Occupational Choice, Retirement, and the Effects of Disability Insurance

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Abstract: There is much variation in the physical requirements across occupations, giving rise to great differences in later-life productivity, disability risk, and the value of Social Security Disability Insurance (SSDI). In this paper, I look at how such differences across occupations affect initial career choice as well as the extent to which SSDI, which insures shocks to productivity due to disability, prompts more people to choose physically intense occupations. Using data from the Health and Retirement Study (HRS) and the Current Population Survey (CPS), I estimate a dynamic model of occupational choice and retirement with heterogeneous agents and equilibrium effects on earnings across occupations. I document the differences between blue-collar and white-collar occupations in the effects of declining health and disability on productivity, which affects labor supply in later life and, in the context of a life-cycle model, influences the occupation decision. Through counterfactual exercises, I show that the additional disability risk in blue-collar jobs relative to white-collar jobs is equivalent to an additional six percentage point reduction in lifetime consumption and that the absence of SSDI, which insures some of this risk, would be equivalent to, respectively, a twelve and seven percent reduction in consumption for those in blue- and white-collar jobs. Furthermore, I find that the presence of SSDI results in three percent more individuals choosing blue-collar occupations, which is comparable to the effect on occupation selection resulting from an eight-percent increase in blue-collar earnings. This overall effect, however, masks the importance of the selection of less risk-averse individuals into blue-collar jobs and the equilibrium effects on wages; earnings for the most risk-averse type would have to be nearly fifteen percent greater to choose blue-collar occupations in the absence of SSDI.

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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 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).[1] 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 be considered when making career decisions at the beginning of ones working life. The goal of this work is to document the interactions among health, occupational tasks and choice, and labor force behavior in later life while providing a framework for understanding the mechanisms generating such behavior among this large and growing population of older individuals.[2]

I aim to contribute to the occupational choice and retirement literatures by accounting for the differences in health and disability risks bringing about variation in the age of exit from the labor force and measuring the effects of such differences in risk on initial occupational choice. Additionally, I seek to add to research on the evaluation of the SSDI program in assessing value of the insurance it provides by occupation in a dynamic setting, including the extent to which it may encourage more people to choose physically intense occupations than would in the program's absence. To do so, I provide both reduced-form evidence and estimates from an equilibrium life-cycle model of occupation selection and labor supply decisions in which productivity and the hazard of disability may evolve differently across jobs as one ages. In this model the difference in the effects of health and the aging process in turn affects the timing of retirement and choice of occupation.

I use data from the Health and Retirement Study (HRS) and Current Population Survey (CPS) to estimate parameters of the structural model, measuring the extent to which the differences in labor force participation patterns towards the ends of one's life is driven by the steeper decline in productivity and greater risk of disability in blue-collar relative to white-collar jobs that accompanies declining physical faculties with age. The presence of this risk prompts higher savings in a life-cycle model, especially for more risk-averse and patient agents,[3] bringing about a distortion in the timing of consumption which is greatest

[1] From the HRS data: 8.27 percent of male white-collar workers have applied for and received SSDI (27,752 person-years), while 20.65 of blue-collar workers have (29,565 person-years).

[2] According to the U.S. Administration on Aging, the U.S. population age 60 and over is projected to grow from nearly 57 million in 2010 to over 112 million in 2050. The population over age 64 is expected to grow from 40 million people in 2010 to 89 million in 2050. Source: `http://www.aoa.gov/AoARoot/Aging_Statistics/future_growth/future_growth.aspx#age`.

[3] This effect on savings is demonstrated in Hall (1978) and Kimball (1990) and applied to injury and

for those in blue-collar work, which I can quantify in this structural model. While disability is not the most common reason for leaving the labor force, it is much more common for those in blue-collar compared to those in white-collar occupations. Here, all agents may apply for SSDI benefits, though it is costly to do so. Individuals know there are differences between the occupations in the effects of aging on productivity and disability hazards, which they take into account when choosing their initial occupation. Relative earnings are determined in an equilibrium framework as in Johnson and Keane (2013), which has the advantage over a partial equilibrium formulation of accounting for the earnings premium necessary from greater risk of being involuntarily or prematurely out of the labor force in blue-collar jobs for individuals to choose them. I estimate preference parameters—with some of which being allowed to differ across agents—using Simulated Method of Moments.

This structural model is able to account for the labor force behavior seen in the data and allows us to assess three issues of behavioral importance as well as policy relevance. The first issue concerns the calculation of the utility cost to individuals of the uncertainty in income lost due to declining health or a work-limiting or prohibiting disability. When health and disability risks are present, a risk-averse agent will accumulate additional precautionary savings, changing his consumption path relative to the no-risk case. I measure the cost of health and disability risks as the difference in lifetime utility for the consumption path with precautionary saving and utility with the optimal consumption path to a baseline scenario in which there are no health and disability risks. Here, the variation in such risk across occupations prompts differences in the degree of precautionary saving and therefore different utility costs. I also calculate the value of SSDI across occupations, finding its value to be greater in the blue-collar jobs, being worth 12 percent of lifetime consumption compared to seven percent in white-collar jobs for a person of the estimated average risk aversion. The degree of risk aversion tends to be lower, however, among those selecting into blue-collar jobs, which diminishes the difference in the average value of SSDI between occupations.

The second problem I address involves the sensitivity of occupational choice to health and disability risks and to existence of SSDI, which attenuates some of this risk. Most studies estimating life-cycle models make the simplifying assumption that all individuals retire by a given age,[4] and understandably so given the that the focus of such studies is not on later-life labor supply. There is, however, a great deal of variety in health and labor force decisions at older ages, with clear differences between the labor supply of those in the more physically intense blue-collar jobs and those in white-collar jobs. As I will document below, at older ages, the wage declines more for blue-collar workers when health declines or functional limitations arise; productivity does not decline with health—which declines with

disability in both Kantor and Fishback (1996) and Chandra and Samwick (2004).

[4]See, for instance, Johnson and Keane (2013), Lee and Wolpin (2006), Lee (2005), and Low and Pistaferri (2010).

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

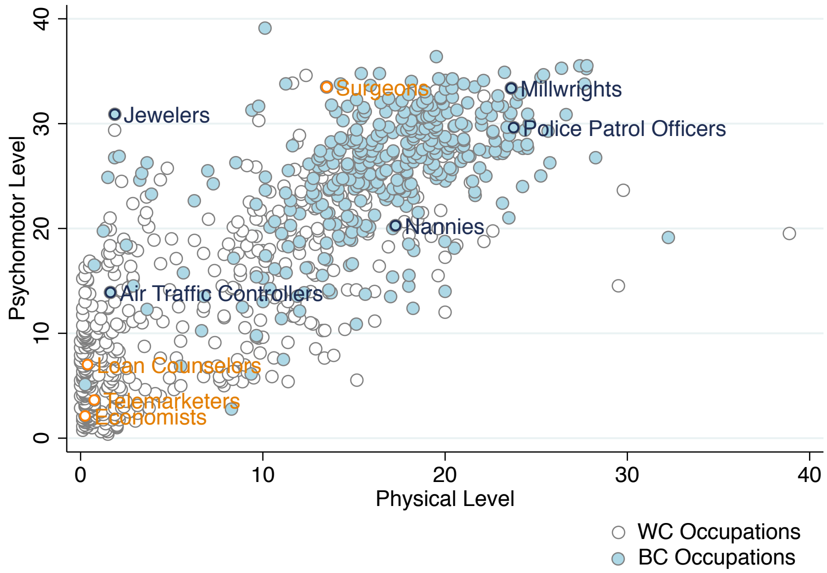


Figure 1: Physical and Psychomotor measures on occupations from O*NET. Each dot represents a three-digit occupation, with select occupations highlighted. Axes are an index of the degree to which physical and psychomotor are skills required in an occupation.

Figure 2: *Labor Force Participation by Age for Blue-Collar and White-Collar Occupations*

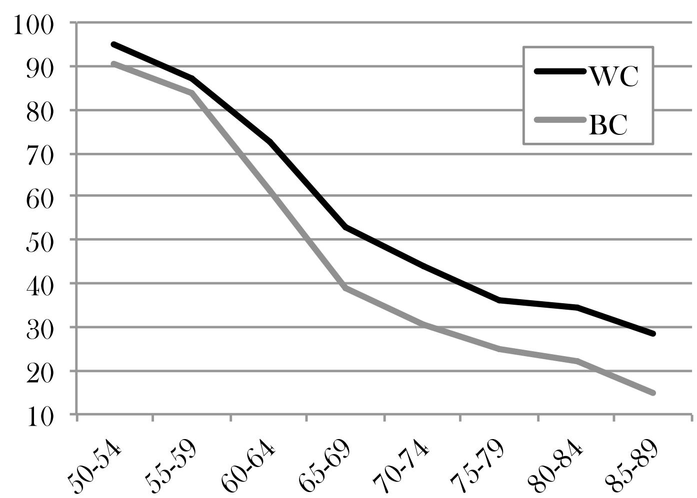


Figure 2: The difference in proportion working in WC and BC jobs, while more similar before age 60, increases with age. Participation observations for 22,176 WC and 21,070 BC person-years. Includes all of HRS respondents who have been observed working at least once (and have reported longest occupation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

age—in white-collar jobs to the extent that it does in blue collar jobs. This difference is in part what drives the divergence in later-life labor force participation between blue- and white-collar workers. Through counterfactual exercises I approximate how much the share of blue- and white-collar workers would change by looking at initial occupation choices in the equilibrium model when there is no uncertain effect on productivity from worsening health or disability, with and without the assumption of retirement by age 65. I find that if risks were equal across the occupations, the share in blue-collar jobs would be five percent greater. Alternatively, wages could be 8 percent lower in blue-collar jobs for the same proportion of individuals to select into such jobs without the higher health and disability risks present in these jobs, which corresponds to about $150K over the work-life of the average earner.

Given that, at all skill and earnings levels, those in blue-collar jobs are more likely to report having a disability that limits work and apply for SSDI, we might expect that such insurance is more valuable to blue-collar workers as physical requirements in their jobs are generally greater. At the same time, the design of the U.S. Social Security Old-Age, Survivors, and Disability Insurance (OASI and DI) programs does not account for such variation in job tasks. Because those in blue-collar jobs are more likely to receive SSDI at some point, this leads us to consider the extent to which SSDI might, in effect, subsidize such jobs by providing this more highly utilized insurance. To determine whether this is the case, I measure (i) how many fewer people would choose the physically demanding blue-collar jobs in the absence of SSDI, and (ii) how much higher wages would need to be in BC jobs for the same proportion to select in to them in the absence of SSDI. I find that the share of blue-collar workers would fall from nearly 58 percent to about 54 percent for the sample of individuals with high school diplomas or some college; holding the share of blue-collar workers fixed, wages would need to be eight percent higher to compensate for the loss of SSDI.

