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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, if not accounted for, would lead to overstating the effects of the SSDI program on behavior. A counterfactual experiment aimed at eliminating the distortion created by uniform SSDI tax rates shows that—even without any additional employer accommodation of disabled workers—occupation-specific tax rates lead to fewer aggregate work-disabled years.

JEL Classification: H31, J14, J24, J26, C63

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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 funding, 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, health, 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 the effects of the SSDI program on behavior.

While there are a number of differences in the work and savings patterns observed across people and occupations, participation in the SSDI program is required for virtually all workers, and the mandatory taxes that contribute to the program are uniform for all. This motivates three sets of questions about the value and effects of SSDI on behavior addressed through the estimated model. The first set of questions is aimed at measuring how much the SSDI program is valued across people with different preferences and occupations. I find that while the value of the program varies greatly—from being worth 2.2 to 14.7 percent of earned income—it is welfare improving for all modeled groups.

The second set of questions concerns what might be considered the moral hazard introduced by the program: 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

[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*

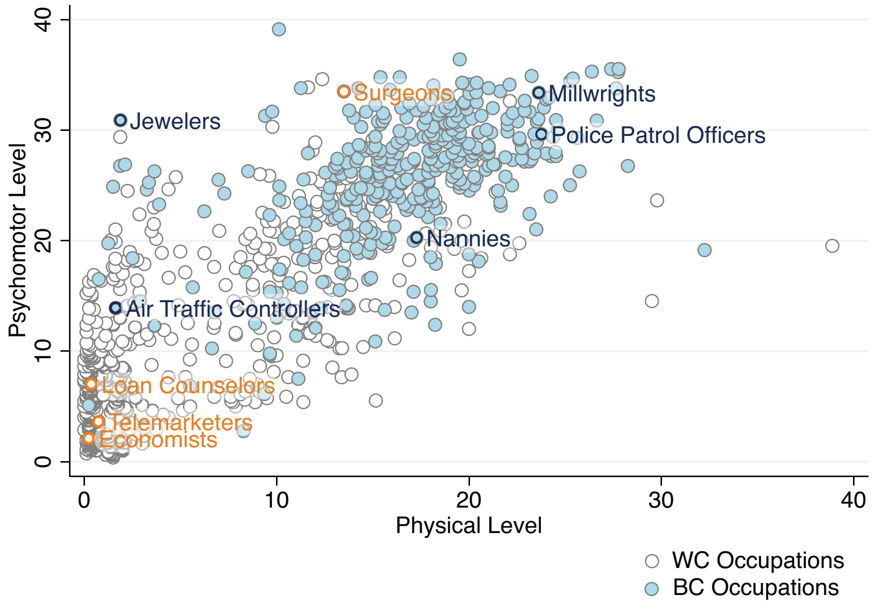


Figure 1: Physical and Psychomotor measures on occupations from O*NET. Each dot represents a three-digit occupation, with select occupations highlighted. Axes are indices of the degree to which physical and psychomotor are skills required in an occupation.

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

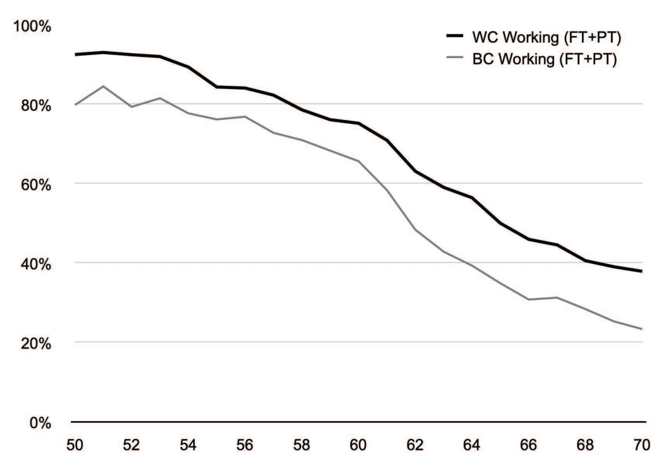


Figure 2: The relative difference in proportion working in WC and BC jobs, while more similar before age 60, increases with age. Participation observations for 22,176 WC and 21,070 BC person-years. Includes all of HRS respondents who have been observed working at least once (and have reported longest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

analysis I find that the program plays an important role in the choice of occupation for older workers with moderate education levels, with the insurance value provided through SSDI 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. So while transitions at older ages tend to be on net from blue-collar to white-collar jobs, the movement to white-collar jobs would be even greater if there were no SSDI. In the same vein, I find 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 for workers with average levels of education would need to be nearly 9 percent greater to compensate for greater risk of being unable to work due to disability in those jobs. Through a counterfactual policy experiment, the apparent distortion created by uniform SSDI tax rates is eliminated through occupation-specific tax rates, which are set so that, within an occupation, SSDI taxes are equivalent to benefits. I find that this has the effect of more people choosing (lower SSDI-taxed) white-collar jobs and fewer average years of work disability.

In addition to older-age occupation decisions, retirement timing and savings decisions are also affected by the presence of SSDI. Through additional counterfactual analyses, I find that SSDI results in what could be categorized as lower precautionary savings or self-insurance against disability—especially for the less risk-averse and patient agents. 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.

The third and final aspect of this paper emphasizes the role of selection into occupations based on risk aversion levels on the overall findings. Working in a blue-collar job, one faces a higher risk of income lost due to disability, making SSDI more valuable to blue-collar workers. However, the results here are that less risk-averse individuals—who, all else equal, value insurance less—select into blue-collar jobs at a greater rate. 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.

This research is complementary to studies across literature in disability and the SSDI program, health and labor supply, and retirement. Recent papers studying the welfare value of public disability insurance like SSDI are Autor et al. (2019) and Cabral and Cullen (2019). Autor et al. (2019) measure the effects of public disability insurance in Norway on earnings, consumption, and own- and spousal- labor supply. They also employ a life-cycle model to estimate the welfare value of public disability insurance and find that, on net, the program is welfare-improving for all types—especially for single households. Likewise, Cabral and Cullen (2019) estimate the value of public insurance like SSDI, though through another approach that is informed by 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. Chandra and Samwick (2009) look at the recent historical prevalence of disability, its effects on savings, and the welfare loss associated with disability. Modeling disability as involuntary permanent retirement, they measure the value of disability insurance for various levels of earnings risk, income replacement rates, and patience in preferences. They find that, on average people would be willing to accept a five percent decrease in lifetime consumption to avoid the average risk of disability, against which SSDI partially insures.

In this paper, I account for preference heterogeneity as well as the effects of occupations, an aspect that aligns with the focus of Michaud and Wiczer (2018). In a calibrated macroeconomic GE model with homogeneous preferences, they measure 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 find that combining this behavior with the finding that selection into occupation is related to risk preferences greatly affects the estimated welfare value of the SSDI program. 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 not only when generating the degree of asset dispersion seen in the data, but also more precisely measuring the value of policy and predicting its influences on behavior.

An important facet of the SSDI program is its relatively complex approval process, which includes a medical determination process and requires the applicant not to have worked for a period of time. The determination process necessarily involves cases of "false rejections" and "false acceptances", which are central to the analysis in Low and Pistaferri (2015). They estimate the effects of making SSDI eligibility criteria less strict and increasing the benefit levels of SSDI and alternative transfer programs. Although these changes would increase false acceptances for the moderately disabled, the changes are on net welfare-improving due to the decrease in false rejections for the severely disabled. Kreider (1999) also models the effect of changes to the application process, finding that eliminating the non-work waiting period and finds that this would increase applications in the same way that increasing benefits by 10 percent would. While the focus of my work here is towards occupations, I do account for such features in the model as the commitment to not working in order to apply—but not necessarily be approved—for SSDI and a similar idea of disability severity through two dimensions of health. These features prove to be important for generating simulated behavior that closely matches the data.

I will proceed with describing patterns in retirement, disability, and occupations from the HRS data, as well as the SSDI program and more related literature 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.

2. Retirement and Disability Patterns Across 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, followed by descriptive statistics from the HRS data that will be captured by the model.

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.[3] The SSDI program alone is substantial, with 9.9 million beneficiaries receiving payments, and total costs of about $148 billion in 2019.

An individual may qualify to receive Social Security Disability Insurance (SSDI) if he is "unable 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 Full-Retirement Age (FRA) for Old-Age benefits.[4] Whether one will meet this criteria and qualify for SSDI benefits is determined through a known, structured evaluation process, however 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 in the HRS sample studied here, which is older than the overall population, a bit over 70 percent are ultimately approved.[5]

The programs under OASDI are closely linked—especially as SSDI benefit calculations are based on Old-Age benefits. I incorporate both programs in the behavioral estimation and analysis here following Benítez-Silva et al. (1999) and Rust and Phelan (1997). If approved for SSDI benefits, the beneficiary will receive a monthly payment equivalent to what he would have received if claiming at his 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 and shorter 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.[6]

In addition to its linkage with Old-Age Social Security benefits, the SSDI program and application behavior may also interact with Medicare and Unemployment Insurance (UI) programs. Beyond monthly cash benefits, SSDI beneficiaries may also receive Medicare coverage. Medicare is a

[3]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.

[4]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 (O'Leary et al., 2012)

[5]More details about the SSDI application and determination process are included in Appendix A.3. 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), estimate a structural model of the timing of SSDI application, emphasizing that while health conditions are precursors to application, timing is affected greatly by SSDI benefits relative to work income.

[6]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.

