, \textit{ func. lim.}\}} + \gamma_8 \mathbb{1}_{\{\text{WC}, \textit{ func. lim.}\}} + \omega t\end{aligned} \tag{16}$$

autoregressive component $\omega_t = \rho_\omega \omega_{t-1} + \nu_t$, with correlation coefficient ρ_ω and transitory shock $\nu_t \sim N(0, \sigma^2_\nu)$. It is assumed that the individual knows ω_{t-1} and the distribution of future ν_t but not ν_t itself, and $EQ^*_{j,e}$ represents the equilibrium component of relative wages in occupation j and

[20] This approach is based on Heckman and Singer (1984) and incorporated in Keane and Wolpin (1997), French (2005), van der Klaauw and Wolpin (2008), French and Jones (2011), and others.

[21] For example, Low and Pistaferri (2015) set a parameter with roughly the same interpretation as η in this paper to 1.5, while Chandra and Samwick (2009) set the coefficient of relative of risk aversion to 3 for their exercises.

for skill measured by education level $e \in \{SK, USK\}$.

Subtracting $EQ^*_{j,e}$ from both sides and expressing the remaining terms on the right hand side of equation (16) as $y_t = y_t(H_t, d_t, N_t, y_{t-1}, \mathbf{occ}, t)$ to get

$$\ln w_{it} - EQ^*_{j,e} = y_t = y_t(H_t, d_t, N_t, y_{t-1}, \mathbf{occ}, t)\,, \tag{17}$$

I calculate coefficients of equation (17) are calculated fixing $EQ^*_{j,e}$ at the value implied from share and substitution parameters of equations (23) and (22) in Appendix A.3 here from Johnson and Keane (2013) Tables 1 and 3, with the proportion of high- and low-skill blue- and white-collar workers being equal to observed proportions in the HRS, as presented in Table 2 of this paper, which are $\frac{L_{SK}}{L_{USK}} = 0.69$, $\frac{L_{\mathrm{BC}}}{L_{\mathrm{WC}}} = 0.90$, $\frac{L_{\mathrm{BC},SK}}{L_{\mathrm{WC},SK}} = 0.71$, and $\frac{L_{\mathrm{BC},USK}}{L_{\mathrm{WC},USK}} = 1.80$, where $L_{j,e}$ is the share of labor in occupation j and skill e.

Table 4 shows the coefficient estimates on age, health, functional limitations or disability, full- versus part-time hours and the effects of switching occupations at older ages. These estimates look similar to those of Aaronson and French (2004) on the effects of part-time work and Johnson and Neumark (1996) on the earnings of older men more generally. There is clearly a much larger effect on wage estimates for those in blue-collar jobs relative to those in white-collar jobs who have poor health (percent loss in earnings is about four times greater for blue-collar workers) or a functional limitation (percent loss is ten times greater, though imprecisely estimated for white collar workers).

To compute the number of individuals choosing each occupation in equilibrium in the second stage, I make the simplifying assumption that the coefficients of equation (17) do not vary with $EQ^*_{j,e}$ as $L_{\mathrm{BC},e}/L_{\mathrm{WC},e}$ varies. In addition, while $EQ^*_{j,e}$ may change over time, I assume this component is deterministic from the point of view of the decision-making agent and persists in to the future, as opposed to agents forecasting the entire equilibrium path, further simplifying the problem. $EQ^*_{j,e}$ is implied by the labor supply ratio $L_{\mathrm{BC},e}/L_{\mathrm{WC},e}$ for ratios centered around one. For each term $EQ^*_{j,e}$,

TABLE 4: *Earnings Equation Estimates*

Outcome: $\ln$ *Annual Earnings* $- EQ^*_{j,e}$		
Variable	*Coefficient*	*(s.e.)*
Age (years)	.109	(.027)
Age^2	-.001	(.000)
Functional Limitation, d_t		
White-Collar	-.008	(.013)
Blue-Collar	-.081	(.012)
Poor Health, H_t		
White-Collar	-.012	(.008)
Blue-Collar	-.047	(.010)
Full-Time Work, N_t	.788	(.043)
Switch Occ.	-.003	(.001)
$\widehat{\rho_\omega}$ (autoreg. coeff.)	.944 (.018)	
$\widehat{\sigma}^2_\nu$ (trans.)	.036 (.009)	

Note: Observations n=11,257, individuals=2,180. Controls for year and Census division. Being just above Early and Full Social Security claiming ages used as exclusion restrictions.

occupation decisions are made by individuals through the process described in steps (5) through (7) in subsection A.4. This processes is repeated until occupational choices giving labor supply ratio $L_{s,\mathrm{BC},e}/L_{s,\mathrm{WC},e}$ satisfying $L_{\mathrm{BC},e} + L_{\mathrm{WC},e} = N_e^{\mathrm{SIM}}$ are found, and N_e^{SIM} is the number of simulated individuals with education level e.

5. Model Estimation Results

5.1. Parameter Estimates

The utility parameter estimates found through the second stage are shown in Table 5, which includes the specifications from Section 3. The top set of estimates include parameters that are constant over time and do not vary across people; the middle set of parameters vary with age; and the lower set shows estimates that are free to vary by preference types.

Constant utility parameters. Of the parameters that do not vary across people or age, two that are of particular interest for the questions studied here φ_{BC^H} and φ_{WC^H}, the utility cost of working while in bad health in blue- and white-collar jobs, which are estimated to be equivalent to having, respectively, 310 and 195 fewer hours of leisure in a year. These are identified through rates of work by health status, occupation, and through participation by age, with health being a function of age. Along with the earnings processes, which declines for both occupations with age and more steeply for blue collar work, this is one of the main drivers of labor force exit as health declines with age, and of the more rapid blue-collar labor force exit.