Finally, along the third line of questions I look at the labor supply in particular of blue-collar workers who do not become disabled. Because blue-collar workers face higher earnings risks, which prompts higher precautionary savings, those who do not become disabled will presumably have accumulated enough savings to stop working sooner. I find that there is an effect on the labor supply at older ages for the more risk-averse types blue-collar workers, but because blue-collar workers are much more likely to have lower risk aversion, the overall effect on blue-collar participation at older ages is small.

Before returning to these questions and counterfactual results in greater detail in Section 7, I present the model in Section 2, the HRS data and descriptive statistics in Section 3, and the OASI and SSDI programs in Section 4. The estimation procedure is outlined in Section 5 and estimation results are presented in Section 6. A discussion of this and future work in Section 8 concludes.

2. A Model of Occupational Choice and Labor Supply in Later Life

In this section I describe the model of behavior I construct to explain the trends and answer the counterfactual questions discussed above in which individual choices are made during *Young* and *Old* stages of potential working life. Through a structural model, we can capture the behavioral channels through which individuals make the decisions that give rise to patterns seen in the data and see responses in behavior to changes in the decision-making environment. I follow Johnson and Keane (2013) in developing and estimating an equilibrium model of sector and occupation choice at younger ages; I extend this model to take into account productivity and disability risk differences across occupations in later life. I model the annual later-life labor force participation and savings decisions of agents most closely to French (2005), who estimates a life-cycle model in older age with uncertainty over future health and wages; I additionally include the decision to apply for SSDI benefits and estimate the differing rates of decline in productivity and risks of disability across occupations.

The model I estimate is a single-sector labor market equilibrium model in which agents choose, in a life-cycle context, (1) occupation type (*blue-collar*, BC, or *white-collar*, WC), (2) labor force participation decisions at older ages, (3) savings and consumption decisions, and (4) whether and when to apply for Social Security Old Age Insurance and Disability Insurance benefits in a setting where agents differ in health and longevity expectations, disutility of blue-collar relative to white-collar work, and degree of risk aversion. The relative return to occupation-sector work depends on skill, experience, and health and disability and is determined in a competitive labor market; so while what can be thought of as "work-life expectancy" is greater in white collar occupations, initial occupational choices are tempered by equilibrium effects on relative earnings and disability risks across occupations.

I will first describe the individual's dynamic decision problem and uncertainty in the *Older* period, followed by the less complex *Younger*-stage decisions. I will then present the equilibrium model through which relative wages arise and the quantity choosing each occupation for both stages is determined.

2.1. The Individual's Problem: Occupation, Labor Supply, Savings, and Social Security Application Decisions

An agent's choices in this model are made over *Younger* and *Older* stages of his potential working life. He chooses an occupation—either blue-collar or white-collar—for each stage given his skill level and, in the *Older* stage, decides whether to work, how much to save, and whether to apply for OASI and SSDI benefits annually. Having richer decisions in the *Older* period yet only two opportunities to choose an occupation is based in part on the age range of the HRS data set, which is the most suitable data set for the questions this paper addresses, as well as on the simplifying and somewhat realistic assumption that individuals tend not to change careers many times over their working lives (see Table A.3 on page 46).

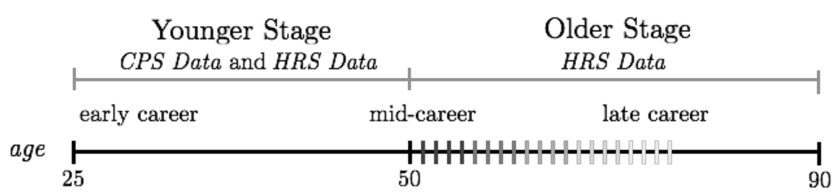
The timing of decisions and information for the agent is summarized in Figure 3 and described below, first over the *Older* stage followed by the *Younger*.

Annual decisions over the* Older *stage, ages 50 and over.

Every annual period t, agents make decisions about:

- Current-period labor supply: participation $p_t \in \{0, PT, FT\}$. This simplification is based on the observation that observed hours worked tend to be centered around 1,000 and 2,000 hours annually.
- Consumption that period, c_t, with $g_t \leq c_t \leq A_t + y_t$ so that consumption is in between a consumption floor and current assets and income. This credit constraint is imposed to reflect the presumed difficulty in obtaining uncollateralized loans at older ages, given the uncertain stream of income and it being illegal to garnish an individual's Social Security benefit payments.

FIGURE 3: *Timing of Information and Decisions*



Decision Variables:	total consumption, $\sum_{t \in \mathbf{Y}} c_t$ occupation, $d^{occ}_{\mathbf{Y}}$	participation, p_t consumption, c_t apply for OAI, OAI^{app}_t apply for DI, DI^{app}_t occupation, $d^{occ}_{\mathbf{O}}$ (when $t = 50$)
State Variables:	skill level, e wages, $w^{occ}_{\mathbf{Y}}$	asset level, A_t wage, w^{occ}_t health status, h_t functional limitations, d_t occupation, $d^{occ}_{\mathbf{O}}$, and skill, e $AIME_t$
Uncertainty Over:	state variables at age 50, $\mathcal{S}_{50}$	whether will receive DI, DI^{rec}_t future health, h_{t+1} future disability, d_{t+1} wages, w^{occ}_{t+1}

- Whether to begin receiving OASI, if ages 62-70: $OASI_t^{app} \in \{0,1\}$. OASI benefits do not increase after age 70, so there is no reason to delay claiming further; indeed, virtually everyone in the sample reports claiming OASI by age 70.
- Whether to apply for SSDI if under normal retirement age: $DI_t^{app} \in \{0,1\}$, which is received with some probability $p(DI_t^{rec}|DI_t^{app}, OCC_t, d_t) < 1$ (described below).

These decisions are summarized as $\mathcal{D}_t = \{p_t, c_t, OASI_t^{app}, DI_t^{app}\}$ and are made given the state space of

- Asset level, A_t.
- Current wage, w_t.
- Current health status. This includes both overall, self reported, $h_t \in \{good, bad\}$, and disability, as measured by existence functional limitation, $d_t \in \{0,1\}$.
- OASI and SSDI status (whether receiving or not): $OASI_{t-1}^{rec} \in \{0,1\}$ and $DI_{t-1}^{rec} \in \{0,1\}$.
- Average Indexed Monthly Earnings at that time, $AIME_t$, which is a function of past earnings and determines the OASI and SSDI benefit level for an individual.
- Occupation, $OCC_t \in \{BC, WC\}$.

The state space in period t is summarized as $\mathcal{S}_t = \{A_t, w_t, h_t, d_t, OASI_{t-1}^{rec}, DI_{t-1}^{rec}, AIME_t, OCC_t\}$. Finally, there is uncertainty over

- Future health, including overall and functional limitations (disability), h_{t+1} and d_{t+1}, which is a function of current health statuses and age.
- Future wages, w_{t+1}, which depends on current wage, occupation, health statuses, and age.
- Whether the individual will receive benefits if he applies for SSDI, which depends on occupation and function limitations: $p(DI_t^{rec}|DI_t^{app}, OCC_t, d_t) < 1$.

The agent's continuation value at time t is

$$V(\mathcal{S}_t) = \max_{\mathcal{D}_t} V(\mathcal{S}_t, \mathcal{D}_t) \tag{1}$$

where

$$V(\mathcal{S}_t, \mathcal{D}_t) = u(c_t, p_t, h_t, DI_t^{app}) + \beta \left[s(h_t, t) EV_{t+1}(\mathcal{S}_{t+1}) + (1 - s(h_t, t)) B(A_t) \right] , \tag{2}$$

with

$$EV(\mathcal{S}_{t+1}) = \max_{\mathcal{D}_{t+1}} \int V(\mathcal{S}_{t+1}, \mathcal{D}_{t+1}, \epsilon_{t+1}) \, dF(\mathcal{S}_{t+1} \,|\, \mathcal{S}_t, \mathcal{D}_t) \tag{3}$$

and

$$\begin{aligned} dF(\mathcal{S}_{t+1}\,|\,\mathcal{S}_t,\mathcal{D}_t) = \quad & f^h(h_{t+1}|h_t,t) \times f^d(d_{t+1}|d_t,t) \times f^d(DI_t^{rec}|d_t, OCC_t, DI_t^{app}) \\ & \times f^w(w_{t+1}|w_t,h_t,d_t,OCC_t)dw_{t+1}\,. \end{aligned}$$

From equation (2), we have that period utility, which is specified below, depends on current consumption, c_t, labor force participation, p_t, health, h_t, and whether one has applied for DI, DI_t^{app}. The future period is discounted at factor β; with probability $s(h_t,t)$ the agent survives to the next period, otherwise he leaves a bequest over which he receives utility $B(A_t)$. The individual does not know what his overall health, disability, DI receipt, wage or survival status will be in the future periods, but he does know the probability distribution conditional on his current health status, age, wage, and occupation. These transition probabilities are described in detail in Section 5. In practice, to calculate $EV(\mathcal{S}_{t+1})$ in equation (3), requires that for each alternative-specific shock vector ϵ, the sample mean of $\max_{\mathcal{D}_t} V(\mathcal{S}_t,\mathcal{D}_t)$ is used as an approximation.

Consumption c_t must satisfy the following budget constraint:

$$c_t \leq \begin{cases} [1+r(1-\tau)]\,A_t + Y(\cdot) & \text{if } \ A_t \geq 0 \\ Y(\cdot) & \text{if } \ A_t < 0 \end{cases}$$

so that in each period savings is allowed but additional borrowing is not. Assets evolve as follows:

$$A_{t+1} = [1+r(1-\tau)]\,A_t + Y\left(w_t + g_t + OASI_{t-1}^{rec} + DI_t^{rec},\, \tau\right) - c_t\,,$$

where r is interest earned on savings, g_t is a consumption floor,[5] and τ captures the tax structure.