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.[7] Many studies focus on the interactions between Medicare and UI, including Kitao (2014) and Staubli (2011). Through a calibrated life-cycle model, Kitao (2014) shows the effects that disability insurance and its associated Medicare benefits have on employment and search intensity. She finds that not incorporating Medicare benefits into the analysis would greatly decrease the applications to the SSDI program. Studying the effects of stricter disability insurance eligibility criteria in Austria, Staubli (2011) finds that reforms increased employment *as well as* the share receiving benefits through the unemployment and sickness insurance programs. While I do not incorporate the relatively shorter-term UI here explicitly as my focus is on longer-term behavior, I do, following many other life-cycle studies, incorporate a broad consumption floor that reflects primarily government transfers one would receive in absence of work or SSDI income.

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 born between 1931–1947 who have at least a high school diploma but not a bachelor's degree, who are described further 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). Indeed, this is consistent with Lahiri et al. (2008) who, studying on factors affecting application propensity and work disincentive effects, find that blue-collar and lower-income workers are more inclined to apply for SSDI.

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

Another important aspect of work disability, in addition to its relationship with occupation, is its increasing prevalence with age. Of those who had ever applied for SSDI in the HRS sample

[7]In absence of this feature of SSDI, many would be *Medicaid* eligible. Medicaid is a means-tested health costs insurance program administered at the state level in the U.S. While the value of Medicare may be quite high to certain potential SSDI applicants, the value relative to private health insurance or the means-tested Medicaid benefits this group might otherwise receive might not be so considerable.

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 of of men born between 1931–1947 with a high school diploma or some college; includes 9,204 person-years.

here, over 60 percent did so after age 55.[8] It is also the case that, under regulatory code, those who are at least age 50 are—all else equal—more likely to have their application approved.[9] I find that this makes the HRS, with its in-depth survey of people age 50 and over, well-suited to this study of disability and work.

Taking together (a) the difference in work disability between occupations and (b) its increasing prevalence with age, a major focus of this paper is how the SSDI program affects work decisions at older ages. Table 2 shows that in this sample, while people may switch to and from blue- and white-collar occupations, on net there is a shift towards the less physical, white-collar work with age. Comparing longest held broad occupations before and after age 50, the share working in blue-collar jobs decreases from 56.4 to 52.6. I measure the extent to which these transitions from blue-collar to white-collar jobs would be even greater at older ages in absence of SSDI. I study this and related issues through the life-cycle model and approach described in the following section.

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.[10] The goal with this model is to find the parameters that replicate a number of patterns in the data in order to ultimately 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;

[8]This is also reflected in the Social Security Administration's current beneficiary age distribution data: https://www.ssa.gov/policy/docs/statcomps/di_asr/2019/sect01.html. While more pronounced among beneficiaries as few people leave the program once on it, there is also a notable increase in applications with age.

[9]See the SSA Code of Federal Regulations here: https://www.ssa.gov/OP_Home/cfr20/404/404-1563.htm.

[10]While focusing on health, disability, and occupation, this follows from the broader literature of life-cycle models of retirement and policy in Gustman and Steinmeier (1986), Berkovec and Stern (1991), Blau (1994), and Rust and Phelan (1997)

SSDI application approval; and earnings from work in each occupation. Each person first 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.[11]

Preferences. An individual's utility over consumption and leisure in time t is modeled to exhibit 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 rationale for non-separable utility over consumption and leisure is to match key empirical moments of consumption—as inferred from income and changes in assets—particularly the co-movement of consumption and work. In the HRS data, there is a decrease in consumption that goes along with the decreases in work that occurs at older ages. Reflecting this in the model is necessary as asset moments are crucial in identifying risk and time preference, and are central to calculating the insurance value SSDI provides.[12]

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 the number of hours worked, N_t, and both time-varying and fixed utility cost parameters.[13] The psychic fixed costs—or possible benefits—of working equal $\varphi_{P,t}$ when participation $P_t = 1$. There are utility costs to applying for disability insurance benefits ($\varphi_{\mathrm{DI},t}$) at time t, 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

[11] This model is of behavior from age 50 on to age $T = 90$ or death. However, in Appendix A.2.5, I describe the effects from a model that also includes decisions over occupation and savings at younger ages.

[12] While consumption data is not used here other than the components of medical expenses, and housing as part of savings, it is constructed from income and changes in assets. This is seen, however, in direct consumption data and suggests non-separability. For instance, Browning and Meghir (1991) find non-separable utility better fits empirical consumption and labor supply data. In French (2005), there is an illuminating discussion and a test of the importance of non-separabilities versus shocks in explaining the empirical fall in consumption around retirement. He shows evidence for the decline not being due to shocks but rather non-separable preferences over consumption and leisure.

[13] In computation, the total number of hours L here is be fixed at 4,000, while N_t can be 0 (not working), 1,000 (working part time) or 2,000 (working full-time).

job while in poor health (φ_{WC^H}). DI_t^{app} is an indicator for disability insurance application at time t, 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.[14] The non-separability of consumption and leisure in equation (2) has implications for the estimation and interpretation of these parameters. The first to note is how the utility costs of applying for SSDI come through in the same way work hours do. This is in part because there is a cost in actual time spent, involving, for instance, activities like visiting physicians and possibly lawyers, understanding the system, filling out paperwork, and being at the Social Security Office; the additional costs of hassle or possible stigma are not in terms of hours, however they arguably intensify these time costs. A second and related feature of this setup is that the costs of applying for SSDI, $\mathrm{DI}_t^{app} = 1$, vary with consumption (income) and hours worked: In particular, the cost of applying is greater for people with a lower income or level of consumption in an absolute sense, and in a relative sense or percentage terms, the cost is worse for those who are working and thus have a lower number of leisure hours.

If the individual does not survive 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.[15]

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}. Preference heterogeneity reflecting conceivable differences in taste for savings and work is incorporated into the model for primarily two reasons. The first is so that the model will generate the savings patterns seen in the data—especially the high variation in assets held across otherwise observably similar households. While it is possible to get asset variation without preference heterogeneity with alternative model specifications and shock processes, it is not sufficient for generating the type of variance in the simulated distribution to match the data. Particularly, such models tend to not exhibit very low savers, who are empirically common and are very relevant for the SSDI policy considered here. Preference heterogeneity is one way of successfully generating behavior that will reflect such moments of the data. The second reason for allowing for preference heterogeneity, and over these elements in particular, arises from the interest here in measuring both (a) occupational choice responses to SSDI policy and (b) the insurance value of the policy. If risk and time preferences are related to occupational preferences and choice, accounting for this interaction is necessary for accurately measuring the welfare and behavioral effects of the policy, given the large differences in disability risk and SSDI utilization across occupations.

[14] 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 (14). This reflects the potential loss of occupation-specific human capital not transferred from past work in another occupation as in Kambourov and Manovskii (2009).

[15] 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.

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 $\mathbf{occ} = (occ_y, occ_o)$.[16]

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

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

The disability transition process works similarly, where one may have a functional limitation ($d_t = 1$) or not ($d_t = 0$).[17] The probability of disability status $d_t = j$ is:

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

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 ($\mathrm{DI}^{app}_t = 1$) depends on health H_t, presence of functional limitations d_t, and occupation $\mathbf{occ}$, so that $\mathit{\Delta}_t = \mathit{\Delta}(H_t, d_t, \mathbf{occ}, t)$. If his application is approved, $\mathrm{DI}^{rec}_t = 1$, and he immediately receives amount ssdi_t—including "back pay" to the onset of the disability—and annually thereafter, which is equal to the Social Security old-age benefits he would receive by claiming at his Normal Retirement Age. These aspects are designed to reflect the Disability Insurance system described in Section 2 and Appendix A.3 as closely as possible, while at the same time keeping the process general enough to be estimated in the model. The average real time to approval happens to not be far from the 12 months in this model, which includes the required period of non-work. However, there is a high degree of variation in approval outcomes and times to approval and this variation could in reality depend on effort.[18]

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 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

[16] 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).

[17] A functional limitation, as described further in subsection 4.2 and A.1, exists when someone has difficulty with a physical activity such as walking, climbing stairs, kneeling, or pushing or pulling a large object.

[18] So, while average timing and cost may be picked up by disutility of application and year of non-work regardless of application outcome, the model does not capture the what could be thought of as an intensive margin on effort. At the same time, many hire disability attorneys who can legally charge up to 25 percent of back pay, which is limited to 10 months of SSDI benefits. This may introduce some uniformity in the actual effort individuals exert.

that

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

Consumption c_t must satisfy the following budget constraint, where in each period savings may occur but additional borrowing may not[19]:

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

Specific sources of income include returns on assets r, own and spousal income, $y_t + y_t^{\mathrm{SP}}$, and any Social Security old-age benefits or disability insurance, $\mathrm{ss}_t + \mathrm{ssdi}_t$, so that

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

with τ reflecting the income tax structure. The agent's own income from work in an occupation is a function of his age, health and functional limitations, whether hours worked are part- or full-time, past earnings, and current older-age occupation and longest occupation held at younger ages, with

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

where $\omega_t^{occ_o}$ is an occupation-specific shock with $\omega_t^{occ_o} = \omega_t^{\mathrm{BC}}\,\mathbb{1}_{\{occ_o=\mathrm{BC}\}} + \omega_t^{\mathrm{WC}}\mathbb{1}_{\{occ_o=\mathrm{WC}\}}$.[20] In computation, wage estimates account for selection into work and ω_t^{BC} and ω_t^{WC} are assumed to be uncorrelated. 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 $\mathrm{med}_t = 1$ if so, and age with error ξ_t:

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

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 uncorrelated shocks $\boldsymbol{\epsilon_t} = (\omega_t^{occ_o}, \xi_{t-1}, \cdot)$ 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 and receives information on earnings through productivity shock $\omega_t^{\mathbf{occ}}$. 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

[19]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.