Time-varying utility parameters. The fixed cost of work, $\varphi_{P,t}$, varies with age and is equivalent to 262 hours of leisure up to age 55, and increases by 31 hours for each year after, generated by the labor force participation rate declining even for those in good health, the rate of part time work, and the transitions from full-time directly to retirement. The stigma or hassle cost of applying for SSDI, $\varphi_{\mathrm{DI},t}$, also varies with age and is estimated to be equivalent to the utility loss of having 302 fewer hours of leisure in the year for ages up to 55. This parameter is identified primarily through the rate at which people with different levels of income and in different occupations apply for SSDI. A higher (lower) measure would generate too few (many) people applying for SSDI relative to the data. Past age 55, when more people apply for SSDI, the utility cost is estimated to be a lower 149 hours. An additional cost of applying for SSDI comes through the requirement—which reflects the SSDI program—that the applicant cannot be approved if gainfully employed. Without this aspect being included in the model, the estimate φ_{DI} would be higher.[22] The cost of switching occupations between ones younger and older years has a utility cost of 99 hours per year up to age 50, and declines to 32 hours annually after age 55.

Parameters varying across preference types. Realistically accounting for preference heterogeneity allows for a better match on several features of the data—here, primarily asset distributions and choice of occupation. For this study, these features are central to the question of the valuation of insurance like SSDI and the effects of the availability of this program on the occupations people choose. I find that preferences in this model vary noticeably across preference types, with time

[22] This is the way in which the risk of stopping work in order to not have one's application summarily rejected, as emphasized in Low and Pistaferri (2015), is captured.

preference β ranging from .79 to .95, and risk aversion η ranging from 3.55 to 7.04, which interacts with many aspects of behavior, especially the spread in assets. The cost of performing blue-collar work as opposed to white-collar work, φ_{BC}, is found to vary across preference Types, ranging from a disutility equivalent to 51 up to 153 fewer hours of leisure. This is identified through choice of occupation by otherwise similar individuals and labor force participation levels across ages and occupations. The Types with the lowest cost of doing blue-collar work, I and II also have the highest shares choosing blue-collar work in the model, as shown in the last row of Table 5. The preference type with the lowest time preference estimate and degree of risk aversion, Type I, is also the type with the lowest estimated cost of performing blue-collar work and highest share choosing blue-collar occupations; Type III has the highest degree of risk aversion and shares the highest rate of time preference, has the highest estimated cost of doing blue-collar work, and the lowest share choosing blue-collar occupations. These particular combinations will have implications for measurements of the value and impacts of SSDI.

5.2. Model Fit: Data and Simulated Profiles

Many of the profiles found in the HRS data are closely replicated through the model. Shown here are the data and simulated moments for labor force participation, various moments related to assets, and SSDI application behavior.

The model is able to reflect two important aspects of labor force participation behavior seen in the HRS data that are central to the research here. The first is the lower levels of work among those in poor health, as seen in the left panel in Figure 3, relative to those in good health, seen in the right panel. The second, also in Figure 3 is the tendency for those in blue-collar jobs to be less likely to work relative to those in white-collar jobs for all ages when in poor health and at older ages for those in good health. These features are driven by the parameters φ_{BC^H} and φ_{WC^H}, while the overall decline in work with age holding health constant is primarily driven by increasing $\varphi_{P,t}$ and declining earnings with age.

Figure 4 shows median total asset levels by age category, occupation, and average income tertile in the HRS data (left panels) and in simulated behavior (right panels). The model generates three

FIGURE 3: *Data and Simulated Labor Force Participation*

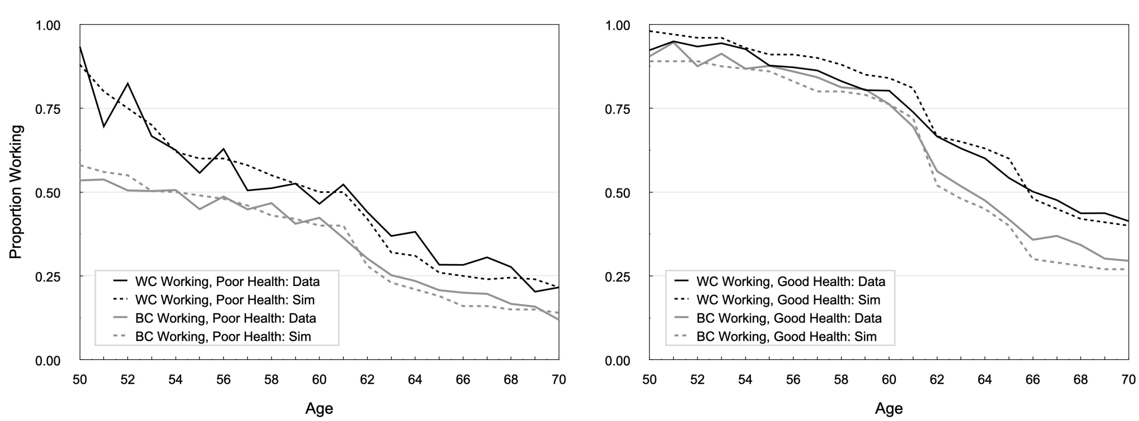


Table 5: *Utility Parameter Estimates*[*]

Utility Specifications

$$u(c_t, L_t) = \frac{1}{1-\eta}\left(c_t^{\alpha_c} L_t^{1-\alpha_c}\right)^{1-\eta} \qquad \text{(Utility)}$$

$$\begin{aligned} L_t = L - N_t - \varphi_{P,\,t} P_t - \varphi_{\mathrm{DI},\,t} \mathrm{DI}_t^{app} - \varphi_{\mathrm{SW},\,t} \mathbb{1}_{\{occ_y \neq occ_o\}} \\ -(\varphi_{\mathrm{BC}} + \varphi_{\mathrm{BC}^H} H_t) \cdot \mathrm{BC} - \varphi_{\mathrm{WC}^H} H_t \cdot \mathrm{WC} \end{aligned} \qquad \text{(Leisure)}$$

$$B(A_t) = \frac{\alpha_B (A_t + K_0)^{(1-\eta)\alpha_c}}{1-\eta} \qquad \text{(Bequests)}$$

Constant Utility Parameters

α_c: consumption weight	.54	K_0: bequest shifter	\$355K
	(.07)		(49K)
φ_{BC^H}: BC working in bad health	310	α_B: bequest weight	.039
	(25)		(.009)
φ_{WC^H}: WC working in bad health	195	$\underline{c}$: consumption floor	\$8,150
	(19)		(308)