Preference specification. Period utility in time t is assumed to be CRRA and is specified by

$$u_t = u(c_t, L_t, p_t, \varepsilon_t) = \frac{1}{1-\eta}\left(c_t^{\alpha_c} L_t^{1-\alpha_c}\right)^{1-\eta} + \alpha_{X^{\mathcal{D}}}\varepsilon_t(\mathcal{D}_t)\,. \tag{4}$$

The weight on consumption relative to leisure is given by α_c, and η measures the degree of curvature of the function from which we obtain measures of risk aversion and labor supply elasticity ($= 1/\eta$). Parameter vector $\alpha_{X^{\mathcal{D}}}$ weighs the preference shocks associated with decisions on occupation labor force participation, OASI or SSDI application, and consumption in that period. The utility costs of work, receiving SSDI, and performing work while in poor health enter through the leisure component of utility. Leisure is given

[5] Following French and Jones (2011) and Hubbard et al. (1994), outside transfers g_t provide a consumption floor so that $c_t \geq \underline{c} > 0$:

$$g_t = \max\{0,\ \underline{c} - (A_t + Y_t(\cdot))\}\,.$$

As discussed further below, consumption floor $\underline{c}$ is important for the identification of estimated risk aversion levels.

by, for $t \in \mathbf{O}$,

$$\begin{aligned} L_t = &L - N_t - \varphi_p \mathbb{1}_{\{p_t=1\}} - \varphi_{DI} \mathbb{1}_{\{DI_t^{app}=1\}} - \varphi_{BC} \mathbb{1}_{\{OCC=BC,\, p_t=1\}} \\ &- \varphi_{BC,h^p} \mathbb{1}_{\{OCC=BC,\, h=\text{poor},\, p_t=1\}} - \varphi_{WC,h^p} \mathbb{1}_{\{OCC=WC,\, h=\text{poor},\, p_t=1\}} \end{aligned} \tag{5}$$

and is measured in hours. It enters utility as a function of total hours available, L, number of hours worked, N_t, and the psychic fixed costs—or possible benefits—of working (φ_p), receiving disability insurance benefits (φ_{DI}), working in a blue-collar job (φ_{BC}), working in a blue-collar job while in poor health (φ_{BC,h^p}), and working in a white-collar job while in poor health (φ_{WC,h^p}).[6]

If the individual does not survive to time t, which occurs with probability $1 - s(h_t, t)$, he gets utility from bequest

$$B(A_t) = \frac{\alpha_B (A_t + K_0)^{(1-\eta_B)\alpha_c}}{1 - \eta_B}$$

and zero utility thereafter to age 90, with the functional form just as in French (2005). Here, α_B represents the utility weight on bequests and K_0 gives the extent to which bequests are a luxury good.[7]

As will be described further in the Estimation section, Section 5, agents can differ by type in preference parameters η (risk aversion) and φ_{BC} (the utility cost of performing blue-collar work).

Annual decisions over the* Young *period, ages 25 to 49.

At the beginning of the *Younger* stage of life, agents choose occupation $d_{\mathbf{Y}^{occ}}$ and accumulated assets by the end of the stage given their skill level e, expected relative wages $w_{\mathbf{Y}^{occ}}$, and associated *Older*-stage payoffs, Emax$V(\mathcal{S}_{50})$.

Period utility is just as in (4), though labor is perfectly inelasticity supplied at full-time hours over this stage and leisure is

$$\text{for } t \in \mathbf{Y}, \;\; L_t = L - N_t - \varphi_{BC} \mathbb{1}_{\{OCC=BC,\, p_t=1\}}$$

so that $\varphi_p, \varphi_{DI}, \varphi_{BC,h^p}$, and φ_{WC,h^p} in definition (5) are all by assumption zero.

Over the younger period, $t \in \mathbf{Y}$, I assume a single commodity with a price normalized

[6]As an alternative to the consequences of working while poor health entering through leisure, in Jacobs (2014), the cost comes through effect on wages, which similarly is allowed to differ depending on occupation. As poor health has larger estimated negative effects on wages for those in blue-collar jobs, we should expect estimates to be such that $\varphi_{BC,h^p} > \varphi_{WC,h^p}$.

[7]It is difficult to distinguish bequest motives from precautionary savings without K_0, which De Nardi et al. (2010) use to measure the level of wealth at which savings can be interpreted as bequest motives as opposed to precautionary savings.

to 1 in each period is consumed, with

$$\sum_{t \in \mathbf{Y}} c_t \leq \sum_{t \in \mathbf{Y}} w_t^j - A_t \, ,$$

so that agents enter the old stage with non-negative asset levels.[8]

2.2. Labor Demand

There is a competitive labor market in both the *Younger* and *Old* stages (s), with all agents being of the same cohort.[9] Within those stages, there is capital K_{st} and labor input L_{st} in stage s at time t, which is made up of skilled and unskilled ($e \in \{SK, USK\}$) based on education level, blue-collar and white-collar workers ($j \in \{BC, WC\}$). Here, while j is a choice in the model, e is treated as an endowment of skills as a simplification, though it will be measured by acquired education category. The rationale for having both stage s and time t, as opposed to t only, is based on assumptions on the substitutability of types of workers differing between the *Younger* and *Old* stages. Within each stage s, 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 in stage s at time t is CRS:

$$Y_{st} = A_{st} L_{st}^{\alpha} K_{st}^{1-\alpha} \, . \tag{6}$$

Here, A_{st} is stage-time productivity, and $\alpha \in (0,1)$ is the share of labor income.

Following Card and Lemieux (2001), Heckman et al. (1998), Johnson and Keane (2013), Katz and Murphy (1992), labor inputs of different occupations and skill levels are imperfect substitutes and are represented here as a nested CES aggregate ordered by occupation type, for $j = BC, WC$, and then skill level e, within a time period t and stage s:

$$L_{st} = \left[\sum_j \theta_{tj} L_{stj}^{\rho_{\mathbf{J}}} \right]^{1/\rho_{\mathbf{J}}} \qquad \text{where} \qquad L_{stj} = \left[\sum_e \varphi_{tje} L_{stje}^{\rho_{\mathbf{E}}} \right]^{1/\rho_{\mathbf{E}}} \, . \tag{7}$$

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

[8] This simplifying assumption is somewhat realistic, as few—less than five percent in my sample—enter the HRS at age 50 with negative assets when housing equity is included.

[9] This model is not OLG, though could it be modified to be such, as discussed in Section 8.

$\frac{1}{1-\rho_{\mathbf{E}}}$.[10]

The demand function for labor with characteristics j, e in stage s at time t is the marginal product of $p_t Y_{st}$ with respect to L_{stje} 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[11]

$$\begin{aligned} \ln W_{stje} = \ln A_{st} + \ln\left(\alpha\left(\frac{(1-\alpha)A_{st}}{r_t^K}\right)^{(1-\alpha)/\alpha}\right) & \\ + \ln\theta_{tj} + \frac{1}{\sigma_{\mathbf{J}}}(\ln L_{st} - \ln L_{stj}) & \\ + \ln\varphi tje + \frac{1}{\sigma_{\mathbf{E}}}(\ln L_{stj} - \ln L_{stje}) \,. & \end{aligned} \tag{12}$$

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

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

$$\ln\left(\frac{W_{stj,SK}}{W_{stj,USK}}\right) = \ln\left(\frac{\varphi_{tj,SK}}{\varphi_{tj,USK}}\right) + \frac{1}{\sigma_{\mathbf{E}}}\ln\left(\frac{L_{stj,SK}}{L_{stj,USK}}\right) + \xi_{stje} \,. \tag{13}$$

[10] L_{st} is then

$$\begin{aligned} L_{st} = \quad & \Big[\theta_{t,BC}\left(\varphi_{t,BC,SK}L_{s,t,BC,SK}^{\rho_{\mathbf{E}}} + \varphi_{t,BC,USK}L_{s,t,BC,USK}^{\rho_{\mathbf{E}}}\right)^{\rho_{\mathbf{J}}/\rho_{\mathbf{E}}} \\ & + \theta_{t,WC}\left(\varphi_{t,WC,SK}L_{s,t,WC,SK}^{\rho_{\mathbf{E}}} + \varphi_{t,WC,USK}L_{s,t,WC,USK}^{\rho_{\mathbf{E}}}\right)^{\rho_{\mathbf{J}}/\rho_{\mathbf{E}}}\Big]^{1/\rho_{\mathbf{J}}} \end{aligned}$$

[11] We have that wage is given by the marginal product of labor

$$W_{stje} = \frac{\partial Y_{st}}{\partial L_{stje}} = \alpha A_{st} L_{st}^{\alpha-1} K_{st}^{1-\alpha} \frac{\partial L_{st}}{\partial L_{stje}} \,, \tag{8}$$

where

$$\frac{\partial L_{st}}{\partial L_{stje}} = \frac{1}{\rho_{\mathbf{J}}}\left[\sum_j \theta_{tj} L_{stj}^{\rho_{\mathbf{J}}}\right]^{\frac{1}{\rho_{\mathbf{J}}}-1} \rho_{\mathbf{J}}\theta_{tj} L_{stj}^{\rho_{\mathbf{J}}-1}\frac{\partial L_{stj}}{\partial L_{stje}} \,, \tag{9}$$

and

$$\frac{\partial L_{stj}}{\partial L_{stje}} = \frac{1}{\rho_{\mathbf{E}}}\left[\sum_e \varphi_{tja} L_{stje}^{\rho_{\mathbf{E}}}\right]^{\frac{1}{\rho_{\mathbf{E}}}-1} \rho_{\mathbf{E}}\varphi_{tje} L_{stje}^{\rho_{\mathbf{E}}-1} \,. \tag{10}$$

Since $\left[\sum_j \theta_{tj} L_{stj}^{\rho_{\mathbf{J}}}\right]^{\frac{1}{\rho_{\mathbf{J}}}-1} = L_{st}^{1-\rho_{\mathbf{J}}}$ and $\left[\sum_e \varphi_{tje} L_{stje}^{\rho_{\mathbf{E}}}\right]^{\frac{1}{\rho_{\mathbf{E}}}-1} = L_{stj}^{1-\rho_{\mathbf{E}}}$, substituting (10) into (9) and for the elasticities of substitution, we get

$$\frac{\partial L_{st}}{\partial L_{stje}} = \theta_{tj}\left[\frac{L_{st}}{L_{stj}}\right]^{1/\sigma_{\mathbf{J}}} \varphi_{tje}\left[\frac{L_{stj}}{L_{stje}}\right]^{1/\sigma_{\mathbf{E}}} \tag{11}$$

Since $r_t^K = \frac{\partial Y_{st}}{\partial K_{st}} = (1-\alpha)A_{st}L_{st}^{\alpha}K_{st}^{-\alpha} \implies K_{st} = \left(\frac{(1-\alpha)A_{st}}{r_{st}^K}\right)^{1/\alpha} L_{st}$. This, along with (11), is substituted for K_{st} in (8). Then $\ln\left(\frac{\partial Y_{st}}{\partial L_{stje}}\right)$ can be expressed as (12).