[20]Earnings risk is an important component as Kreider (1998) finds that SSDI applications would be about 15 percent higher in a scenario without earnings risk.

benefit amount, 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 ssdi_t annually, which are equal to the level of OASI benefits he would have received if claiming at Normal Retirement Age.[21] Vector $\mathbf{OASDI}_t = (\mathrm{DI}_{t-1}^{rec}, \mathrm{SS}_{t-1}, \mathrm{AIME}_t)$ 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 $occ_o = o$ over occupation o' if $V_t(\mathcal{S}_t^o) > V_t(\mathcal{S}_t^{o'})$, where

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

with

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

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 $\mathcal{S}_t^o = (A_t, H_t, d_t, P_{t-1}, \mathbf{OASDI}_t, \mathbf{occ}, e, \boldsymbol{\epsilon_t})$ with uncertainty over, but knowing the distribution of uncertain outcomes, $F(\mathcal{S}_{t+1}^o \,|\, \mathcal{S}_t^o, \mathcal{D}_t, t)$, 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 $\mathit{\Delta}_t$.[22] 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.5.

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.[23] 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

[21] 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.

[22] These do not all appear explicitly as state variables since some state variables are functions of these outcomes.

[23] This method was developed in McFadden (1989) and Duffie and Singleton (1993).

Table 2: *Some Characteristics of the HRS and Sample (Unweighted)*

Education, HRS Males Born 1931–47[1]	
<High School	23.4%
GED	5.8
High School	28.9
Some College	20.0
College+	22.0

Percent in Occupations, Within Sample	Younger Ages	Older Ages
Blue-Collar	56.4	52.6
White-Collar	43.6	47.4

Permanent Income at Percentiles, Within Sample[2]	Centile: 25th	50th	75th
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 education categories included in the sample estimated are "High School Graduate" and "Some College".
[2]Corresponds to AIME percentiles within birth year cohort, 2010$.

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. This birth year range allows for a high number of person-year observations for the variables used, and about half of this cohort is represented under the selected education categories. While this less heterogeneous sample allows for arguably more precise model estimates, the results will necessarily be less reflective of those not in the sample. Indeed, for these birth years, not having obtained a high school diploma was more common—at nearly one-quarter of men—than for later cohorts. More details on sample selection are provided in Appendix A.1. 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).

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 composite 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, especially for reasons outlined in Bound (1991) which is that subjective measures are less biased than objective measures alone.[24] The bias from subjective health measures used with the objective measures is even lower, especially in forming mortality expectations. Both the functional limitation and health transition probabilities are estimated separately by occupation, and a snapshot of the estimates is shown in Table 3. The figures in the upper left corner show the probability of remaining in good health at $t+1$ for someone who is in good health at t by age group and occupation. For someone ages 50–54 in good health and in a white-collar occupation, 88 percent can expect to remain in good health at $t+1$, while for someone in a blue-collar occupation it is 87 percent. The lower left area shows that probability of remaining in poor health by age group and occupation. While, perhaps surprisingly, transition probabilities do not differ greatly by occupation, the initial distribution of health is somewhat worse for those in blue-collar jobs. The upper right figures of Table 3 show the probabilities for continuing to have no functional limitations at $t+1$ for someone who had no functional limitations at time t by age and occupation. The figures in the lower right area show the probability of continuing to have any functional limitation by age and occupation. For instance, for someone with a functional limitation at t and age 60–64, the probability of continuing to have a functional limitation at time $t+1$ is 94 percent for white-collar workers and a slightly lower but still high 93 percent for blue-collar workers. 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.[25]

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

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

for $H \in \{\text{good, bad}\}$. In estimation I assume that the final $T = 90$ regardless of health status.[26]

[24] These data variables are detailed in Appendix A.1. Self-reported health and the objective presence of a functional limitation are assumed to be independent conditional on age, which is not strictly true but is a close approximation of the data.

[25] 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.

[26] Survival probabilities are obtained for the 1945 birth-year cohort 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.

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

Probability of SSDI Approval. 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 $\mathit{\Delta}_t = \mathit{\Delta}(H_t, d_t, \mathbf{occ}, t)$. Using the HRS data, 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.[27] 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—which has declined from an allowance rate around 60 to about 50 percent for workers over the past two decades—likely owing to this sample being older than the national population.[28]

Earnings from Work. Earnings depend on age, health, and functional limitations interacted with occupation estimated in this first stage as well as an equilibrium component of relative earnings between high- and low-skilled blue- and white-collar workers estimated in the second stage described in 4.3.3. Specifically,

$$\begin{aligned} \ln y_t^{j,e} = \quad & EQ^*_{j,e} + \gamma_0 + \gamma_1 \mathbb{1}_{\{N_t = \textit{full-time}\}} + \gamma_2 \mathrm{Age}_t + \gamma_3 \mathrm{Age}^2 + \gamma_4 \mathbb{1}_{\{occ_y \neq occ_o\}} \\ & + \gamma_5 \mathbb{1}_{\{\mathrm{BC}, \textit{poor H}\}} + \gamma_6 \mathbb{1}_{\{\mathrm{WC}, \textit{poor H}\}} \\ & + \gamma_7 \mathbb{1}_{\{\mathrm{BC},\ \textit{func. lim.}\}} + \gamma_8 \mathbb{1}_{\{\mathrm{WC},\ \textit{func. lim.}\}} + \omega_t^j \end{aligned} \tag{14}$$

[27] In the presence of any cost associated with application, those with a lower perceived chance of approval or for whom SSDI benefits are relatively lower are less likely to apply. To the extent that this non-applicant group could face a lower approval rate, not accounting for selection would lead to high simulation application rates and understate costs associated with applying for SSDI. To adjust for this, I apply a Heckman correction in estimating $\mathit{\Delta}_t$ where the first-step selection probability of application depends on presence of a spouse, health, income, and occupation.

[28] The "allowance rate" excludes pending applications and applications denied for technical reasons, such as not meeting the required waiting period or not having enough work history to be covered by the program, shown in the SSA data here: https://www.ssa.gov/policy/docs/statcomps/di_asr/2019/sect04.pdf.

Table 4: *Earnings Equation Estimates*

Outcome: $\ln$ *Annual Earnings*$-\overline{EQ}^*_{j,e}$		
Variable	*Coefficient*	*(s.e.)*
Age (years)	.109	(.027)
Age^2/100	-.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.

autoregressive component $\omega^j_t = \rho_\omega \omega^j_{t-1} + \nu_t$, with correlation coefficient ρ_ω and transitory shock $\nu_t \sim N(0, \sigma^2_\nu)$. It is assumed that the individual knows ω^j_{t-1} and the distribution of future ν_t but not ν_t itself. I estimate the coefficients of equation (14) using $\overline{EQ}^*_{j,e}$, representing the equilibrium component of relative wages in occupation j and for skill measured by education level e.[29]

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. The coefficient on N_t, $\gamma_1 = .788$, suggests that annual earnings for part-time work are about 45 percent of full-time annual earnings.[30] The coefficient on switching occupations between older and younger years is small at -0.003, however this is not capturing only an initial, one-time annual cost but rather is an annual reduction over all working years at older ages. I have accounted for selection into work based age, health, and being above Social Security Old-Age benefits Early and Full claiming ages.[31] 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

[29] That is, while $EQ^*_{j,e}$ adjusts with the second stage estimates, for the purposes of estimating coefficients in (14) in the first stage, $\overline{EQ}^*_{j,e}$ is fixed at the value implied from share and substitution parameters of equations (22) and (23) in Appendix A.4. Here I set the substitution parameters to the values estimated by Johnson and Keane (2013) Tables 1 and 3, with the proportion of high- and low-skill blue- and white-collar workers being equal to the observed proportions in this HRS sample, as presented in Table 2 above. These 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.

[30] Indicator $\mathbb{1}_{\{N_t = \textit{full-time}\}}$ is 0 for part-time work and 1 for full-time work, where the cutoff between the two categories is 25 hours on average per week worked. $\gamma_1 = .788$ implies that annual earnings for full-time workers are nearly 120 percent higher than the earnings of part-time workers ($(e^{.788} - 1) \times 100\%$), or that the annual earnings of an otherwise similar part-time worker is about 45.4 percent of a full-time counterpart.

[31] Alternatively, selection into work could be accounted for by estimated earnings coefficients in the second stage, as in French (2005). I have not done so for computational simplicity, yet the simulated earnings match the earnings in the data quite well, overestimating slightly earnings at older ages, shown in Figure 7.

estimated for white collar workers). The differences in these coefficients appear reflective of the differences in the primary tasks required in blue- and white-collar jobs. For instance, someone working in a white-collar job who experiences a functional limitation may still be able to continue doing his past work with minor modifications, while the same person working in a more physically intense blue-collar job may need to reduce work in a given year or even be unable to do his past work entirely.

Medical Expenses, Return on Assets, and Spousal Earnings This first stage includes basic estimates of log out-of-pocket medical expenses M_t, which are function of state variables health, income Y_t, age, and whether one receives Medicare insurance coverage, indicated by $\text{med}_t = 1$. 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, 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.