Time-Varying Utility Parameters

$\varphi_{P,t}$: fixed cost of work, $t = 50$ to 55	262	$\varphi_{P,t}$ for $t > 55$[a]	293
	(9)		(11)
$\varphi_{\mathrm{DI},t}$: applying for SSDI, $t = 50$ to 55	302	$\varphi_{\mathrm{DI},t}$ for $t > 55$	149
	(22)		(17)
$\varphi_{\mathrm{SW},t}$: switching occupations, $t = 50$ to 55	99	$\varphi_{\mathrm{SW},t}$ for $t > 55$	32
	(10)		(8)

Preference Type-Varying Parameters	Preference Type I	II	III	IV
β: time preference	0.79	0.88	0.95	0.95
	(0.06)	(0.04)	(0.02)	(0.11)
η: risk aversion	3.55	6.71	7.04	5.90
	(0.42)	(0.37)	(0.32)	(1.03)
φ_{BC}: cost of blue-collar work	51	110	153	126
	(13)	(13)	(22)	(19)
Proportion in Type category	0.22	0.28	0.34	0.16
Proportion of Type in BC jobs	75%	55%	36%	47%

[*]With bootstrapped standard errors for 80 resamples of 250 simulated individuals in parentheses.
[a]Parameter estimates for some t ages are not displayed; past age $t = 55$, $\varphi_{P,\,t}$ starts at 62 increases linearly with age by $31(t-55)$.

patterns in the data closely. The first is the increase in median assets with age until the late 60s, with a slight decline thereafter for all income tertiles and occupations. If looking at asset levels for each age instead of over age categories, the data moments (not shown here) look somewhat more erratic in a way that is difficult to model, which is the rationale behind the 5-year age groups.

The second pattern in median asset holdings captured is the fairly substantial difference in median levels for those with different levels of regular income when working, also in Figure 4.[23] Looking within each occupation, for nearly all ages those in the highest income tertile have far higher median assets than those in the middle, and those in the middle income tertile hold significantly higher assets than those in the lowest tertile. Controlling for income yields better estimates of η, while estimated of β were less sensitive to this choice. Two aspects the model was not able to replicate is the nearly identical median assets held by blue-collar workers ages 50–54 and the dip in median assets for white-collar workers age 60-64.[24]

Finally, the third feature of median assets in the HRS data that the model captures is the higher median assets held by white-collar workers (lower panels of Figure 4) relative to blue-collar workers (upper panels) *within the same regular income tertile*. This is primarily accounted for in the Table 5 estimates that show that those who select into blue-collar jobs are more likely to be of a preference types with lower risk aversion η and discount factor β. The difference is most pronounced among those in the highest income tertile, where, depending on the age category, median total assets are between 1.5 times to double for white-collar relative to median assets held by blue-collar workers.

The performance of the model in capturing the distribution of total assets held is shown in Figure 5, which gives the ratio of total assets held at the 75th to the 25th percentiles by age and occupation, with moments from the HRS data on the left and the simulated data on the right. The difference between the ratios is somewhat more pronounced in the simulated data than the HRS data for blue-collar workers but is quite close for white-collar workers. The higher ratio at all ages for blue-collar workers is primarily due to a higher share being in the lowest income tertile, a group that holds low assets especially at the 25th percentile, making the 75/25 ratio quite sensitive. Interacting with the spread in income, many preference parameters are connected with the spread in the distribution of assets, though primarily consumption weight α_C, differing risk aversion levels η and discount factor β.

The final collection of HRS data and simulated moments, shown in Figure 6 includes SSDI application rates by regular income quartile, occupation, and first age at application. The data and simulated share of people who applied for SSDI between ages 50 and 55 is shown on the left, while the share of people who had ever applied—which is possible up to OASI Normal Retirement Age of 65 for most of this sample—is on the right. For application rates at both younger and all ages, a lower earned income quartile is associated with a higher rate of SSDI application. Also, within all earnings quartiles, those in blue-collar jobs are more likely—and at ages past 55 *far* more likely—to apply for SSDI.[25] The model generates simulated SSDI application rates that are close to the data for all moments shown here. Allowing for the stigma or hassle cost $\varphi_{DI,t}$ to vary proved

[23]Regular income tertiles are determined across occupations, not within. It is the case that the lowest tertile is made up of more blue-collar workers and the highest includes more white-collar workers.

[24]It's important to note that, in the HRS data, a larger proportion of assets is in housing for those with lower regular income levels, however there is also a higher proportion of people no housing assets among this group.

[25]Regular income categorization could potentially be affected by disability that predates any SSDI application, so that being in the bottom income quartile does not induce SSDI application so much as disability puts one in a