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

Once estimates from equation (13) have been obtained, I proceed by measuring the relative productivity of and elasticity of substitution between blue-collar and white-collar workers: For stage s, time t, and skill level$e \in \{SK, USK\}$, the relative wages are

$$\begin{aligned}\ln\left(\frac{W_{st,BC,e}}{W_{st,WC,e}}\right) = \ln\left(\frac{\varphi_{t,BC,e}}{\varphi_{t,WC,e}}\right) + \frac{1}{\sigma_{\mathbf{E}}}\left(\ln\left(\frac{L_{st,BC}}{L_{st,WC}}\right) - \ln\left(\frac{L_{st,BC,e}}{L_{st,WC,e}}\right)\right) \\ + \ln\left(\frac{\theta_{t,BC}}{\theta_{t,WC}}\right) + \frac{1}{\sigma_{\mathbf{J}}}\ln\left(\frac{L_{st,BC,e}}{L_{st,WC,e}}\right),\end{aligned} \tag{14}$$

where the first line of the right-hand side in (14) is estimated by (13). To identify substitution elasticity $\sigma_{\mathbf{E}}$, the relative supply of blue-collar to white-collar workers, $\ln\left(\frac{L_{st,BC,e}}{L_{st,WC,e}}\right)$, is instrumented through the changes in the proportion of blue- to white-collar jobs across states. The estimation and identification of the relative wages are described further in Subsection 5.2.4.

2.3. Labor Market Equilibrium

The equilibrium in the *Young* and *Old* labor markets in each stage consists of high- and low-skill, blue- and white-collar wages and proportion in each skill and occupation type satisfying:

- individuals selecting the sequence of choices $\mathcal{D}_t$ solving (1) over both the *Young* and *Old* stages of their lives;
- firms choosing the output level Y_{st}^* that maximizes profit; and
- labor demand and labor supplied of each type being equal at wages W_{stje} given in equation (12).

A key simplifying assumption will be that the relative wage equilibrium component will persist in each stage—as opposed to agents forecasting an equilibrium path—so as to simplify the problem computationally. The computation of this labor market equilibrium is described below in Subsection 5.2.4.

3. Data and Descriptive Statistics

The data used to estimate the parameters of the model presented in Section 2 come from the Current Population Survey (CPS) for earnings and occupation selection moments over ages 25-49 and from the Health and Retirement Study (HRS) for labor force participation decisions, health transitions, and more for ages 50 and over. This section describes the sample selected and contains some relevant descriptive statistics from the HRS on health, occupation, and disability.

The HRS subsample I use to estimate the parameters of the model includes 1,389 male respondents, with a total of 9,155 person-year observations over 10 biennial Waves, who were (1) born between 1931–1941 (the original HRS cohort) and 1942–1947 ("War Babies" cohort), (2) have a high school diploma and possibly some college experience and career-related training but no four-year degree, and (3) either have a spouse who is not observed working at the time of the first HRS interview or is unmarried. This baseline HRS cohort was first interviewed in 1992 (at ages 51 to 61), and respondents from the War Baby cohort were added to the study in 1998 (at ages 51 to 56). Respondents are interviewed biennially, and the most recent Wave I use here is from 2010. Since inclusion in the HRS can be based on the birth year of either spouse in a household, the birth years for the male-only sample here roughly align with these years; I take responses for individuals with ages ranging from 50 to 75. This selection criteria was chosen so as to have a sample of respondents differing only to a certain extent in skill and in birth year cohort, while abstracting from joint household work decisions by considering only the behavior of those without working spouses when first observed.[12]

[12]This birth year restriction keeps 6,265 respondents out of a possible 13,313 males; using only those with a high school diploma or some college experience leaves 3,053 of those 6,265; keeping only those with no spouse or a spouse who was not working when the respondent was first interviewed in the HRS leaves 1,389 of those 3,053 respondents remaining in the sample. Table A.1 of the Appendix (page 45) shows the proportion of married respondents whose spouses are working when first interviewed by education level and income category. Those with less than a high school diploma or GED tend to be less likely to have a working spouse (and are themselves less likely to work at older ages) compared to other education categories, and those with a college degree or more are more likely to have a working spouse with the exception of those in the top income quintile. The figures in Table A.2 indicate that by excluding those with working spouses among high school graduates and those with some college, the remaining sample is not any more or less likely to receive SSDI. Also, surprisingly, the number of children ever born to the respondent does not differ greatly depending on whether a spouse is present and if so whether she is working within the education and birth-year cohort used here: The working-spouse mean is 2.8 children, for those with a non-working spouse it's 2.9, and for those with no spouse when first interviewed the average is 2.3 children. While there is some variation in the percent of respondents with a working spouse across education and earnings levels, observing the behavior of the possibly less representative married with non-working spouses (who presumably have a high enough reservation wage) and non-married respondents allows us to abstract from the joint working decisions of household and better proceed asking the questions of work, health, and

Some characteristics of the sample population are shown in Table 1, which include labor force participation status, assets, and health when first and last observed in the HRS data in the upper panel, and education, occupation type, and earnings in the lower panel. We can see that over the course of the ten Waves, a majority have transitioned out of the labor force, with 72 percent working either part- or full-time when first observed to nearly 77 percent not working in Wave 10. Both total assets and non-housing financial assets are higher when we last observe these respondents, though peak asset holding, while not shown here, occurs somewhat earlier as most have begun to draw down assets prior to Wave 10. The self-reported general health of respondents is somewhat lower, going from 81 percent down to 72 percent reporting good, very good, or excellent health. The share who report having health problems that limit work, however, nearly doubles, increasing from 22 up to 40 percent.

Within the HRS subsample of those with either a high school diploma or some college but no four-year degree, 60 percent are high school graduates with no college experience. Nearly 58 percent are employed in the more physically intense, "blue-collar" jobs and the other 42 percent are categorized as being in the less physically intense "white collar" jobs. The level of physical intensity is based on O*NET measures of the degree to which psychomotor and physical skills are required by three-digit occupation.[13] The median earnings for each quartile for each occupation type within education level is found in the bottom portion of Table 1, as is the percent in blue-collar and white-collar jobs for each education level. We can see that high-school graduates are more likely than those with some college experience to be employed in blue-collar occupations (67 percent versus 43 percent). Finally, the average income over ages 50 to 60 of those with a high school diploma only does not differ by occupation to the extent that it does for those with some college experience; the median earnings of white-collar workers is about 11 percent higher than for blue-collar workers who are high school graduates, while it's nearly 35 percent higher for those with some college.

3.1. Occupation, Health, and Work Limitations

The HRS gives responses to a great number of health and occupation characteristics. Here I will describe the variables used here and how the measures vary with age and affect ability to work.

In the model I estimate, declining physical ability may correspondingly decrease pro-

disability that are central to this paper.

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

Table 1: *Characteristics of the HRS Sample of 1,389 Respondents*

	Wave 1	Wave 10
Labor Force Status		
Full-Time	67.3%	12.9
Part-Time	4.9	10.2
Not Working	27.9	76.9
Total Assets, Including Housing		
Centile		
25th	$ 39,844	61,200
50th	141,406	182,500
75th	318,750	487,813
Non-Housing Financial Assets		
Centile		
25th	$ 0	0
50th	11,250	10,000
75th	54,688	95,000
Self-Reported Health Status		
Good/Excellent	81.1%	71.6
Fair/Poor	18.9	28.4
Health Problem Limiting Work	21.9%	39.6

Education[1]	
High School	60.2%
Some College	39.8
Occupation	
Blue-Collar	57.9
White-Collar	42.1

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

ductivity in the labor force, prompting, possibly, earlier labor force exit. Furthermore, the decline in productivity that results from a decline in ability is, as we will see, greater in physically intense jobs. While there are a number of ways to capture physical ability in the HRS data, I use a measure of *functional limitation*—that will be proxy for physical ability—as well as the *self-reported health* measure, which is a popular choice in many studies using HRS data and will be useful here as well, especially in forming mortality expectations.[14]

There is a relationship between the functional limitations total and self-reported health. In Table 2, we have the average number of functional limitations for the two self-reported health categories. We can see in the first two columns that the difference between the number of functional limitations of those with *Poor* self-reported health and those in *Good* health is fairly similar across age categories. Though the average number of functional limitations increases with age for both health categories is increasing with age, for all age categories, those in the *Poor* health category have approximately 3 to 3.5 more functional limitations on average than do those with *Good* self-reported health. The proportion in *Good* health declines with age, while the average number of functional limitations for all respondents increases (shown in the rightmost two columns in Table 2).

The proportion of individuals having at least one functional limitation by age category is also shown in Table 2 in the lower panel.[15] Both the proportion with at least one functional limitation and those reporting *Poor* health increase with age. Nearly 45 percent have at least one functional limitation at ages 50–54, and 72 percent do by ages 75–79; those with self-reported *Poor* health increases from 15 percent at ages 50–54 to 34 percent at ages 75–79. While the more general self-reported health measure is certainly related to productivity and thus labor force participation, the functional limitations measure more palpably corresponds to physical efforts required in work.

To understand the extent to which the effects of health on productivity and ability to perform work tasks varies by occupation, I use the HRS variable for which respondents report having a concurrent "health problem limiting [but not necessarily prohibiting] work." Though the response is subjective, this health-related variable seems most directly related

[14] The functional limitation measure is the total number of physical limitations out of a possible fourteen. This was formed by totaling the number of physical limitations under three of the six RAND HRS Functional Limitation indices: Mobility (`rWmobila`), Large Muscle (`rWlgmusa`), and Gross Motor Skills (`rWgrossa`). The other three categories are Activities of Daily Living (`rWadlwa`, `rWadla`), Fine Motor Skills (`rWfinea`), and Instrumental Activities of Daily Living (`rWiadle`, `rWlmcoga`, `rWiadlza`). These are explained in the RAND Version L documentation page 15. I chose to not make use of these measures because (1) the relationship with physical work is somewhat less direct as difficulty in these areas may limit any work and (2) there is not as much variation with age for these measures. I use responses from `rWslht` as the self-reported health measure. While there are five possible responses, I combine *Excellent*, *Very Good*, and *Good* under the category "*Good*" and *Fair* and *Poor* under "*Poor*" as the distinction among the finer categories did seem to make for a noisier measure while not enhancing the analysis.