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

$$\widehat{\theta} = \underset{\theta}{\operatorname{argmin}}\ \widehat{\boldsymbol{\phi}}\,(\theta, \widehat{\chi})'\,\boldsymbol{\Omega}\ \widehat{\boldsymbol{\phi}}\,(\theta, \widehat{\chi}) \tag{15}$$

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 $\boldsymbol{\Omega}$ 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 determining the parameter estimates of the model come from the HRS and simulated data on choice of occupation, SSDI application and health, work and retirement, and savings. Below I list sets of moments and the parameters they are intended to target. Although the estimated parameters are all determined jointly, some data moments are particularly important for estimating the parameter values.[32] The groups of moments are:

[32] To formalize the relationship and measure the relative degree to which certain parameter estimates are driven by certain moments, post-estimation I apply methods from Andrews et al. (2017) and report in Appendix A.6

- *Share in Occupations, Switching* (M1). 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* (M2a-b) 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 (M2a) and (ii) disability application ever (for this model, after age 50) by regular income quartile and occupation (M2b). (*8 + 8 = 16 moments.*)

- *Work and Retirement Timing* (M3a-b) 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 (M3a) (ii) the proportion working (either full- or part-time) by health status, occupation, and age (M3b). Together these target the 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* (M4a-b) These moments include (i) median total assets by five age group,[33], tertile of regular permanent income (corresponding to AIME and occupation (M4a) and (ii) the ratio of assets at the 75th/25th percentiles by age group, occupation (M4b). These are intended to 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.*)

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.[34] 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.[35] 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

$$\Pr(i{=}\textit{Type } n) = \frac{\exp(\boldsymbol{b}_n \boldsymbol{X}_i)}{1 + \sum_{k \neq n} \exp(\boldsymbol{b}_k \mathbf{X}_i)} \tag{16}$$

[33]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.

[34]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.

[35]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.

where

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

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 estimated in the first stage, described in Section 4.2. Subtracting $EQ^*_{j,e}$ from both sides of the first-stage earnings equation (14) and expressing the remaining terms on the right hand side as $y_t(H_t, d_t, N_t, y_{t-1}, \mathbf{occ})$, we can restate (14) as

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

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 (14) do not vary with $EQ^*_{j,e}$ as $L_{\text{BC},e}/L_{\text{WC},e}$ varies. In addition, while $EQ^*_{j,e}$ changes over time, I assume this component is deterministic and constant from the point of view of the decision-making agent, as opposed to agents forecasting the entire equilibrium path, further simplifying the problem. $EQ^*_{j,e}$ is implied by the labor supply ratio $L_{\text{BC},e}/L_{\text{WC},e}$ for ratios centered around one. In computation, occupation decisions are made by individuals for candidate parameters θ from equation (15), and for each θ the market-clearing $EQ^*_{j,e}$ is found. This process described in steps (5) through (7) in subsection A.5. The processes is repeated iteratively until occupational choices yield the labor supply ratio $L_{\text{BC},e}/L_{\text{WC},e}$ satisfying $L_{\text{BC},e} + L_{\text{WC},e} = N_e^{\text{SIM}}$, where 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 applying the HRS sample data using methods described in Section 4 for the second stage are shown in Table 5, along with the utility 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 are 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 process—where there is decline for both occupations at older ages, but more so for blue collar workers when health is worse—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 from age 50 up to 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 50 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.[36] The cost of switching occupations between ones younger and older years has a utility cost of 99 hours per year up to age 55, and declines to 32 hours annually thereafter.

Parameters varying across preference types. Realistically accounting for preference heterogeneity allows for a better match on several features of the data—here, primarily high-variance 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. While there are alternative methods to generate asset dispersion, and occupation-specific productivity heterogeneity could also generate some of the features of the data, not accounting for possible preference type correlations would lead to misstating the influence of SSDI on occupational choice. This is discussed further in Appendix A.2.

I find that preferences in this model vary noticeably across preference types, with time 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 choice of occupation is influenced by both one's preference type-varying parameters and also—within a preference type—one's initial occupation and health status. The preference type with the

[36] 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.

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 varied preference parameters 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 in our cohort of men with a high school diploma or some college are closely replicated through the model. Shown here are the data and simulated moments for labor force participation, assets, and SSDI application behavior.

The model is able to generate several important aspects of labor force participation behavior to match the HRS data. The first is the choice of occupation at older ages, shown in Table 6. In the HRS data, 52.5 percent work in blue-collar occupations at older age, coming from the 90.7 percent of those who were in blue-collar jobs when younger remaining in blue collar jobs, as well as the 3 percent of those who were in white-collar jobs switching to blue-collar jobs at older ages. The simulated percent in blue-collar jobs at older ages is close at 51.7 percent, with similar transitions into occupations from younger to older.

The second feature of the data that is also generated in the model 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 third feature, 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 3: *Data and Simulated Labor Force Participation*

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

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

Time-Varying Utility Parameters

$\varphi_{P,t}$: fixed cost of work, $t = 50$ to 55	262 (9)	$\varphi_{P,t}$ for $t > 55$	$262 + 31(t-55)$ (11)
$\varphi_{\mathrm{DI},t}$: applying for SSDI, $t = 50$ to 55	302 (22)	$\varphi_{\mathrm{DI},t}$ for $t > 55$	149 (17)
$\varphi_{\mathrm{SW},t}$: switching occupations, $t = 50$ to 55	99 (10)	$\varphi_{\mathrm{SW},t}$ for $t > 55$	32 (8)

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

[*]Bootstrapped standard errors for 80 re-samples of 250 simulated individuals in parentheses.

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.[37] 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.[38]

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

TABLE 6: *Data and Simulated Occupations*

	HRS Data Young Ages	HRS Data Older Ages	Simulated Older Ages
% in Blue-Collar	56.4%	52.5	51.7
% in White-Collar	43.6	47.5	48.3

	HRS Data	Simulated
% of Blue-Collar when young remaining at older ages	90.7	89.5
% of White-Collar when young remaining at older ages	97.0	97.2

[37] 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.

[38] 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.

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.[39] 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 to be important for generating 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 have SSDI application costs vary 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.

Finally, in addition to the model matching targeted moments, the earnings and health generated through estimation processes in the first stage also match the data reasonably well and, in the case of earnings, account sufficiently for selection into work. Seen in Figures 7 and 8.

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 several 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. Next, I estimate the degree to which SSDI program induces more people to choose blue-collar occupations, and what effects this has on savings and working years for those with moderate levels of education. Following that, I consider how much, given the higher utilization of SSDI for those in blue-collar work, the current SSDI program's uniform payroll tax subsidizes earnings in blue-collar work. Finally, I implement a counterfactual policy that eliminates this distortion where SSDI taxes differ by occupation, being set such that total revenues and SSDI benefits are equal within each occupation.

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. Setting occupation-specific tax rates results in a move towards more white-collar work and an overall lower number of work-disabled years per person.

[39] 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 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.