Figure 4: *Data (left) and Simulated (right) Assets*

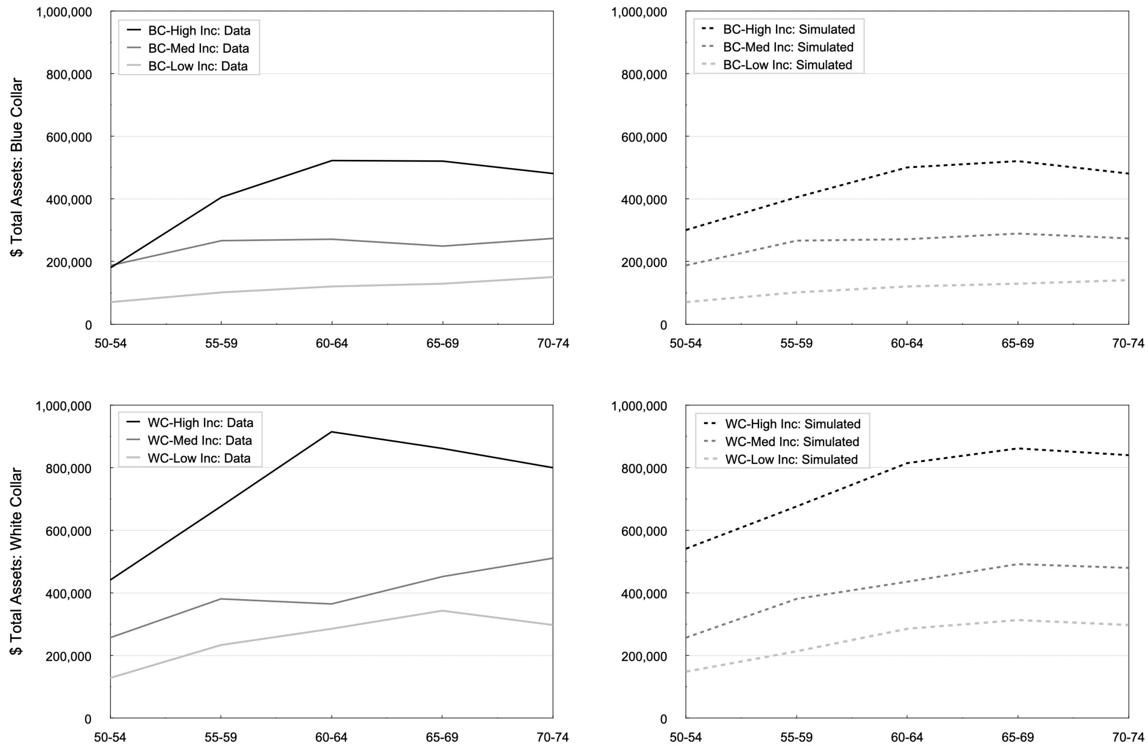
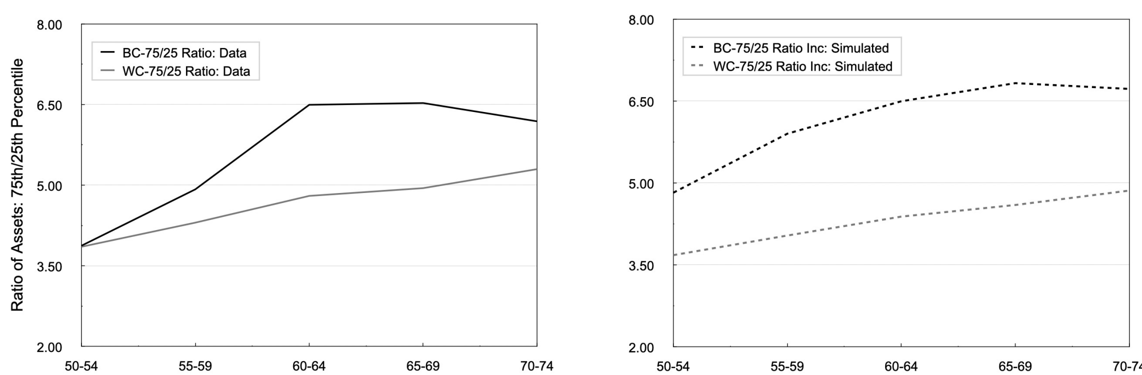


Figure 5: *Data (left) and Simulated (right) 75/25 Asset Ratios*



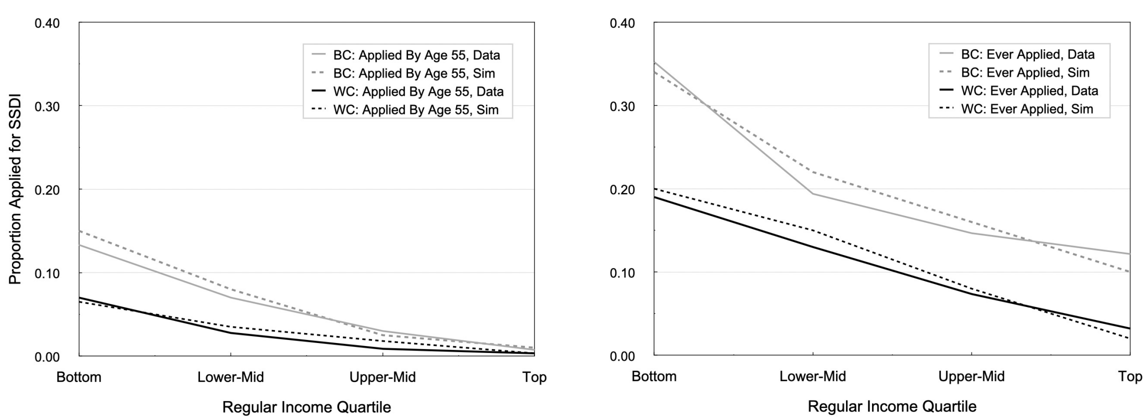
to be important for estimating this model to emit the higher application rates at older ages, which differences in health and disability rates alone could not generate (though not shown here). At the same time, it was not necessary to include related preferences on SSDI application directly with income or occupation, as the differences in application rates for these groups can be attributed to the attractiveness of SSDI benefits relative to earnings when disabled, which differs by occupation as seen in the estimated of equation (17) in Table 4.

6. Counterfactual Analyses on the Impact of SSDI

Having results for the preferences parameters, I use the model to measure responses in behavior and utility under counterfactual scenarios without the SSDI program to address three main questions. The first is what the SSDI program is worth to different types of people—who regardless of their preferences or occupation are taxed in the same way—measured in terms of how much they would be willing to pay to be covered by the program. The second addresses the degree to which SSDI program induces more people to choose blue-collar occupations. Finally, the third question addresses how much, with the higher utilization of SSDI for those in blue-collar work, SSDI subsidizes earnings in blue-collar work. Overall, I find that SSDI is highly valued—at particularly high rates for some preference types—and that there is a degree of moral hazard in the sense that more people choose blue-collar jobs due to SSDI. The moral hazard, however, is mitigated by selection patterns into occupations.