[15] In all age categories, a substantial proportion of those having at least one functional limitation have no more than two out of the possible fourteen measured by the Functional Limitation variable used here.

Table 2: *Functional Limitations, Health, and Age*

Average Number of Functional Limitations by Self-Reported Health Status

Age Category	*Self-Reported Health* Poor	*Self-Reported Health* Good	Percent with Good Health	Average Number of Functional Lim.
50-54	4.18	.94	85.3	1.46
55-59	4.46	1.13	78.3	1.85
60-64	4.58	1.19	75.7	2.02
65-69	4.62	1.33	73.7	2.20
70-74	5.14	1.63	69.3	2.71
75-79	5.12	1.85	66.1	2.96

Age	*Proportion with* At Least One Functional Limitation	*Proportion with* In Fair or Poor Self-Reported Health
50-54	44.5	14.7
55-59	52.1	21.7
60-64	56.2	24.3
65-69	59.9	26.4
70-74	65.5	30.7
75-79	72.3	33.9

to what would be considered in the SSDI application evaluation process.[16] First note that, as is shown in the first two columns of Table 3, those in blue collar careers—whether working or not—are more likely to report having a health problem that limits their work in some manner. The relative difference is greater at the youngest ages, though the absolute difference across all ages is between 5 and 10 percentage points in this HRS subsample of similarly skilled workers (the difference between blue-collar and white-collar workers is much greater when comparing the two for all education levels).[17]

Not only are blue-collar workers more likely to report having a health problem limiting work, they are also less likely to continue working when there is a functional limitation present. In the rightmost two columns of Table 3, we can see that, of the respondents who report that they have a health problem limiting work, those in white-collar careers are more likely to be working despite the reported health limitation. For those in blue-collar types of work, on the other hand, health problems seem to be much more likely to prohibit

[16]Indeed, Benítez-Silva et al. (1999) argue that this is nearly a sufficient statistic for predicting disability application.

[17]Furthermore, in Table A.8 of the Appendix (page 48), we see that of those not working, respondents who were in BC careers are more likely to report that they have a health problem that limits work; health limitations, then, presumably matter more for those in BC careers. Indeed, estimates of wages confirm this. Among those working, however, there is not much difference in the proportions with health problems that limit the work they do.

Table 3: *Percent with Health Problem Limiting Work and Percent Working:*

Age Category	Percent with Health Problem Limiting Work[1]		Of Those with Health Problem, Percent Working[2]	
	White-Collar	*Blue-Collar*	*White-Collar*	*Blue-Collar*
50-54	13.9	20.6	52.2	39.4
55-59	20.2	25.6	42.9	31.9
60-64	24.0	29.9	32.5	22.8
65-69	22.2	32.2	21.3	12.5

[1] 3,156 WC person-year observations; 4,347 for BC career respondents.
[2] 743 WC person-year observations; 1,255 for BC career respondents.

Table 4: *Effects of Age, Education, and the Interaction Between Functional Limitations and Job on Participation*

Outcome Variable: Labor Force Participation[1]

	Coeff.	Std. Error	Probability at Means
Function Limitation with			
BC Job	-.315	.077	*
WC Job	-.164	.064	**
Education Category			
Less than HS	-	-	.740
GED	-.015	.165	.735
High School	.017	.085	.745
Some College	-.012	.091	.736
College and Above	.279	.088	.822
Age	-.024	.013	-
Constant	2.267	.852	-

Marginal Effects

Age	Predicted Probability of Working***		
	No Functional Limitations	At Least One Functional Limitation	
		WC	*BC*
62	.813	.766	.718
63	.807	.759	.710
64	.800	.752	.702
65	.794	.744	.694
66	.787	.737	.685
67	.780	.729	.677
68	.773	.721	.668
69	.766	.713	.660
70	.759	.705	.651

[1] Outcome variable is whether working in the next period. 2,466 obs., over age 61.

working altogether. Table 4 on page 19 presents results from a probit regression of the effects of functional limitations on labor force participation in the next period. Controlling for education and age, we see that the effects of having at least one functional limitation is much more likely to be followed by exit from the labor force for those in BC jobs compared to those in WC jobs. The lower panel of Table 4 gives the predicted probability of work in the next period for high school graduates by age for those with no functional limitations, those with at least on limitation who work in a white-collar job, and those with at least one functional limitation who work in blue-collar jobs. Those with no functional limitations have a higher probability of continuing work in the following period for all ages. Those with at least one functional limitation who worked in white-collar jobs have a probability of continuing work that is about five percentage points lower than those with no limitations, while those in the blue-collar jobs had a probability of continued work that was about 10 percentage points lower at all ages.

3.2. Occupation and SSDI Application and Utilization

Declining health and the presence of functional limitations are more likely to be followed by labor force exit for those in blue-collar work. Such factors are also associated with higher utilization of Social Security Disability Insurance among blue-collar workers, even conditioning on average income level and educational attainment. Results from a probit regression of the probability of SSDI application, controlling for demographic factors and interactions, is shown in Figure 4 for high school graduates, ages 55-60. That there would be significantly higher SSDI application and receipt even at higher income levels for blue-collar workers is somewhat surprising given that income replacement from SSDI decreases greatly with income, as is discussed in Section 4. Overall, within our sample of individuals with a high school diploma or some college experience, 10.1% of those in white-collar work have received SSDI, while 18.1% of blue-collar workers have.

As we saw before, there are differences between blue- and white-collar workers in the proportion having health problem limiting work, and in Table 5, we see that there at similarly differences in SSDI application controlling for health problems. Over all ages, among those who have had a health problem limiting work, 28 percent of white-collar workers have ever applied for SSDI, while nearly 47 percent of blue-collar workers have. In the second column, we see that 3.7 percent of white collar workers and 8.5 percent of blue-collar workers who did not have health problems limiting work when responding had at some point prior applied for SSDI and presumably recovered by the time of interview; these individuals were more likely to report having their application rejected. Overall, however, in this sample, 77 percent of those who report having ever applied for SSDI also report receiving it, which is only two percentage points higher than in the entire male HRS sample but about 7 percentage points higher than national figures, possibly due to those who had applications rejected being less likely to report ever having applied. Benítez-Silva et al. (1999) analyze the application and award process for SSDI using the first three waves of the HRS data. They note the high acceptance at the appeal stage and the large fraction who appeal. The rate of award is 73 percent when including awards from initial application, appeal, and reapplication, though the significant delay of award for those not approved in the initial stage (15 months versus 5 months) may deter appeal. They find that an individual's self-assessed disability status is the best predictor of whether an individual will apply for benefits. For estimation of the model here, whether one ultimately receives SSDI benefits if he applies depends on overall self-reported health, functional limitations, and occupation, abstracting from the reapplication and appeal process.

4. Social Security Old Age and Disability Insurance

In this section I will describe some aspects of the design—especially those relevant to individuals' decision making—of the Old Age and Disability Insurance programs, which are operated federally under the U.S. Social Security Administration (SSA).[18] This is important for understanding the behavior of the agents studied here as labor supply and savings decisions are made in the context of mandatory participation in these programs.[19] The growth of the Old Age and Disability Insurance programs continues to attract a great deal of attention—with expenditures now being over $800 billion annually (2014 USD), comprising nearly a quarter of the Federal budget[20]—as does its uncertain fiscal viability, with both the absolute size of the older population and the ratio of retirees to younger workers having grown substantially over the past decades. The expenditures and beneficiaries of the SSDI program have risen considerably in the past decades and, while there is a cyclicality in applications that fluctuations in the roles can be tied to, it's difficult to account for the long running trend. The expansion is especially surprising given that the health status of older individuals has been steadily improving and an increasing share of jobs requiring low levels of physical work.[21]

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[18] The program, Old-Age, Survivors, and Disability Insurance (OASDI), also includes Survivors Insurance, which provides benefits to any spouse surviving a deceased person covered. The SSA also administers TANF, Medicaid and Medicare, SSI, and SCHIP.

[19] Participation is mandatory for almost any person employed in the sense that 12.4 percent of all earnings are taxed (6.2 percent paid directly by both the employer and employee) for the purposes of the program, with 1.8 percent dedicated to funding SSDI. Over 90 percent of all workers pay Federal Insurance Contribution Act (FICA) taxes on income, while self-employed persons are required to pay a Self-Employed Contributions Act (SECA) tax. An additional 2.9 percent on top of the 12.4 percent Social Security taxes is paid to the Medicare trust fund.

[20] Source: U.S. Social Security Administration, `http://www.ssa.gov/OACT/FACTS/`. An additional cost of the Disability Insurance program comes from the Medicare benefits that DI beneficiaries become eligible for within two years of the onset of disability. Annual Medicare expenditures currently total over $500 billion, with 16 percent of those covered by the program being covered as DI beneficiaries.

[21] Autor and Duggan (2003) attribute the rise in part to changes in the evaluation process, relative increase in benefits, and the declining demand for lower-skilled work. They predicted a further 40 percent increase in SSDI receipts beyond the 5.3 million beneficiaries in 2001, which has in the last decade been

Figure 4: *Probability of Applying for SSDI*

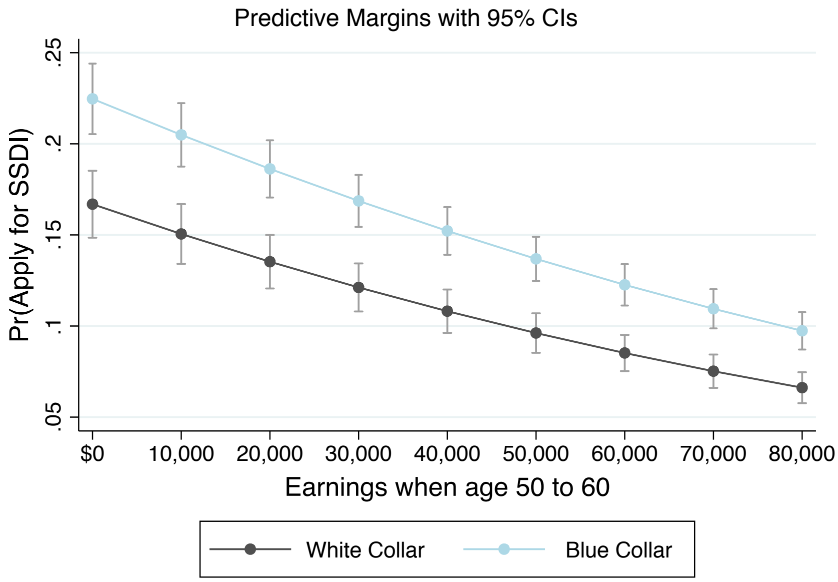


Table 5: *Differences between BC and WC in Health Problems and SSDI:*

	Health Problems Limiting Work	
White-Collar	Yes (23.6%)	No (76.4%)
Ever Applied for SSDI?		
Never Applied	72.0	96.3
Applied	28.0	3.7
Blue-Collar	Yes (28.9%)	No (71.1%)
Ever Applied for SSDI?		
Never Applied	53.4	91.5
Applied	46.6	8.5

Note: 3,156 WC person-years; 4,347 BC person-years.