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

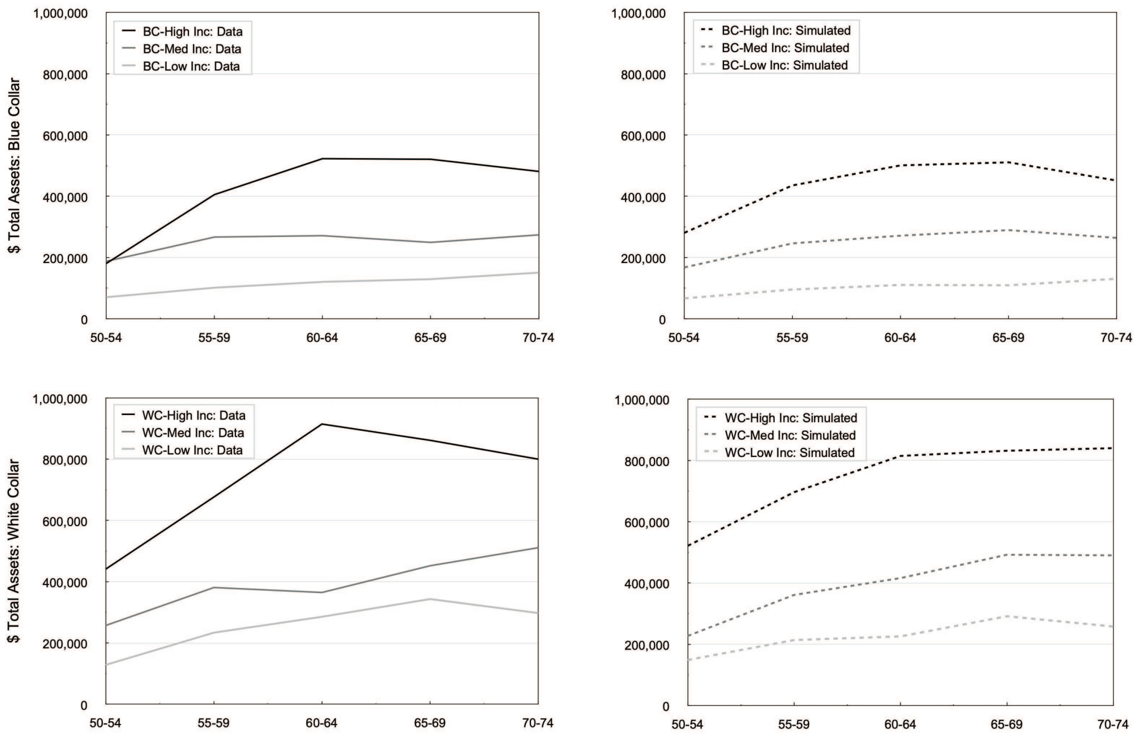


Figure 5: *Data (left) and Simulated (right) 75/25 Asset Ratios*

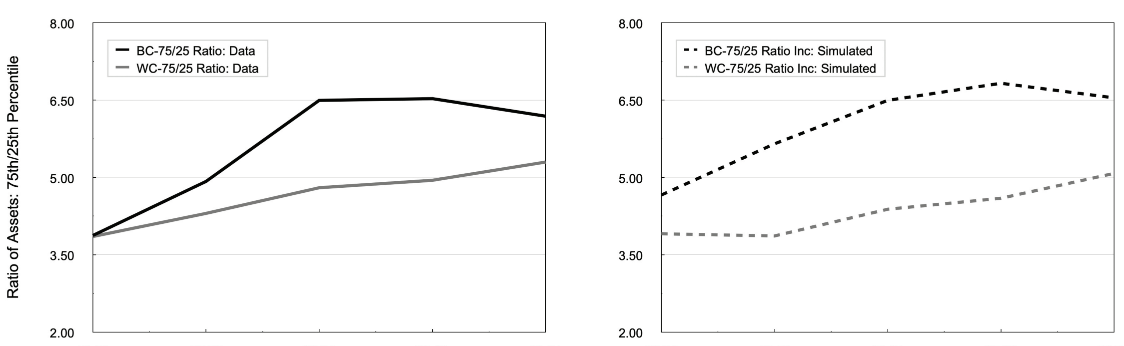
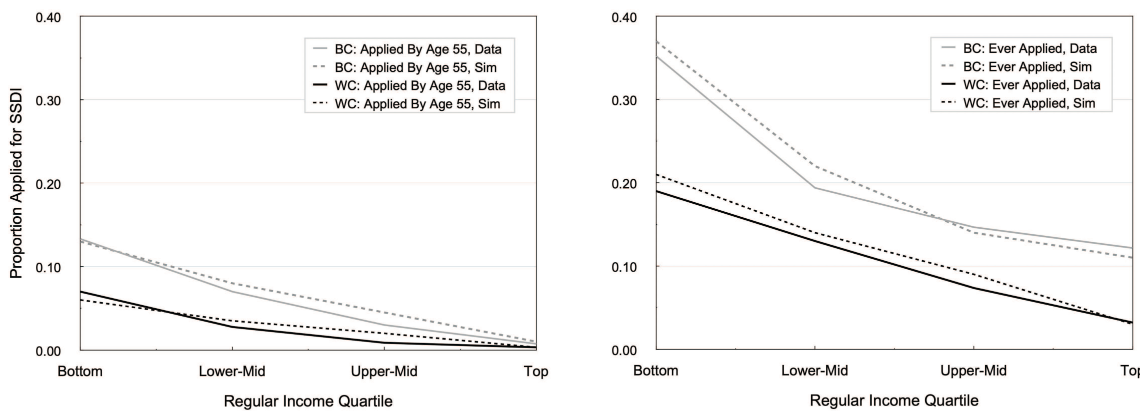


FIGURE 6: *Data and Simulated SSDI Application*



6.1. 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 be in the status quo world with SSDI coverage. Analytically, compensating variation is the $\vartheta^{CV}_{n,j} > 0$, for Type n in occupation j, that solves

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

so that receiving earned income $(1+\vartheta^{CV}_{n,j})y_t$ but not having SSDI—or the accompanying 1.8 percent payroll taxes deducted—gives the same utility as a world with SSDI. This is calculated for a state space with median or modal starting values, $\overline{\mathcal{S}}_t$.[40]

The results on the left panel in Table 7 give the calculated compensating variations, $\vartheta^{CV}_{n,j}$, interpreted as how much the average person of each preference type and occupation values SSDI, expressed as a percent of their earnings while holding all labor force decisions fixed.[41] For all preference Type-Occupation combinations, the value of SSDI is greater than the required tax on income—for some, far greater. The group that places the lowest value on the presence of SSDI 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

[40]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, individuals can no longer apply for and receive SSDI, and they no longer pay the 1.8 percent 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.

[41]If in practice earned income y_t from equation (10) increased by some percent, labor participation decisions would of course also respond. The goal of this exercise, however, is to express the compensation required to achieve the same level of utility experienced with SSDI in terms of income, allowing for easier comparison against the 1.8 percent of income taxed to fund the SSDI program.

Figure 7: *Log Annual Earnings by Age by Occupation (Including Full- and Part-Time)*

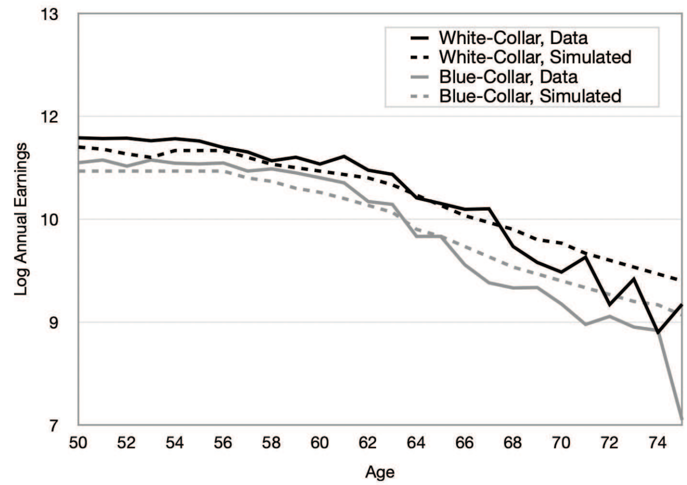


Figure 8: *Percent in Good Health by Age and Occupation*

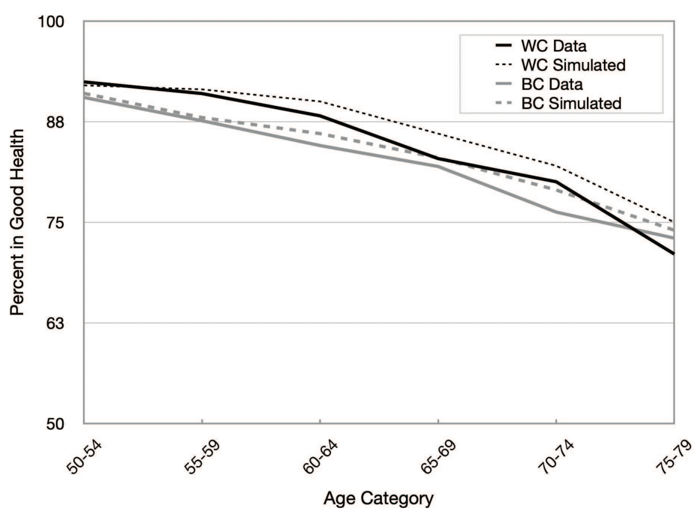


Table 7: *What is SSDI Worth?*

Willingness to Pay for SSDI Program,
CV as Percent of Earnings, $\vartheta^{CV}_{n,j}$ for Median Characteristics

By Preference Type	Blue-Collar	White-Collar	Both	*By Income Percentile*	
Type I	3.2 % (.16)	2.1 % (.06)	2.9%	20th	5.9%
Type II	6.5 (.15)	4.0 (.13)	5.3	40th	5.8%
Type III	14.5 (.12)	7.1 (.22)	9.1	60th	6.0%
Type IV	5.9 (.08)	3.5 (.08)	4.5	80th	6.2%
All Types	8.4 %	4.6 %	5.9 %		

The proportion in each Type-Occupation combination is given in the gray parenthesized share below the calculated willingness to pay for SSDI within that combination.

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 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.

The rightmost column in Table 7 shows the CV weighted for the actual, simulated preference type (and occupation) distribution around that income percentile, with median characteristics otherwise. Holding preference type fixed, it is the case that those at higher incomes have a lower CV amount; however there are somewhat more of the risk averse preference Types II and III at higher incomes who value SSDI more and so the calculated CV actually increases with income past the 20th percentile.[42] This highlights the strong influence of preferences—for this exercise, having more of an impact than even an observable such as income.

6.2. 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 be working in physically intense, blue-collar jobs at older ages? 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 8, I find that about ten percent (or about five percentage points) more people in our HRS sample 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.[43]

[42] The same calculation for CV across income levels controlling for preference type is shown in an expanded version of this column in Appendix A.7, Table A.3.

[43] Please see Appendix A.2.4 for a discussion of the effect of removing SSDI when relative wages are fixed. Without offsetting wage changes, eliminating SSDI causes the blue-collar share to fall to 0.43. This highlights the importance of the equilibrium component of the model in more accurately estimating—in this case, not overstating—the effect

Table 8: *The Effect of SSDI on the Distribution of Occupations*

Preference Type	*Proportion in Blue-Collar Occupations* SSDI (baseline)	No SSDI Scenario	% Increase in Blue-Collar Earnings to Maintain Blue-Collar Baseline Share
Type I	0.75	0.73	1.7 %
Type II	0.55	0.52	6.2
Type III	0.36	0.27	12.8
Type IV	0.47	0.42	4.5
All Types	0.52	0.47	7.1 %

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.[44] From the model results in the bottom two rows of Table 5, there's a stronger selection of less risk-averse individuals—who, ceteris paribus, 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 on this account. This pattern makes 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, the proportion choosing blue-collar occupations falls only from 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.