How much is SSDI worth? This question considers what the SSDI program is worth to people who (i) have different preferences, thus valuing the insurance SSDI provides differently, and (ii) work in occupations that make them more or less likely to utilize SSDI. The worth of SSDI is measured here as the percent of earnings people of various preference types and in different occupations would, in the absence of SSDI, need to be compensated in order to make them as well off as they would

Figure 6: *Data and Simulated SSDI Application*



lower income quartile relative to the rest of the sample. The sample analyzed here does not include those who began receiving SSDI and stopped working prior to age 50, which mitigates this issue to an extent. Also, income does not interact with a behavioral parameter but does make any SSDI benefits higher relative to income from work.

be in the status quo world with SSDI coverage. Analytically, compensating variation is the $\vartheta_{n,j}^{CV}$, for Type n in occupation j, that solves

$$V_t(\overline{\mathcal{S}}_t;\,(1+\vartheta_{n,j}^{CV})y_t, \text{no SSDI}) = V_t(\overline{\mathcal{S}}_t;\,y_t, \text{SSDI}) \tag{18}$$

so that receiving earned income $(1+\vartheta_{n,j}^{CV})y_t$ but not having SSDI gives the same utility as a world with SSDI. This is calculated for a state space with median or modal starting values, $\overline{\mathcal{S}}_t$.[26]

The results in Table 6 gives the calculated compensating variations, $\vartheta_{n,j}^{CV}$, interpreted as how much the average person of each preference type and occupation values SSDI, expressed as a percent of their earnings. While there are many other possible ways to express this, the current measure allows for easier comparison against the 1.8 percent of income taxed to fund the SSDI program. For all preference Type-Occupation combinations, the value of SSDI is greater than the required tax on income—for some, far greater. We can the group that places the lowest value is the estimated 6 percent of people who are Type I, which has the lowest degree of risk aversion and time preference (Table 5), and work in white-collar jobs, valuing SSDI at 2.1% of income. The group that places the highest value on SSDI includes the 9 percent of people who are preference Type III, which has the highest level of risk aversion and time preference, and are working in blue-collar jobs. For this group, having the SSDI program is worth a very high 14.5% in additional income. Across the population, the income insurance coverage of SSDI is highly welfare-improving, with an estimated worth of nearly three times the cost, measured at 5.9% of earnings.

Does the SSDI program influence choice of occupation at older ages? Given that those in blue-collar occupations are more likely to apply for and receive SSDI—all else equal—without SSDI, would fewer people would be working in physically intense, blue-collar jobs at older ages?

Table 6: *What is SSDI Worth?*

	Willingness to Pay for SSDI Program, CV as Percent of Earnings, $\vartheta_{n,j}^{CV}$		
Preference Type	Blue-Collar	White-Collar	Both
Type I	3.2 % (.16)	2.1 % (.06)	2.9%
Type II	6.5 (.15)	4.0 (.13)	5.3
Type III	14.5 (.09)	7.1 (.25)	9.1
Type IV	5.9 (.08)	3.5 (.08)	4.5
All Types	8.4 %	4.6 %	5.9 %

The proportion in each Type-Occupation combination is given in the gray parenthesized share below the percent valuation for that combination.

[26] This is represented by an individual who enters the modeled ages with about \$320K in assets, in good health with no functional limitations, and working with median regular earnings of \$48K. In the counterfactual policy with no SSDI, taxes on income are reduced by 1.8 percent, which is the proportion of the FICA/SECA tax on income that funds the SSDI program. Also, people may choose occupations that are different from what they chose in the baseline, SSDI scenario.

The question could alternatively be posed as: "What's the 'moral hazard' SSDI introduces in occupational choice?" To answer this, I measure the share of people who choose each occupation in absence of the SSDI program, where the equilibrium component of wages adjusts with these shares. As shown in the columns on the left in Table 7, I find that while about ten percent (or about five percentage points) more people work in blue-collar occupations because of the existence of the program: 52% choose blue-collar occupations at older ages with SSDI in the baseline scenario, only about 47% do without an SSDI program.

Whether this might be interpreted as a very large difference or not is subjective, though in any case the degree to which a program like SSDI affects older-age occupation choice is tempered by the particular dimensions on which people are estimated to select into occupations. From the model results in the bottom two rows of Table 5, there's a stronger selection of less risk-averse individuals—who for that reason, isolated, should value insurance less—into blue-collar work—in which there is a higher likelihood of work disability and SSDI utilization, making the program more valuable in isolation. This pattern make the counterfactual measure in response to the question of moral hazard in occupation selection more nuanced. For instance, for preference Type I, with its low degree of risk aversion and utility cost of performing blue-collar work for instance, the proportion choosing blue-collar occupations falls only form 75 to 73 percent. For preference Type III, however, with its high risk aversion and cost of performing blue-collar work, the share choosing blue-collar work goes from a low 36 percent to an even lower 27 percent in the absence of SSDI—making it the most affected Type in relative and absolute terms. In other words, the most responsive Type already had the lowest share of the blue-collar workers who would be most affected by the absence of SSDI.

Does SSDI subsidize blue-collar work? The third question addressed through counterfactual analysis using the results of the model asks, given the finding that more people would choose blue-collar jobs if there were no SSDI, what additional amount would need to be paid in blue-collar occupations to achieve the current share choosing blue- and white-collar work *without* the income insurance provided by SSDI. That is, to what extent does SSDI subsidize blue-collar work? To answer this question, for each preference Type I find the percent increase earned in blue-collar jobs that, in a scenario where there is no SSDI program, would be required to result in the same share of each preference Type choosing blue-collar occupations as had in the baseline SSDI scenario. The results are in the rightmost column of Table 7. This is a similar concept to the compensating variation found above, however restricting the choice of occupation makes this figure mechanically at least as high as the $\vartheta^{CV}_{n,j}$.

Overall, maintaining a 52 percent share in blue-collar jobs in a scenario with no SSDI program would require that earnings in blue-collar jobs are 8.9 percent higher. The preference type with occupational choice behavior least responsive to the no SSDI scenario is Type I, which requires an increase of 3.5 percent in blue-collar earnings to increase its share in blue-collar jobs from 73 to 75 percent. For Type III, the most risk-averse, having 36 percent choose blue-collar work instead of 27 percent in the absence of SSDI would require blue-collar jobs pay 14.6 more.