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 the Normal Retirement Age (NRA) for Social Security Old-Age and Survivor's Insurance (SSOASI).[22] Whether one will meet this criteria and qualify for SSDI benefits is determined through a known, structured evaluation process, though qualification is somewhat less than deterministic in the sense that it depends on one's age, training, and type of work performed in the past. Criteria is not necessarily constant, and there have been changes in the definition of what constitutes disability with, for instance, more mental health conditions being eligible now than in the past.

The applicant 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. He must not be "substantially gainfully employed" at time of application, with full-time work will typically resulting in automatic denial.[23] If he is not working, the severity and expected duration of his condition or impairment is evaluated. While the time from application to an approval or rejection (including appeals) averages over twelve months (Benítez-Silva et al. (1999)), there is an expedited process for easily diagnosable illnesses, including many cancers and most terminal illnesses.

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

surpassed; the current number of beneficiaries is nearly 11 million, which includes 2 million spouses and children of disabled workers. Liebman (2014) suggests, however, that the increase in roles is due in part to the increase in female labor force participation as well as an increase in the proportion of females on SSDI, a population outside the one I am focused on. Murray (2012), on the other hand, advances the idea that diminishing expectations that prime-age males be working has contributed to the growing SSDI roles, being used essentially as a replacement for unemployment insurance. It would be possible to consider Murray's explanation in this model accounting for a trend in the "stigma" or "hassle" cost of applying for and receiving DI benefits possibly declining over time (this cost is not currently time-dependent).

[22]Source: Social Security Administration website: `www.socialsecurity.gov`. It is important to note the difference between SSDI and state-run Workers' Compensation programs, which, unlike SSDI, insure more temporary injuries having occurred on the jobs.

[23]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, though this situation is somewhat uncommon.

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.

The benefit amount that the SSDI recipient receives are equal to the Primary Insurance Amount (PIA) he would receive as SSOASI benefits at Normal Retirement Age (NRA), which is currently 65 to 67, depending on birth year. The PIA, which is a function of one's income in his top 35 earning years, amounts to a minimum of about $800 per month for those with work history but low Average Indexed Monthly Earnings (AIME) with the average monthly benefit for disabled workers being $1,145.[24] Once the SSDI recipient reaches the Social Security NRA, the SSDI benefits cease and an equivalent of SSOASI benefits begin.[25]

5. Estimating the Model Through SMM

In this section I will describe how I obtain the preference parameters and transition processes in the model presented in Section 2, as well as address identification issues. The model is estimated in two stages, as in French (2005), French and Jones (2011), Gourinchas and Parker (2002) and others. In Section 5.1 I describe the first stage, in which I estimate all parameters that are determined outside of the model. This includes the health and disability transition processes and survival probabilities, which I estimate from the HRS data, and the discount rate and return on assets, which are estimates taken on existing literature. These parameters enter into the model in the second stage, in which the preference and equilibrium wage parameters generating the behavior using select moments to that which is "closest"—in a GMM sense—to what is seen in the data are found, a procedure described in Section 5.2.

5.1. Transition Processes (First-Stage Estimates)

The transition processes are estimated using HRS data and are assumed to be determined outside the model. This assumption is meant to simplify the problem, though it is likely that health and disability not only affect capacity for work, but are affected by the work in which one engages. We might imagine that some physically intense, blue-collar work could help one stay active, maintaining better health with age; on the other hand,

[24]The average for all SSDI recipients, including spouses and children of disabled workers is $1,000. The PIA of disabled workers is less than the PIA of all retired workers who are SSOASI recipients, which is $1,302, as disabled workers tend to have a weaker earnings history. Source: `http://www.ssa.gov/policy/docs/quickfacts/stat_snapshot/`, accessed September 2014.

[25]After two years of receiving SSDI or upon reaching NRA, whichever comes first, one is automatically enrolled in Medicare, and with certain illnesses one is enrolled in Medicare immediately upon SSDI application approval. While I do not include health expenses here, the value of the Medicare benefits tied to SSDI could be accounted for with an extension of this model to include health expenses as in French (2005). While the value of Medicare may be quite high to certain potential SSDI applicants, the value relative to the means-tested Medicaid benefits this group might otherwise receive might not be so considerable.

work requiring exposure to harsher physical environments or resulting in strain from repetitive motion might have the opposite effect. In any case, within the model estimated in this study, the agent takes these processes as his expectation over future events, independent of choices in the model, when making decisions.

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

$$\begin{aligned}\Pr(s_{t+2} = \ell \mid s_t = j) &= \sum_{k \in \mathbf{S}} \Pr(s_{t+2} = \ell \mid s_{t+1} = k) \cdot \Pr(s_{t+1} = k \mid s_t = j) \\ &= \sum_{k \in \mathbf{S}} \pi_{k\ell,t+1} \pi_{ik,t}\end{aligned}$$

where

$$\pi_{ik,t} = \frac{\exp(\mathbf{x}'_{i,t}\beta_k)}{\sum_{m \in \mathbf{S}} \exp(\mathbf{x}'_{i,t}\beta_m)} .$$

Coefficient β_k is estimated using maximum likelihood and used to approximate the corresponding figures in the transition matrices.

5.1.1. Health Transition Process

The transition processes for overall, self-reported health (h) that may diminish productivity in work and lead to greater levels of precautionary savings is shown, conditional on current health and age, in Table 6 for select ages. In this table, we see that the probability of remaining in good health declines with age, as does the probability of transitioning from poor to good health. The transition processes could certainly depend on the occupation one is working in; I find, however, that, although the distribution of health is somewhat different for those in blue-collar and white-collar occupations, the transition probabilities themselves do not differ. While the transition process faced by individuals does not depend on occupation, we will see in the wage estimates shown in Table 8 that the effects on productivity of worsening health are greater for those in blue-collar occupations.

5.1.2. Functional Limitation Transition Process

The probability of a functional limitation being present in the next period and limiting work depends on an individual's current self-reported health (h_t), occupation (OCC_t), and existing functional limitation status (d_t). The probability of having at least one functional limitation in the next period, given that an individual is in good health in the current period is shown in Table 7. We can see that the conditional probability of a functional limitation arising is always greater for those in blue-collar jobs; though interpretation of this is not entirely straightforward. Because more physical jobs have a higher standard for physical capability, whether significant loss of a function prohibits work depends on the nature of the work. Furthermore, even if the functional limitation does not prohibit work altogether, as with worsening general health, it does result in a greater loss of earnings for those in blue-collar jobs, as presented in Table 8.

5.1.3. Survival Transitions

Both Casanova (2011) and French (2005) compute their conditional survival probabilities using Bayes' Rule, with

$$\begin{aligned} s(h_t, t) &= \Pr(\text{Survive}_t \,|\, t_{t-1} = h) \\ &= \frac{\Pr(h_{t-1} = h \,|\, \text{Survive}_t)}{P(h_{t-1} = h)} \times \Pr(\text{Survive}_t) \quad \text{for } h\text{=good, bad.} \end{aligned}$$

I assume that individuals die with probability one at age 90 regardless of health status, so $P(\text{Survive}_{90}|H_{89} = h) = 0$ for all h.[26]

Table 6: *Sample Health Transition Probabilities*

		Next Period Health		
	Current Health	G/VG/E	Fair	Poor
Age=55	G/VG/E	.87	.12	.01
	Fair	.46	.37	.17
	Poor	.15	.36	.49
Age=65	G/VG/E	.84	.14	.02
	Fair	.42	.39	.20
	Poor	.12	.34	.54
Age=72	G/VG/E	.82	.15	.02
	Fair	.39	.39	.22
	Poor	.11	.32	.57

[26]Survival probabilities are obtained from the U.S. Social Security Administration's *Office of the Chief Actuary* reports: Actuarial Study 120, "Life Tables for the United States Social Security Area 1900-2100" by Felicitie C. Bell and Michael L. Miller. Available at `http://www.ssa.gov/oact/NOTES/as120/LOT.html`. These give one-year survival probabilities at age t by sex and birth year cohort, conditional on survival up to age t. I use the 1945 birth year cohort (the birth years in the sample ranging from 1938 to 1953).

Table 7: *Probability of Having at least one Functional Limitation Preventing Work Next Period for Select Ages and Good Health by Occupation*

	BC Career		WC Career	
	Current Limitation		*Current Limitation*	
Age	No	Yes	No	Yes
55	.46	.54	.59	.41
65	.41	.59	.53	.47

5.2. Second-Stage Estimation

The agents' beliefs over uncertain future health, functional limitations, and survival match the transition processes from the first stage are taken as fixed parameters of the model in the second stage of estimation. In this stage, we solve for the preference parameters of heterogeneous agents and parameters determining the equilibrium relative wage in both blue- and white-collar occupations. These parameters are found through the process described below in 5.2.1 using the moments defined in subsection 5.2.2.