6.3. What is the effect of SSDI on savings and working years?

This analysis addresses the extent to which the presence of SSDI affects levels of savings and, through affecting savings, the number of total years worked. I find that asset levels of the simulated sample are higher in the counterfactual scenario 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 very 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 preferences 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 the absence SSDI resulting in higher precautionary

that SSDI policy has on occupational choice.

[44] Further, these results hold for the sample on which the model was estimated, which excludes those who report education levels at less than a high school diploma or a bachelor's degree or higher—who combined make up about half of the cohort studied. While the degree to which SSDI would induce a different occupation among these excluded education groups may be smaller, the inclusion of these groups would change the equilibrium wage effects and aggregate estimates of the influence of SSDI on choice of occupation.

savings or self-insurance against disability.[45]

As time passes, however, the years for which a work-disabling event also pass and savings looks more like retirement savings. This higher precautionary-turned-retirement savings without SSDI should result in fewer working years needed to finance retirement. Indeed, I find that blue-collar workers stop work 1.5 years earlier and white-collar workers stop 0.2 years earlier in a scenario without SSDI.

6.4. Does SSDI subsidize blue-collar earnings at current occupation levels?

The fourth question addressed through counterfactual analysis using the results of the model asks, given the finding that fewer 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—or the required payroll tax contributions to—SSDI. That is, to what extent does SSDI subsidize blue-collar earnings? As one approach to answering 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 based on the estimated sample are in the rightmost column of Table 8. 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 7.1 percent higher. The preference type with occupational choice behavior least responsive to the no SSDI scenario is Type I, which requires an increase of 1.7 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 12.8 percent more.

6.5. The design and effects of occupation-specific tax rates.

The results above indicate the presence of moral hazard in occupation selection and an effective subsidy for blue-collar work as a result of the uniform SSDI payroll tax rates despite significantly higher utilization among blue-collar workers of the SSDI benefits. Here, I will present the results of a counterfactual policy with occupation-specific tax rates to fund the SSDI system, where rates are set such that tax revenues are equivalent to benefits within an occupation.

This counterfactual policy will reflect one of a set of possible reforms that have been proposed for the SSDI program. These reforms include incentivizing greater employer accommodation of otherwise disabled workers and implementing experience-rated employer SSDI taxes.[46] While occupation-specific SSDI payroll taxes may have long-run effects of decreasing SSDI rates due to greater employer accommodation of partially disabled workers, what I show here is, rather, the tax rates that balance revenues and benefits within an occupation given current SSDI utilization

[45] Such an effect on savings is demonstrated in Hall (1978) and Kimball (1990) and applied to injury, workers' compensation and disability in both Kantor and Fishback (1996) and Chandra and Samwick (2009).

[46] See Burkhauser et al. (2014). Some proposed changes are inspired by a series of major reforms to the Dutch disability insurance system, which have been considered largely successful.

Table 9: *The Effects of Occupation-Specific DI Tax Rates*

	Sample, with current 1.8% SSDI payroll tax				
	SSDI Payroll Tax	Avg. Years on SSDI	Avg. Paid to SSDI*	Avg. SSDI Benefits	Percent in Occ.
Blue Collar	1.8%	2.59	$24.0K	$31.1K	51.7%
White Collar	1.8	1.29	27.2K	18.8K	48.3

	Payroll Tax Balancing Program Revenues and Benefits by Occupation		
	Occupation-Specific SSDI Payroll Tax	Avg. SSDI Tax Paid and Benefits Received	Percent in Occ.
Blue Collar	2.30%	$31.1K	49.2%
White Collar	1.26	18.8K	50.8

probabilities by occupation.

On average, revenues for the SSDI program have been nearly equal to the benefits paid out over the last three decades (Social Security Administration, 2018). That is also true for the sample population studied here overall, where the lifetime estimated SSDI payroll tax revenue is $25.6 thousand per person and SSDI benefits are $25.1 thousand per person. However, looking within each occupation for the sample, while everyone is taxed 1.8 percent of income through employee payroll and employer contributions, those in blue-collar occupations receive about $31 thousand in SSDI benefits and contribute about $24 thousand, while those in white-collar occupations receive an expected $18.8 thousand and contribute $27.2 thousand on average. This is shown in the upper panel of Table 9.[47]

Taking the estimated model preference parameters, I simulate behavior while solving for the occupation-specific SSDI payroll tax rates that would equate the total revenues to expected benefits paid out within each occupation. I find that the rates that achieve this balance are 2.30 percent of earnings for blue-collar workers, and 1.26 percent for white collar workers (shown in Table 9). These differential tax rates also affect the composition of occupations, with a higher percent choosing white-collar occupations at older ages: 50.8 percent compared to 48.3 percent under the status quo, uniform SSDI payroll tax rates.

With the occupation composition changing, removing the apparent distortion of uniform SSDI tax rates leads to fewer average years of non-work due to disability and SSDI benefit receipt. The average number of SSDI beneficiary years per person decreases slightly from 1.97 to 1.92 years due to more people working in white-collar jobs. While seemingly small, the total number of person-years spent not working is reduced by a considerable amount over the whole population.

[47] Note that while blue-collar workers are around twice as likely to receive SSDI at some point, it is not necessarily the case that the occupation-specific SSDI payroll tax rate should be twice as high for blue-collar (BC) workers in order to balance revenues and benefits. Recall these facts, discussed throughout this paper: (1) SSDI benefits depend on earnings history, which are slightly lower on average for BC workers at all ages, leading to lower annual BC revenues and benefits. (2) Blue-collar workers exit work through disability or retirement somewhat earlier, and at a time when earnings are otherwise rising with age, leading to lower annual BC revenues and benefits, but more years of benefits. (3) The SSDI benefits formula is progressive, leading to higher BC benefits relative to revenue. (4) Occupation-specific taxes will affect selection into occupations and relative earnings across the occupations, meaning that equilibrium effects will also influence the within-occupation balancing of revenues and benefits. Taken together, these factors make the calculation less straightforward and necessitate the analysis that follows.

While the political desirability of implementing occupation-specific SSDI payroll tax rates is uncertain, it is already the case that state-administered workers' compensation programs covering short-term injury contain this element of "experience rating"—employers with greater claims history are required to pay higher premiums. Combining this with the finding that the estimated willingness to pay exceeds even this higher blue-collar SSDI payroll tax rate for all preference types (Table 7) suggests such a reform may be politically feasible. A deliberate exploration of such policy changes would, however, necessitate a model covering the broader population and estimates of long-term funding implications for the program.

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, for the sample population studied here, the presence of the SSDI program results in more people choosing to work in blue-collar occupations at older ages.

From counterfactual analyses, a chief takeaway was that accounting for heterogeneity in preferences is necessary for understanding the effects and value of SSDI across the population of similarly education individuals here. 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, in another context—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 would require specifying how society should weigh trade-offs. However, the counterfactual policy of an SSDI program with occupation-specific tax rates—rates that eliminate the distortion in occupation selection created by the current uniform tax rates—suggests political feasibility: The outcome is that differential tax rates are also welfare-improving for all preference types and lead to fewer work-disabled years across the population.

In summary, the aim of this work has been to highlight 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. Future work could enhance this analysis in studying three lines of research related to retirement and SSDI in particular: (1) The decline in SSDI beneficiaries, (2) changes in the SSDI evaluation and approval process, and (3) employer accommodation and the adoption of disability-reducing technologies. As for the first, while there had been a substantial rise in the number and share of people receiving SSDI benefits, 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 potential 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. Finally, employers already invest measures aimed at short-term injury reduction. It would be worthwhile to estimate the extent to which occupation-specific, experience rated SSDI taxes would increase the adoption of disability-reducing or accommodating technologies.

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.

Sample Selection. The HRS sample used in estimating the model includes 2,507 men born between 1931–47 who have a high school education or some college, are observed in at least two interview waves and working in at least one of them. Beyond this, if a survey respondent was not asked or did not give a response to any one of the questions corresponding to the variables that are part of the model, that observation cannot be used in estimation. In selecting the sample, there is a trade-off between how representative it is of the population and how well the model is able to capture the behavior of a wide range of people. The main motivations for studying this group in particular are that they represent the largest share of the cohort and—compared to those without a high school diploma or those with at least a bachelor's degree—appear to be most at the margin between blue-collar and white-collar work. Those with less than a high school diploma (which was more common for older birth cohorts) are more likely to remain in blue-collar work, while those with at least a college degree (somewhat less common for older birth cohorts) are much more likely to remain in white collar work regardless of any counterfactual scenario presented here. The results presented in this paper are inherently limited to the extent that are based on modeling the behavior of only a subset of the population. However, the sample restrictions here do leave a sample that is fairly representative of a large share of the birth year and education cohort when used with the survey respondent sample weights to generate the initial distribution for simulated individuals.

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).

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 (where I base the level of physical intensity on O*NET measures of the degree to which psychomotor and physical skills are required by three-digit occupation); categorization is the same about 94 percent of the time.

An alternative way to handle occupations is to use 2-digit occupation categories (e.g., professional, sales, operators, etc.). A benefit of this a categorization is that it is finer than the current blue- vs. white-collar categorization and is also a widely used and familiar grouping. However, even with these categories, there remains wide variation in physical and other tasks within each category, so categorization similar to but finer than what is used here–that is, one linked to either subjective or O*NET detailed tasks–would be more fitting. The motivation for using the broad categories in this paper to maintaining both computational and expositional simplicity. Taking a closer or more serious look at, for instance, the counterfactual policy of occupation-specific taxes in section 6.5 would necessitate a model with finer categories.