What is effect of SSDI on savings and working years? The final analysis addresses the extent to which the presence of SSDI affects levels of savings and, through affecting savings, the number of total years work. I find that level of assets is higher in the counterfactual scenario

Table 7: *How does SSDI affect the distribution of occupations?*

	Proportion in Blue-Collar Occupations		% Increase in Blue-Collar Earnings to Maintain
Preference Type	SSDI (baseline)	No SSDI Scenario	Blue-Collar Baseline Share
Type I	0.75	0.73	3.5 %
Type II	0.55	0.52	8.0
Type III	0.36	0.27	14.6
Type IV	0.47	0.42	6.3
All Types	0.52	0.47	8.9 %

with no SSDI, and the asset level for those in blue-collar jobs is somewhat more affected than for those in white collar-jobs. For example, for ages 50-54, the simulated level of total assets at the median (a moment which matches vary closely with the HRS data) was about $180K for blue-collar workers, and $259K for white-collar workers. In the no-SSDI counterfactual scenario, those median asset levels rise to $197K for blue-collar workers, and $271K for white-collar workers. So despite blue-collar workers having less risk-averse and patient preference as a whole (as seen in Table 5 estimates), they are more responsive to the scenario where there is no SSDI program. I interpret this as SSDI resulting in lower precautionary savings or self-insurance against disability. As time passes, however, the years for which a work-disabling event also pass and savings looks more like retirement savings. This lower precautionary-turned-retirement savings with SSDI should result in more working years needed to finance retirement. Indeed, I find that blue-collar workers stop work 1.5 years later and white-collar workers stop 0.2 years later than they would if there were no SSDI.

7. Conclusion

The interactions between the physical requirements of different occupations and rising health and disability risks with age constitute a rich environment for studying labor force participation decisions in later life and the effects on occupational choice. The motivation for this study in particular is the large difference in Social Security Disability Insurance utilization rates along with earlier retirement for those in more physically intense, blue-collar occupations. Results strongly suggest that the presence of the SSDI program results in more people choosing to work in blue-collar occupations at older ages.

From these counterfactual analyses, a chief takeaway is that accounting for heterogeneity in preferences is necessary for understanding the effects and value of SSDI. For all preference types, the SSDI program is welfare-improving, though the SSDI program does introduce moral hazard in occupational choice and subsidize blue-collar jobs. The degree of moral hazard, however, is masked somewhat by the selection of less (more) risk-averse people into blue-collar (white-collar) occupations at older ages. This pattern of selection greatly affects estimates for the value and effects of the SSDI program. Results indicate that increases to SSDI benefits may be welfare improving, but that not all preference Types (potential voters) would value increases highly. Whether differences in utilization rates imply that workers or employers should be taxed differently based on occupation characteristics to eliminate moral hazard (so that, like worker's compensation programs there is an element of "experience rating") would require knowing more about how to weigh societal trade-offs.

Future work could use this analysis as a basis for studying two lines of research related to retirement and in SSDI in particular: (1) The decline in SSDI beneficiaries and (2) changes in the SSDI evaluation and approval process. As for the first, there had been a substantial rise in the number and share of people receiving SSDI benefits, however, in the last several years, the rate of application for SSDI benefits and number of beneficiaries has leveled off. While the more recent decline has yet to be widely studied, given the significant difference in SSDI utilization by occupation modeled here, related research could study the role that the changing occupational composition has had on SSDI overall use. The second, related line of research is regarding very probable changes in eligibility criteria on the horizon, motivated by the change in work demands over time and a desire to make the application process more predictable and less burdensome. This study has many of the elements required to analyze the effects of such policy changes.

In summary, this work highlights the important role of occupations as well as heterogeneity in work and risk preferences in studying disability and retirement, allowing us to better understand the value and effects of a significant policy in the U.S. and elsewhere.

A. Appendix

A.1. Details on the HRS Sample

I use the RAND version of the data for most variables (RAND HRS Data, Version L, 2014) and the HRS (Health and Retirement Study, 2014) data directly for variables on some aspects of work conditions, and restricted three-digit occupations and Social Security earnings.

Occupation Categorization. There are alternative ways of categorizing jobs, including through responses in the HRS on how physical one's jobs is, whether kneeling, lifting objects, or other physical demands are required. One drawback for that approach is that these questions are only asked for the respondent's current job, not allowing for categorization of past work, which is critical for this paper. For jobs they are observed working in in the HRS, however, this method aligns very well with the categorization through O*NET characteristics; categorization is the same about 94 percent of the time.

Functional Limitation Variables. The functional limitation measure is the total number of physical limitations out of a possible fourteen. This was formed by totaling the number of physical limitations under three of the six RAND HRS Functional Limitation indices: Mobility (`rWmobila`), Large Muscle (`rWlgmusa`), and Gross Motor Skills (`rWgrossa`). I use responses from `rWslht` as the self-reported health measure. While there are five possible responses, I combine *Excellent*, *Very Good*, and *Good* under the category "*Good*" and *Fair* and *Poor* under "*Poor*" as the distinction among the finer categories did seem to make for a noisier measure while not enhancing the analysis.

Sample Selection. Notably, this sample does not include female HRS respondents, which is common in studies most closely related to this one. Women have, especially for the birth cohorts analyzed here, have significantly lower rates of labor force participation and history; including women in the estimation would necessitate a different model to account for this non-random selection into the workforce. There are several studies in the retirement literature where modeling these decisions is central, e.g. Casanova (2011) on coordination of retirement timing, and Lee (2020) on spousal response to disability. While I do include estimates of spousal earnings in the model, I do not model the work decisions of spouses explicitly, with the expectation that doing would have little effect on the main results. Indeed, Gallipoli and Turner (2011) document that the added-worker effect upon disability is close to zero, similar to Lee (2020).

Within the HRS subsample of those with either a high school diploma or some college but no four-year degree, 60 percent are high school graduates with no college experience. Nearly 58 percent are employed in the more physically intense, "blue-collar" jobs and the other 42 percent are categorized as being in the less physically intense "white collar" jobs. The level of physical intensity is based on O*NET measures of the degree to which psychomotor and physical skills are required by three-digit occupation.[27] The median earnings for each quartile for each occupation type within education level is found in the bottom portion of Table 2, as is the percent in blue-collar and white-collar jobs for each education level. We can see that high-school graduates are more likely than

[27] Alternatively, I have done the same analysis by both categorizing workers by the level of physical effort they report having in their jobs in the HRS and by occupation code using the same categorization as in other models of occupational choice. The former measure makes comparisons across individuals problematic, and the latter left too much variation of the physical requirements within occupation category.

those with some college experience to be employed in blue-collar occupations (67 percent versus 43 percent). Finally, the average income over ages 50 to 60 of those with a high school diploma only does not differ by occupation to the extent that it does for those with some college experience; the median earnings of white-collar workers is about 11 percent higher than for blue-collar workers who are high school graduates, while it's nearly 35 percent higher for those with some college.