5.2.1. Computational Procedure in Second Stage

I adopt a computational procedure following French and Jones (2011), French (2005) for labor supply decisions with uncertainty, and Lee (2005)'s solving for equilibrium relative wages. First, the agents problem expressed in equation (1) is solved for a given set of parameters, in which the optimal savings (and equivalently consumption) is computed conditional on each labor supply choice p_t (full-time, part-time, and not working), Social Security Old-Age and Survivor's Insurance (OASI) benefit claiming choice $OASI^{app}$ (which can be claimed at age 62 or later), and Disability Insurance (DI) application DI^{app}. Next, whether to apply for DI and then whether to apply for OASI. Finally, the optimal participation choice in any period is the one that yields the greatest value given the optimal savings, DI and OASI application choice, and the realization of the preference shock $\epsilon_t(P_t)$. Next the outer maximization problem of searching across parameters to find the set which generates the behavior of simulated individuals that best matches the data is solved using the two-stage approach.

The parameters estimated in the first stage are represented by $\widehat{\chi}$. Further, let θ denote the vector of parameters estimated in the second stage, which includes parameters of utility function, fixed costs of work, and type prediction. The estimator $\widehat{\theta}$ is given by

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

where $\widehat{\varphi}$ denotes the vector of moment conditions described below, and Ω is a symmetric weighting matrix. The weighting matrix contains the inverse of the estimated variance-covariance matrix of the estimates of the sample moments along and off the diagonal.

The solution to (15) is obtained by the following procedure

1. First compute sample moments and corresponding weighting matrix Ω from the sample data.

2. From the same data, generate an initial joint distribution for wages, health, functional limitations and disability, AIME, assets, occupation type, and variables used in estimating the preference type assigned using the type prediction equation (described below). Some of the first-stage parameters contained in χ are also estimated from these data.

3. Using $\widehat{\chi}$, generate matrices of random health, disability, wage, mortality, and work preference shocks for 1,000 simulated individuals.

4. Each simulated individual receives a draw from the initial distribution in Step 2, and is assigned one of the simulated sequences of shocks from Step 3.

5. Given $\widehat{\chi}$ and an initial guess of parameter values contained in θ, compute the decision rules over the entire state space and generate simulate decision profiles for the decision variables.

6. Compute moment conditions by finding the distance between the simulated moments from Step 5 and true moments, solving equation (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.

5.2.2. Moments

The moments in the CPS and HRS data I choose to match the simulated behavior from my model to are those which will help to identify decisions and responses of interest here. I choose a total of 216 such moments, while additional moments are used to validate the model:

- *Median assets by age category (55-59 and 60-64), income quintile, occupation, skill level.*[27] This gives $2 \times 5 \times 2 \times 2 = 40$ moments. These moments are relevant since, given the same level of permanent income, we would expect a blue-collar worker who faces on average fewer potential productive working years to save more than the white collar worker. Variation in assets held helps identify risk aversion parameters for types as well as the bequest motive at higher asset levels.

- *Proportion choosing BC and WC occupations by stage (Young and Old), skill level, and preference type (described below).* This gives $1 \times 2 \times 2 \times 2 = 8$ moments. Because the central counterfactual question asks how these proportions change with policy, it is desirable to match this in-sample behavior precisely. These moments identify the cost of blue-collar work, ϕ_{BC}.

- *Proportion working part-time and full-time by age (55-59, 60, 61, 62, 63, 64, 65, and 66-70), occupation, skill level, and health status.* This makes $2 \times 8 \times 2 \times 2 \times 2 = 128$ moments. These moments reflect the primary labor supply decisions of interest, which should be generated by the model. Distinguishing between part- and full-time work is particularly important at these ages, as the proportion choosing part-time work is especially high compared to younger age groups. This, in addition to the asset moments, helped identify η, as more risk averse types would tend to work more hours at younger ages in order to save more.

- *Percent receiving SSDI by age (55-59 and 60-64), permanent income quintile, health status, and occupation.* This gives $2 \times 5 \times 2 \times 2 = 40$ moments. Since to receive SSDI in this model one must experience some functional limitation and incur some hassle or psychic stigma cost, a parameter that I seek to recover, I measure the proportion who ultimately receive SSDI.

Additional moments are used to test the performance of the model in capturing behaviors of interest here, including assets by age, occupation, and disability status, which is described further in Section 6.

5.2.3. Preference Types

The preference type prediction parameters are also found in the second stage. I assume that there are four preference types, with agents possibly differing on the coefficient of relative risk aversion η and cost of doing blue-collar work φ_{BC} parameters: (1) *Type A* is more risk averse (high η) and has a lower cost of performing blue-collar work (low φ_{BC}); (2) *Type B* is more risk averse (high η) and has a higher cost of performing blue-collar work (high φ_{BC}); (3) *Type C* is less risk averse (low η) and has a lower cost of performing blue-collar work (low φ_{BC}); and (4) *Type D* is less risk averse (low η) and has a higher cost

[27] Income here is a "permanent income" measure that come from respondents' AIME levels.

of performing blue-collar work (high φ_{BC}). Though η is sometimes determined outside of the model in similar studies,[28] 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. I allow for heterogeneity in φ_{BC} to more realistically reflect behavior in choice of occupation, which is a central decision in this model.

To predict the types, I estimate a multinomial logistic regression within the second stage, where the probability of individual i being *Type n*, $n = A, B, C, D$, is

$$\Pr(i{=}\mathit{Type}\ n) = \frac{\exp(\beta_n \mathbf{X}_i)}{1 + \sum_{k \neq n} \exp(\beta_k \mathbf{X}_i)} \tag{16}$$

where

$$\begin{aligned}\beta_n \mathbf{X}_i =& \beta_{n,0} + \beta_{n,1}(\text{Assets at 50})_i + \beta_{n,2}(\text{Work Enjoyment})_i \\ &+ \beta_{n,3}(\text{Physical Activity})_i + \beta_{n,4}(\text{Income Gamble})_i\,,\end{aligned}$$

so that the probability of having a high or low η and φ_{BC} is predicted by an HRS respondent's assets relative to permanent income at age 50, responses to a work enjoyment question, physical activity enjoyment question, and responses to a gambling question intended to capture risk aversion.

5.2.4. Wages and Computing Labor Market Equilibrium

Estimated wages include an equilibrium component of relative earnings between high- and low-skilled blue- and white-collar workers, as well as terms depending on age, health, and functional limitations interacted with occupation. Specifically,

$$\begin{aligned}\ln w_t =& EQ^*_{s,j,e} + \gamma_0 + \gamma_1 N_t + \gamma_2 \text{Age}_t + \gamma_3 \text{Age}^2 + \gamma_4 \mathbb{1}_{\{BC, poor\ H\}} \\ &+ \gamma_5 \mathbb{1}_{\{occ^{\mathbf{O}} \neq occ^{\mathbf{Y}}\}} + \gamma_6 \mathbb{1}_{\{WC, poor\ H\}} \\ &+ \gamma_7 \mathbb{1}_{\{BC,\ func.\ lim.\}} + \gamma_8 \mathbb{1}_{\{WC,\ func.\ lim.\}} + \varsigma_t\end{aligned} \tag{17}$$

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

Subtracting $EQ^*_{s,j,e}$ from both sides and expressing the remaining terms on the right

[28] For example, Low and Pistaferri (2010) set a parameter with roughly the same interpretation as η in this paper to 1.5, while Chandra and Samwick (2004) set the coefficient of relative of risk aversion to 3 for their exercises.

hand side of equation (17) as $w(N_{it}, \text{Age}_{it}, h_{it}, d_{it}, occ_{it})$ to get

$$\ln w_{it} - EQ^*_{s,j,e} = w(N_{it}, \text{Age}_{it}, h_{it}, d_{it}, occ_{it})\,, \tag{18}$$

I calculate coefficients of equation (18) are calculated fixing $EQ^*_{s,j,e}$ at the value implied from share and substitution parameters of equations (14) and (13) here from Johnson and Keane (2013) Tables 1 and 3, with the proportion of high- and low-skill blue- and white-collar workers being equal to observed proportions in the HRS, as presented in Table 1 of this paper, which give, for $s = \mathbf{O}$ and all t (assumed), $\frac{L_{j,SK}}{L_{j,USK}} = .661$, $\frac{L_{BC}}{L_{WC}} = 1.375$, $\frac{L_{BC,SK}}{L_{WC,SK}} = .748$, and $\frac{L_{BC,USK}}{L_{WC,USK}} = 2.040$.

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 (18) do not vary with $EQ^*_{s,j,e}$ as $L_{s,BC,e}/L_{s,WC,e}$ varies, for $e \in \{SK, USK\}$. In addition, while $EQ^*_{s,j,e}$ may change over time, I assume this component is deterministic from the point of view of the decision-making agent and persists in to the future, as opposed to agents forecasting the entire equilibrium path, further simplifying the problem.

I compute the term $EQ^*_{s,j,e}$ implied by the labor supply ratio $L_{s,BC,e}/L_{s,WC,e}$ for ratios centered around one. For each term $EQ^*_{s,j,e}$, occupation decisions are made by individuals through the process described in steps (5) through (7) in subsection 5.2.1. This processes is repeated until occupational choices giving labor supply ratio $L_{s,BC,e}/L_{s,WC,e}$ satisfying $L_{s,BC,e} + L_{s,WC,e} = N^{\text{SIM}}_{s,e}$ are found, where $s \in \mathbf{Y}, \mathbf{O}$ and $e \in SK, USK$, and $N^{\text{SIM}}_{s,e}$ is the

TABLE 8: *Wage Equation Estimates*

Outcome: $\ln$ *Annual Earnings* $- EQ^*_{s,j,e}$		
Variable	*Coefficient*	*(s.e.)*
Age (years)	.1130	(.0225)
Age^2	-.0011	(.0002)
Functional Limitation, f_{it}		
White-Collar	-.0093	(.0162)
Blue-Collar	-.0785	(.0197)
Poor Health, h_{it}		
White-Collar	-.0102	(.0159)
Blue-Collar	-.0421	(.0110)
Full-Time Work, N_{it}	.8109	(.0202)
Switch Occ.	-.0017	(.0008)
$\widehat{\rho}$ (autoreg. coeff.)	.9502 (.0162)	
$\widehat{\sigma}^2_\nu$ (trans.)	.0325 (.0084)	

Note: Observations n=18,052, individuals=5,216. Controls for year and Census division. Being just above Early and Full Social Security claiming ages used as exclusion restrictions.

number of simulated individuals in stage s with education level e.

6. Estimation and Results

In this section, I present results on parameter values using the estimation procedure and data moments outlined in Section 5 using the HRS data described in Section 3 as well as results from model validation exercises.