Functional Limitation and Health Variables. The functional limitation measure is the total number of physical limitations out of thirteen possible tasks. This was formed by totaling the number of tasks the respondent reports having difficulty with under three of the six RAND HRS Functional Limitation indices: Mobility (variable `RwMOBILA`), Large Muscle (`RwLGMUSA`), and Gross Motor Skills (`RwGROSSA`). The activities include things like walking one or several blocks, walking across the room, climbing one or several flights of stairs, sitting for two hours, getting up from a chair, stooping or kneeling or crouching, and pushing or pulling a large object. In computation, the functional limitation variable d_t takes on a value of 0 if there are difficulties with 0 of these activities, and a value of 1 if there is difficulty with at least one activities.

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 among this and the functional limitation variable did seem to make for a noisier measure while not enhancing the analysis.

A.2. Selecting the Features of the Model

A.2.1. 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.

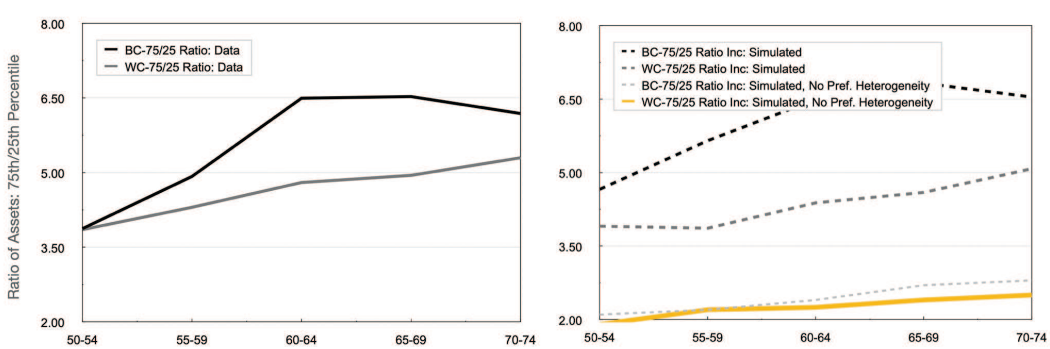
A.2.2. Employer Accommodation

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.

A.2.3. Preference Heterogeneity

Heterogeneity is incorporated in part to reflect conceivable differences in taste for different types of work, but in larger part so that the model can generate the empirically large dispersion in savings in a way similar to Keane and Wolpin (1997), van der Klaauw and Wolpin (2008), and

FIGURE A.1: *Data and Simulated 75/25 Asset Ratios, With and Without Preference Heterogeneity*



French and Jones (2011). Allowing for the possibility that heterogeneous φ_{BC} is related to η (but not restricted to be so) is based on a descriptive observation in the sample that savings relative to earnings is, controlling for many factors, lower among blue-collar workers.

Matching this aspect of behavior is particularly important of course for measuring the value of insurance. To show the importance of heterogeneity in generating assets distributions that reflect the data, I re-estimated this model with without allowing for heterogeneous preferences. What stands out the most by imposing uniform preferences, but keeping the preference specification, is that there is much less dispersion in savings. Figure A.1 shows 75th/25th percentile asset ratios by age group when there is no preference heterogeneity. It differs from the data (and current simulated behavior) in that its much lower for all age groups and does not differ much for blue- and white-collar workers.

A.2.4. The Effect of Equilibrium Earnings on Occupation Choices Without SSDI

Section 6.2 showed that more people choose white-collar jobs instead of blue-collar jobs in the absence of the SSDI program. This effect is tempered to a degree as the relative earnings of white-collar work falls as more people select into those occupations. How important is the inclusion of this equilibrium aspect of the model? By excluding the equilibrium feedback component of the model, so that increasing labor supplied to one occupation does not affect the relative earnings in blue- and white-collar occupations, I find that an even lower share of people choose blue-collar jobs when there is no SSDI system. Hence the equilibrium aspect is an important feature of this model: If the equilibrium were excluded, the difference in the share of people in blue-collar jobs with and without SSDI would be greatly overstated.

The first two columns of Table A.1 come from Table 8 in section 6.2. These columns show, by preference type, the share of simulated respondents choosing blue-collar occupations under (1) the status quo scenario that includes the SSDI system and corresponding taxes and (2) the counterfactual scenario with neither SSDI nor the corresponding payroll taxes, with the equilibrium component allowing for relative earnings to adjust as the share choosing each occupation changes. The third column shows estimates for the the proportion of people who would choose blue-collar occupations if there were no SSDI program and there were no change to relative earnings when the share in each occupation changes. (In this case, the relative earnings for white-collar work does not fall as more people select white-collar instead of blue-collar jobs.) For all preference types, the share who would select into blue-collar jobs falls, particularly for Types III and IV, who have a higher disutility associated with blue-collar work. Overall, the share in blue-collar occupations falls from 52 to 43 percent, compared to falling from 52 to 47 percent, as was the case when equilibrium earnings effects were incorporated.

From this exercise, we can conclude that it is indeed important to incorporate the equilibrium component in order to more precisely measure the effects of the SSDI policy on occupation choices.

A.2.5. Adding Young-Stage Behavior to the Model

In the model estimated here, individuals arrive at age 50 with histories of earnings, savings, and occupations. However, these histories are not randomly assigned and are the manifestation of deci-

Table A.1: *SSDI's Effect the Distribution of Occupations, With and Without Equilibrium Earnings*

	Proportion in Blue-Collar Occupations		
Preference Type	SSDI (baseline status quo)*	No SSDI Scenario With Equilibrium Wage Effects*	No SSDI Scenario Without Equilibrium Wage Effects
Type I	0.75	0.73	0.71
Type II	0.55	0.52	0.49
Type III	0.36	0.27	0.22
Type IV	0.47	0.42	0.38
All Types	0.52	0.47	0.43

*Figures in the first two columns of this table are also shown in Table 8.

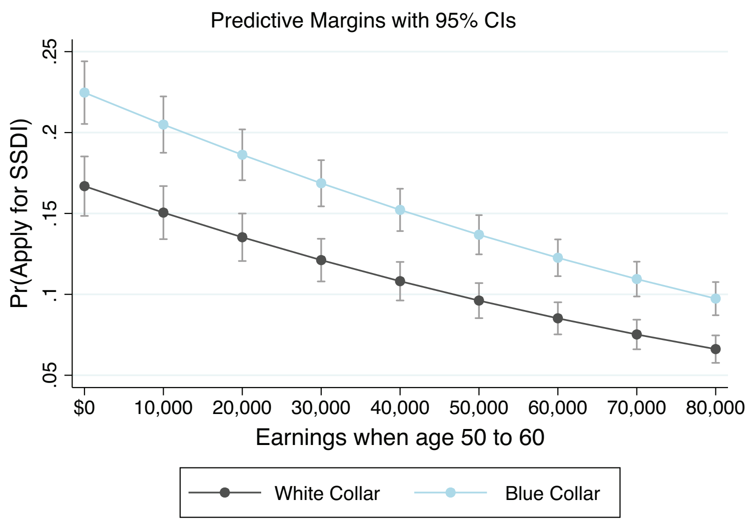
sions made—decisions that would presumably have looked forward into the older stage modeled in this paper. Earlier versions of this paper also included a younger (before age 50) stage, though with fewer dimensions and without the annual granularity of the older stage; in that model, individuals chose primarily occupation and savings before age 50. The most notable differences between that and the current model were that asset moments were not matched as well at the lower and higher income levels, and counterfactual results suggested that the SSDI program had less of an effect on both its estimated value and its influence on occupation choice.

There are two reasons for moving toward a model without the younger stage. The first is related to the design HRS data. While there is retrospective information in the HRS—some of which is used here—it does not include many of the variables employed in modeling older-age behavior the evolution of variables over ages, and the younger-stage modeling is necessarily limited by this. Using data with a broader age range, however, would provide the unique, high-quality health and aging variables which are unique to the HRS. The second consideration is that both the SSDI program and the physical aspects are arguably more salient in later life, and generally more connected with work behavior at older ages. To the extent that this is the case, having a model that reflects this may allow for a more accurate measure of the primary counterfactuals: the value of the SSDI program and its effects on occupation choices.

A.3. 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

Figure A.2: *SSDI Application Predictive Margins, Good Health*



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, and in practice leads to slightly higher approval rates for the more physically intense, blue collar jobs. It is worth noting that, with this standard for approval in mind, we also see a large difference in *applications* to SSDI between people working in blue- and white-collar jobs. Figure A.2 shows the probability of application through the predictive margins of a probit model by regular income level for people previously reporting "Good" health. All else equal, application rates are higher for lower income levels and also for those in blue-collar jobs.

An 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.

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.