A.2. SSDI Application and Award Process

The applicant to SSDI begins a multi-stage screening process, providing information about his medical condition in his application to the SSA, when the condition began to affect and how it affects work, history of prior jobs and the types of duties in the longest job held, as well as level of education and any training received. Application is frequently done with the assistance of paid legal representation, where payment is a share of retroactive benefits paid out. The applicant must not be "substantially gainfully employed" at time of application, with full-time work will typically resulting in automatic denial. The applicant may continue to perform some compensated work, earning up to approximately \$1K per month. He may also return to work if his condition improves and earn more than this amount in a return trial period and continue to receive SSDI benefits if he finds himself unable to continue working during the trial run. This situation is somewhat uncommon but increasingly of interest to the SSA. If he is not working, the severity and expected duration of his condition or impairment is evaluated. While the time from application to an approval or rejection (including appeals) averages over twelve months (Benítez-Silva et al. (1999)), there is an expedited process for easily diagnosed illnesses, including many cancers and most terminal illnesses.

In the next stage of the application process, as described in Lahiri et al. (1995), it is determined whether the applicant is capable of doing work he has performed in the past if not other types of work for which he might be qualified to do. At younger ages, for those having worked in more physically intense jobs having trouble finding a non-physical, or less physically demanding job following the onset of disability, whether or not an SSDI application is approved depends on the particular physical limitations, work history, age, as well as education, training, and transferable work skills. At older ages, the standard for disability is no longer having the capacity to perform jobs performed in the past. At this stage, the application is approved once it has been determined that the applicant is unable to be "substantially gainfully employed" in past or other work, at which point he receives SSDI benefits retroactively to the time of application or onset of disability.

A.3. Labor Market Demand and Equilibrium Earnings

Adapting models from Card and Lemieux (2001), Heckman et al. (1998), Johnson and Keane (2013), Katz and Murphy (1992) to this setup, there is a competitive labor market with capital K_t and labor input L_t at time t, which is made up of skilled and unskilled ($e \in \{SK, USK\}$) based on education level, blue-collar and white-collar workers ($j \in \{BC, WC\}$). Here, while j is a choice in the model, e is treated as an endowment of skills as a simplification, though it will be measured by acquired education category. The substitutability between different types of workers is allowed to vary with time to account for possible skill-biased technological change and furthermore to help identify relative blue- and white-collar wages.

Aggregate production is CRS:

$$Y_t = A_t L_t^{\alpha} K_t^{1-\alpha} . \tag{19}$$

Here, A_t is stage-time productivity, and $\alpha \in (0,1)$ is the share of labor income. Labor inputs of different occupations and skill levels are imperfect substitutes and are represented here as a nested CES aggregate ordered by occupation type, for $j = BC, WC$, and then skill level e, within a time period t and stage s:

$$L_t = \left[\sum_j \theta_{tj} L_{tj}^{\rho_{\mathbf{J}}} \right]^{1/\rho_{\mathbf{J}}} \qquad \text{where} \qquad L_{tj} = \left[\sum_e \varphi_{tje} L_{tje}^{\rho_{\mathbf{E}}} \right]^{1/\rho_{\mathbf{E}}} . \tag{20}$$

Here, θ_{tj} represents the relative productivity of occupation j, which is the same across stages, with $\theta_{t,BC} + \theta_{t,WC} = 1$ as a normalization, while $\sigma_{\mathbf{J}} = \frac{1}{1-\rho_{\mathbf{J}}}$ is the elasticity of substitution between blue-collar and white-collar occupations. Similarly, φ_{tje} is relative productivity for individuals with skill e within an occupation, again with $\varphi_{tj,SK} + \varphi_{tj,USK} = 1$. The elasticity of substitution between skilled and unskilled workers is given by $\sigma_{\mathbf{E}} = \frac{1}{1-\rho_{\mathbf{E}}}$.

The demand function for labor with characteristics j, e in stage s at time t is the marginal product of $p_t Y_t$ with respect to L_{tje} assuming perfect competition in the output market. Normalizing output price at time t to $p_t = 1$ and assuming capital supply is perfectly elastic at price r_t^K, log wages are

$$\begin{aligned} \ln W_{tje} = \ln A_t &+ \ln \left(\alpha \left(\frac{(1-\alpha) A_t}{r_t^K} \right)^{(1-\alpha)/\alpha} \right) \\ &+ \ln \theta_{tj} + \frac{1}{\sigma_{\mathbf{J}}} (\ln L_t - \ln L_{tj}) \\ &+ \ln \varphi tje + \frac{1}{\sigma_{\mathbf{E}}} (\ln L_{tj} - \ln L_{tje}) . \end{aligned} \tag{21}$$

Estimating labor demand. Labor demand is measured from the lower to the upper nest in the CES production function as in Card and Lemieux (2001).

The first step is then to measure the relative productivity of and elasticity of substitution between skilled and unskilled workers for stage s, time t, and occupation type j:

$$\ln \left(\frac{W_{tj,SK}}{W_{tj,USK}} \right) = \ln \left(\frac{\varphi_{tj,SK}}{\varphi_{tj,USK}} \right) + \frac{1}{\sigma_{\mathbf{E}}} \ln \left(\frac{L_{tj,SK}}{L_{tj,USK}} \right) + \xi_{tje} . \tag{22}$$

The term ξ_{tje} represents other factors contributing to differences in skilled and unskilled wages, and $\ln \left(\frac{\varphi_{tj,SK}}{\varphi_{tj,USK}} \right)$ represents "skill-biased technological change" explored in Card and Lemieux (2001). The choice of skill level (education or training acquisition) is determined outside this model. A *skilled* worker is one who has completed at least some college (but has not obtained a four-year degree) or reports having received a certain number of hours of training related to his work (e.g., an apprenticeship). Since ξ_{tje} may be correlated with the relative size of skilled to unskilled labor supplied, $\ln \left(\frac{L_{tj,SK}}{L_{tj,USK}} \right)$, I instrument for this using the variation in past skill ratios across time as in Johnson and Keane (2013) and others prior, which affects choice but not necessarily relative wages, which I describe further below. Substitution elasticity $\sigma_{\mathbf{E}}$ is identified by how the exogenous skill type supply shifts across time change relative wages.

Once estimates from equation (22) have been obtained, I proceed by measuring the relative productivity of and elasticity of substitution between blue-collar and white-collar workers: For stage s, time t, and skill level$e \in \{SK, USK\}$, the relative wages are

$$\ln\left(\frac{W_{t,BC,e}}{W_{t,WC,e}}\right) = \ln\left(\frac{\varphi_{t,BC,e}}{\varphi_{t,WC,e}}\right) + \frac{1}{\sigma_{\mathbf{E}}}\left(\ln\left(\frac{L_{t,BC}}{L_{t,WC}}\right) - \ln\left(\frac{L_{t,BC,e}}{L_{t,WC,e}}\right)\right) + \ln\left(\frac{\theta_{t,BC}}{\theta_{t,WC}}\right) + \frac{1}{\sigma_{\mathbf{J}}}\ln\left(\frac{L_{t,BC,e}}{L_{t,WC,e}}\right), \tag{23}$$

where the first line of the right-hand side in (23) is estimated by (22). To identify substitution elasticity $\sigma_{\mathbf{E}}$, the relative supply of blue-collar to white-collar workers, $\ln\left(\frac{L_{t,BC,e}}{L_{t,WC,e}}\right)$, is instrumented through the changes in the proportion of blue- to white-collar jobs across states. The equilibrium in the *Young* and *Old* labor markets in each stage consists of high- and low-skill, blue- and white-collar wages and proportion in each skill and occupation type satisfying: (i) individuals selecting the sequence of choices $\mathcal{D}_t$ solving (13); (ii) firms choosing the output level Y_t^* that maximizes profit; and (iii) labor demand and labor supplied of each type being equal at wages W_{tje} given in equation (21).

A.4. Computational Details for the Second Stage

I adopt a computational procedure following French and Jones (2011), French (2005) for labor supply decisions with uncertainty, and Lee (2005)'s solving for equilibrium relative wages. First, the agents problem expressed in equation (13) is solved for a given set of parameters, in which the optimal savings (and equivalently consumption) is computed conditional on each labor supply choice p_t (full-time, part-time, and not working), Social Security Old-Age and Survivor's Insurance (OASI) benefit claiming choice $OASI^{app}$ (which can be claimed at age 62 or later), and Disability Insurance (DI) application DI^{app}. Next, whether to apply for DI and then whether to apply for OASI. Finally, the optimal participation choice in any period is the one that yields the greatest value given the optimal savings, DI and OASI application choice, and the realization of the preference shock $\epsilon_t(P_t)$. Next the outer maximization problem of searching across parameters to find the set which generates the behavior of simulated individuals that best matches the data is solved using the two-stage approach.

The solution to (14) is obtained by the following procedure:

1. First compute sample moments and corresponding weighting matrix Ω from the sample data.
2. From the same data, generate an initial joint distribution for wages, health, functional limitations and disability, AIME, assets, occupation type, and variables used in estimating the preference type assigned using the type prediction equation (described below). Some of the first-stage parameters contained in χ are also estimated from these data.
3. Using $\widehat{\chi}$, generate matrices of random health, disability, wage, mortality, and work preference shocks for 1,000 simulated individuals.
4. Each simulated individual receives a draw from the initial distribution in Step 2, and is

assigned one of the simulated sequences of shocks from Step 3.

5. Given $\widehat{\chi}$ and an initial guess of parameter values contained in θ, compute the decision rules over the entire state space solving the individual's problem in equation (12), and generate simulate decision profiles for the decision variables.
6. Compute moment conditions by finding the distance between the simulated moments from Step 5 and true moments, solving equation (14).
7. Using an updated value of θ, evaluate the value function over the state space and compute decisions for the simulated distribution of preference types, repeating Steps 4 through 7 until the $\widehat{\theta}$ that minimizes (14) is found.

Not all numerical methods are well suited to find global optima for objective functions such as the MSM objective that $\widehat{\theta}$ in equation (14) solves. The parameters that are found to be numerically optimal by these methods are often quite close to the starting parameter values supplied, even with reasonable careful attention to inputs such as steps and tolerance levels. To address this, the method I use here is a combination of grid search (where I generate a very large number parameter combinations) and built-in numerical optimization software taking these combinations as starting values. This supplies a very large number n of starting values for candidate parameters $\{\theta_i\}_{i=1}^n$, and for each of these starting values the set of optimal parameter values found through built-in numerical optimization methods is returned as $\{\widehat{\theta}_i\}_{i=1}^n$. Of these $\{\widehat{\theta}_i\}_{i=1}^n$, what solves (14) is the minimum $\widehat{\theta}$. The script is primarily written in Matlab, with the exception being a portion which calls a C function to fill out the value function for a candidate parameter set, as this particular part of the process is noticeably faster in C than Matlab with the state space being very large. This is done with the aid of computing resources through the University of Wisconsin–Madison Center for High Throughput Computing's *HT Condor*. Size of state space $\mathcal{S}_t = (A_t, H_t, d_t, P_{t-1}, \mathbf{OASDI}_t, \mathbf{occ}, \boldsymbol{\epsilon_t})$

$A_t(10), H_t(2), d_t(2), P_{t-1}(3), \mathbf{OASDI}_t(2,2,5), \mathbf{occ}(2), \boldsymbol{\epsilon_t}(\mathcal{D}_t)(??)$

discretization

From JG: Additionally, each period households receive a set of shocks εit to the payoffs from available choices. These shocks are distributed i.i.d Type I extreme value, with one shock εit(dit) associated with each element dit = [lit, hit] of a household's choice set. As in a standard static logit model, the values of other parameters scale the importance of the model's components relative to the importance of unobservables. The nature of the results remains the same, but the magnitudes of some outcomes have changed. The most notable changes are in improved precision, as some moments are much more closely matched.

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