A.4. Labor Market Demand and Equilibrium Earnings

To incorporate equilibrium earnings into this model of occupational choice, I adapt models from Card and Lemieux (2001), Heckman et al. (1998), Johnson and Keane (2013), Katz and Murphy (1992), and apply some estimates from Johnson and Keane (2013). In this adaptation, 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 ($j \in \{\mathrm{BC}, \mathrm{WC}\}$). 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 constant returns to scale (CRS)

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

where A_t is 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 constant elasticity of substitution (CES) aggregate ordered by occupation type, for $j = BC, WC$, and then skill level $e = SK, USK$, within a time period t:

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

Here, θ_{tj} represents the relative productivity of occupation j, 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 $\sigma_{\mathbf{E}} = \frac{1}{1-\rho_{\mathbf{E}}}$.[48]

The demand function for labor with characteristics j, e 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

[48] Expanded, L_t is then

$$L_t = \Big[\theta_{t,BC} \left(\varphi_{t,BC,SK} L_{t,BC,SK}^{\rho_{\mathbf{E}}} + \varphi_{t,BC,USK} L_{t,BC,USK}^{\rho_{\mathbf{E}}} \right)^{\rho_{\mathbf{J}}/\rho_{\mathbf{E}}} + \theta_{t,WC} \left(\varphi_{t,WC,SK} L_{t,WC,SK}^{\rho_{\mathbf{E}}} + \varphi_{t,WC,USK} L_{t,WC,USK}^{\rho_{\mathbf{E}}} \right)^{\rho_{\mathbf{J}}/\rho_{\mathbf{E}}} \Big]^{1/\rho_{\mathbf{J}}}$$

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

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 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". 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). A limitation to the approach I use here is that labor input L_{tje} measures a simple total number of workers which, as a simplifying assumption, are all assumed to have the same level of productivity within a skill level and occupation. Thus, ratios of workers do not adjust for selection on hours worked and productivity. Once estimates from equation (22) have been obtained, the relative productivity of and elasticity of substitution between blue-collar and white-collar workers in the sample for time t and skill level $e \in \{SK, USK\}$ is found through estimating relative wages

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

where the first line of the right-hand side in (23) is estimated by (22).

The equilibrium consists of high- and low-skill, blue- and white-collar wages and employment in each skill and occupation type satisfying: (i) individuals selecting the sequence of choices $\mathcal{D}_t$ solving (13); (ii) firms choosing cost-minimizing inputs L_{tje}; and (iii) labor demand and labor supplied of each type being equal at wages W_{tje} given in equation (21). The substitution parameters $\sigma_{\mathbf{E}}$ and $\sigma_{\mathbf{J}}$ equal the values reported by Johnson and Keane (2013), Tables 1 and 3, while $\varphi_{t,j,e}$ and $\theta_{t,j}$ are set so that (22) and (23) are held at the wages and employment levels observed in the HRS sample. See footnote 29 in the main text.

Finally, log earnings equation (14) contains an equilibrium component of relative wages $EQ_{j,e}$, which is defined such that

$$EQ_{\mathrm{BC},e} - EQ_{\mathrm{WC},e} = \ln\left(\frac{W_{t,\mathrm{BC},e}}{W_{t,\mathrm{WC},e}}\right) \tag{24}$$

for skill level e. Setting $EQ_{\text{WC},e} = 0$, $EQ^*_{\text{BC},e}$ will give the difference in logs between blue- and white-collar work, holding the other terms on the right-hand side of (14) constant. Here, $EQ^*_{\text{BC},e}$ is associated with a difference of $(\exp(EQ^*_{\text{BC},e}) - 1) \times 100$ percent between blue- and white-collar earnings ($y^{\text{BC},e}$ and $y^{\text{WC},e}$), all else equal.

A.5. 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, following the nested algorithm approach described in Lee and Wolpin (2006), the inner-most nest solves market-clearing relative wages EQ for a given set of parameters θ; outside of this nest the agent's 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 and hours (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 (15) is obtained by the following procedure:

1. First compute sample moments and corresponding weighting matrix $\mathbf{\Omega}$ 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. For each candidate θ, the fixed-point, market-clearing equilibrium component $EQ(\theta)$ is solved.
6. Compute moment conditions by finding the distance between the simulated moments from Step 5 and true moments, solving equation (15).
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 (15) 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 (15) 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 (15) is the minimum $\widehat{\theta}$.

The states in $\mathcal{S}_t = (A_t, H_t, d_t, P_{t-1}, \mathbf{OASDI}_t, \mathbf{occ}, e, \boldsymbol{\epsilon_t})$ are discretized, with quadratic interpolation between points for A_t and $\mathbf{OASDI}_t = (\mathrm{DI}_{t-1}^{rec}, \mathrm{SS}_{t-1}, \mathrm{AIME}_t)$. The number states for each variable is: $A_t = 10,\ H_t = 2,\ d_t = 2,\ P_{t-1} = 3,\ \mathbf{OASDI}_t = (2,2,5),\ \mathbf{occ} = (2,2),\ e = 2\ \boldsymbol{\epsilon_t} = 2$ for each age $t = 51, \ldots, 90$. The script is primarily written in Matlab, with the exception being a portion which calls a C function to fill out the value function over the state space (with quadratic interpolation in between) 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*.

A.6. Parameter Estimate Sensitivity

While all moments jointly influence the parameter estimates, each parameter will have some moments for which the association is stronger. I will present the set of moments that have the most influence on each parameter using the methods proposed by Andrews et al. (2017). This involves calculating measures of relative influence, particularly the share of the variance of a parameter estimate that is explained by the data moments, through sensitivity matrix

$$\mathbf{S} = (\varDelta G \boldsymbol{\Omega} \varDelta G)^{-1} \varDelta G' \boldsymbol{\Omega}\,. \tag{25}$$

Here, $\boldsymbol{\Omega}$ is that weighting matrix of the objective function from equation (15) and $\varDelta G$ is a vector of numerical derivatives of the targeted moments with respect to the model parameters, with each moment scaled by its standard deviation. Following the implementation of Andrews et al. (2017) in Aizawa (2019) and Gayle and Shephard (2019), for each parameter I find the moment with the highest sensitivity, and consider any moment whose sensitivity is at least 20% of the maximal as being important. A set of moments, as described in subsection 4.3.1), is considered influential if at least one moment in the set meets this criteria and the summary results of the analysis is found in Table A.2. While the moments that were most influential for each parameter were not unexpected—indeed, in developing the model, moments were included by design to be informative about the model parameters—there were a couple of exceptions. These include the influence of work by age and occupation (M3a) on bequest weight α_B and risk aversion η, as well as the influence on overall application rates for SSDI by income and occupation (M2b) for the cost of working in a blue-collar job in bad health φ_{BC^H}. Overall set of moments M3b, which includes moments for rates of work by age, health, and occupation, was influential for a variety of parameter estimates.

Table A.2: *Parameter Sensitivity Estimates*

	Parameter Estimate	(s.e.)	Influential Moments*
Constant Utility Parameters			
α_c: consumption weight	.54	(.07)	M3a, M4b
K_0: bequest shifter	\$355K	(49K)	M4a, M4b
α_B: bequest weight	.039	(.009)	M3a, M4b
φ_{BC^H}: BC working in bad health	310	(25)	M2b, M3a, M3b
φ_{WC^H}: WC working in bad health	195	(19)	M3b
$\underline{c}$: consumption floor	\$8,150	(308)	M3a, M4a
*Time-Varying Utility Parameters***			
$\varphi_{P,t}$: fixed cost of work	262	(9)	M3a, M3b
$\varphi_{\mathrm{DI},t}$: applying for SSDI	302	(22)	M2a, M2b, M4a
$\varphi_{\mathrm{SW},t}$: switching occupations	99	(10)	M1, M3b
*Preference Type-Varying Parameters***			
β: time preference	0.95	(0.02)	M4a, M4b
η: risk aversion	7.04	(0.32)	M3a, M4a, M4b
φ_{BC}: cost of blue-collar work	153	(22)	M1, M3a, M3b

Moment Descriptions:
M1: Share in Occupations, Switching
M2a-b: Disability Application and Approval
M3a-b: Work and Retirement Timing
M4a-b: Assets and Savings

*Parameters are considered to be sensitive to a set of moments if at least one moment in the set exceeds 20% of the maximal moment.
**Time-varying utility parameters are shown for $t = 50$ to 55; preference type-varying parameters are for Type III.

A.7. CV by Income and Preference Type

The table below is an expansion of the rightmost column of Table 7 in Section 6.1, which presented the compensating variation (CV) under the counterfactual scenario with no SSDI program or payroll taxes. The calculations in Table 7 had shown the CV weighted for the actual, simulated preference type (and occupation) distribution around the income percentiles, with median characteristics otherwise. The calculated CV decreases and then increases going up the income distribution. However, this runs counter to two facts that would suggest decreasing CV at higher incomes: (i) the lower marginal disutility at higher incomes from an income loss that SSDI may cover and (ii) the benefit formula being such that the marginal benefits decrease at an increasing rate with income history. This pattern of increasing CV with income in Table 7 is due to the composition of preference types across income: There are somewhat more of the risk averse preference Types II and III at higher incomes who value SSDI more.

In Table A.3 here, I expand the rightmost column of Table 7 (which is now the bottom row of this Table A.3) to show CV across the same income percentiles for each preference type, where indeed there is a pattern of decreasing CV at higher incomes *within each preference type*.

Table A.3: *What is SSDI Worth? (An Expansion and Variation of Table 7, Rightmost Column)*

Willingness to Pay for SSDI Program by Income Percentile,
CV as Percent of Earnings, $\vartheta^{CV}_{n,j}$ for Median Characteristics

By Preference Type	20th	40th	60th	80th	All*
Type I	3.1 %	3.1 %	2.6 %	2.2 %	2.9 %
Type II	5.8	5.6	5.3	4.9	5.3
Type III	10.0	9.6	8.8	8.5	9.1
Type IV	5.2	5.1	4.5	4.1	4.5
All Types*	5.9 %	5.8 %	6.0 %	6.2 %	

*Note that types and occupations are distributed differently across income percentiles.

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