6.1. Parameter Estimates

Utility Parameter Estimates

Utility parameter estimates are shown in the upper portion of Table 9. The consumption weight α_c relative to leisure time is .59. The risk aversion parameter η is estimated to be 4.5 for what we will refer to as Types A and B, and 1.2 for the less risk-averse Types C and D. The average value of η for all types is comparable to other models' estimates with a single type; given the large differences in assets held for otherwise similar individuals in the data and hours worked with age, however, allowing for heterogeneity in this value helps account for the source of such differences.[29]

The cost of working in a given period in while in bad health is allowed to differ by occupation. This is measured in terms of equivalent hours of leisure time lost and is identified by differences in the participation rates of those in good health for each occupation. The cost of working while in bad health in a blue-collar job, $\varphi_{BC,\ ph}$, is about 300 hours while the cost in white-collar jobs, $\varphi_{WC,\ ph}$, is about 79 hours. The difference seems reasonable considering that, in the data, fewer people work—holding other characteristics fixed—when in bad health regardless of occupation, and moreso for those who do work blue-collar occupations.

What can be interpreted as the psychic stigma or hassle of applying for and receiving SSDI is estimated to be equivalent to a loss of 195 hours of leisure, which is identified by the individuals who report being in bad health and have a functional limitation impeding work who do not apply for SSDI. The cost of performing work in a blue-collar occupation, φ_{BC}, is allowed to vary across types, with Types A and C having a low cost of blue-collar work, which is normalized to zero hours, and Types B and D having a high cost, estimated to be approximately 241 hours. This is identified by choice of occupation for otherwise similar individuals and labor force participation levels across ages.

Finally, parameters from the bequest function include bequest weight α_B and bequest

[29] Alternatively, we could allow for different rates of time preference across types. I have set the discount rate to $\beta = .96$ in this model, as it would be difficult to identify both parameters in the data off of assets held.

TABLE 9: *Utility Parameter Estimates**

Utility Specification

$$u_t = u(c_t, L_t, p_t, \varepsilon_t) = \frac{1}{1-\eta}\left(c_t^{\alpha_c} L_t^{1-\alpha_c}\right)^{1-\eta} + \alpha_{X^{\mathcal{D}}}\varepsilon_t(\mathcal{D}_t) \tag{4}$$

$$\begin{aligned} L_t = L - N_t - \varphi_p \mathbb{1}_{\{p_t=1\}} - \varphi_{DI}\mathbb{1}_{\{DI_t^{app}=1\}} - \varphi_{BC}\mathbb{1}_{\{OCC=BC,\, p_t=1\}} \\ -\varphi_{BC,h^p}\mathbb{1}_{\{OCC=BC,\, h=\text{poor},\, p_t=1\}} - \varphi_{WC,h^p}\mathbb{1}_{\{OCC=WC,\, h=\text{poor},\, p_t=1\}} \end{aligned} \tag{5}$$

Utility Parameters

α_c, consumption weight	.59 (.06)	φ_{DI}, DI stigma/hassle cost	195 (13)
η, risk aversion:		φ_{BC}, cost of BC work:	
Types A, B	4.5 (.41)	Types A, C	0 (hours)
Types C, D	1.2 (.19)	Types B, D	241 (hours) (27)
$\varphi_{WC,\ ph}$, WC, bad health	79 (11)	K_0, bequest shifter	493 ($1,000s) (58)
$\varphi_{BC,\ ph}$, BC, bad health	300 (32)	α_B, bequest weight	.02 (.03)

Preference Type Proportions		*Percent Blue-Collar*
All Types	1.00	55%
Type A (high η, low φ_{BC})	.12	59%
Type B (high η, high φ_{BC})	.45	27%
Type C (low η, low φ_{BC})	.39	88%
Type D (low η, high φ_{BC})	.04	31%

Type Prediction Parameters

	Type A	Type B	Type C	Type D (base)
$\beta_{n,1}$, Assets at 50	4.32	3.29	-0.91	-
	(2.98)	(1.33)	(0.76)	
$\beta_{n,2}$, Work Enjoyment	0.60	0.94	0.47	-
	(1.17)	(1.22)	(0.98)	
$\beta_{n,3}$, Physical Activity	-2.22	0.50	-1.32	-
	(1.60)	(1.04)	(0.83)	
$\beta_{n,4}$, Income Gamble	0.86	0.91	0.05	-
	(0.19)	(0.32)	(0.11)	

*With bootstrapped standard errors for 50 resamples of 200 simulated individuals in parentheses.

shifter K_0. Weight α_B is estimated to be very close to zero, with K_0 of \$493K indicating the level at which savings can be interpreted as intended bequests as opposed to consumption smoothing. This is identified by the levels of wealth held close to the end of one's expected lifetime. The fact that the weight α_B is so low may very well be due to the choice of asset definition I use here, which excludes housing assets, which are indeed large compared to non-housing financial assets for even middle-income individuals.

Type Prediction Parameter Estimates

Next in Table 9 are the preference type estimates and the percent who choose blue-collar occupations, with coefficients from the multinomial probit (16) below. From these estimates, we see that the most common types are Types B, with high risk aversion and cost of performing blue-collar work, at 45 percent, and Type C, who exhibit less risk aversion and the lower cost of blue-collar work. The proportion of individuals predicted to be Type B working in blue-collar occupations is the lowest at about 27 percent, while those predicted to be Type C have the highest proportion in blue-collar jobs at 88 percent. The relative proportion in each job comports with the notion that those more (less) risk averse who have a higher (lower) cost of performing the more risky blue-collar work should choose such work at lower (higher) rates.

Data and Simulated Moments

In Figure 5, we see non-housing, financial wealth levels by permanent income quintile. The left graph shows assets for blue- and white-collar unskilled workers; the right gives assets for skilled workers. The level of assets accumulated increases with income for these simulated and observed samples of men ages 60 to 64 for both blue- and white-collar skilled workers. However, while the model predicts that assets should be higher for those in blue-

FIGURE 5: *Data and Simulated Assets: Skilled and Unskilled*

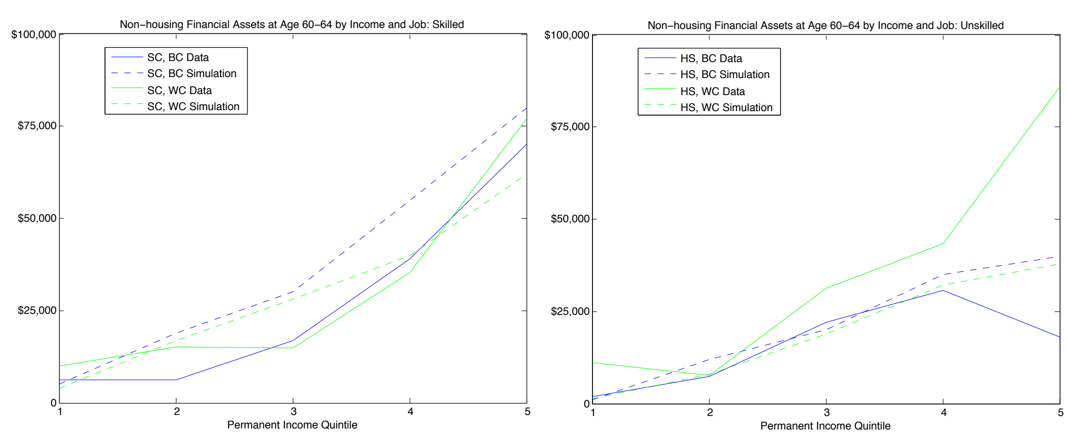


Figure 6: *Data and Simulated Work Decisions*

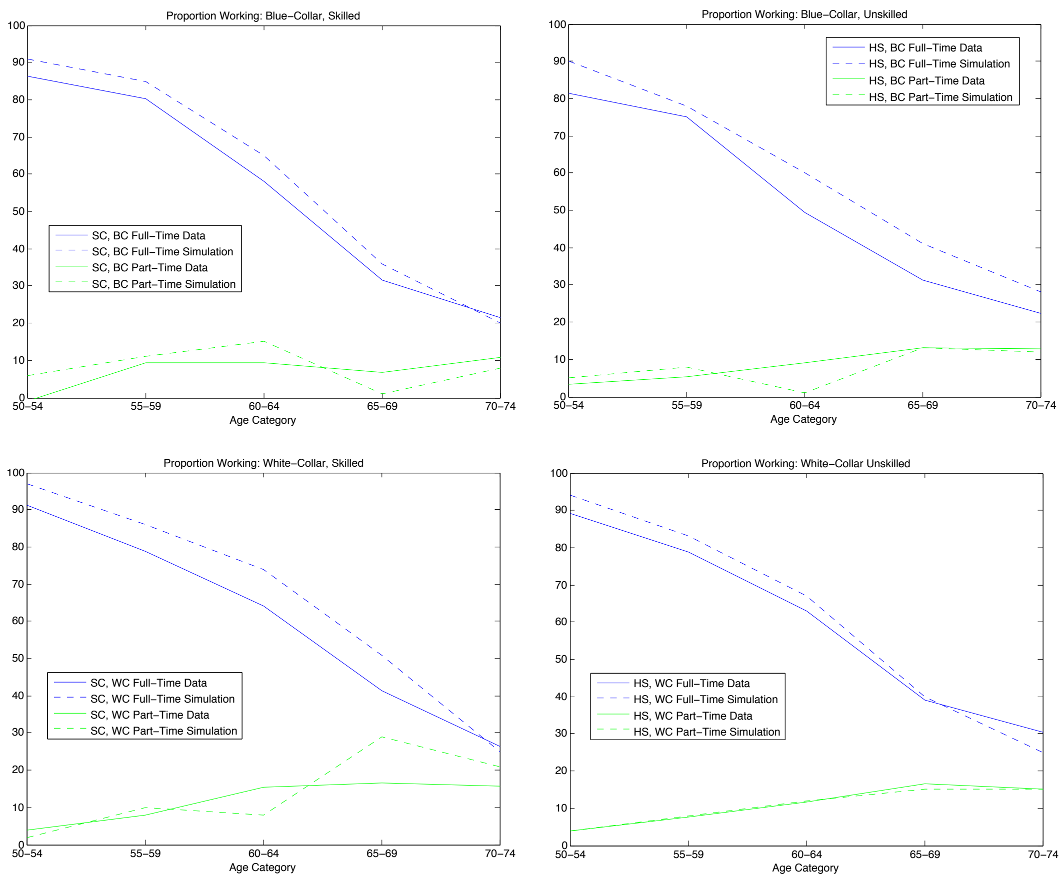
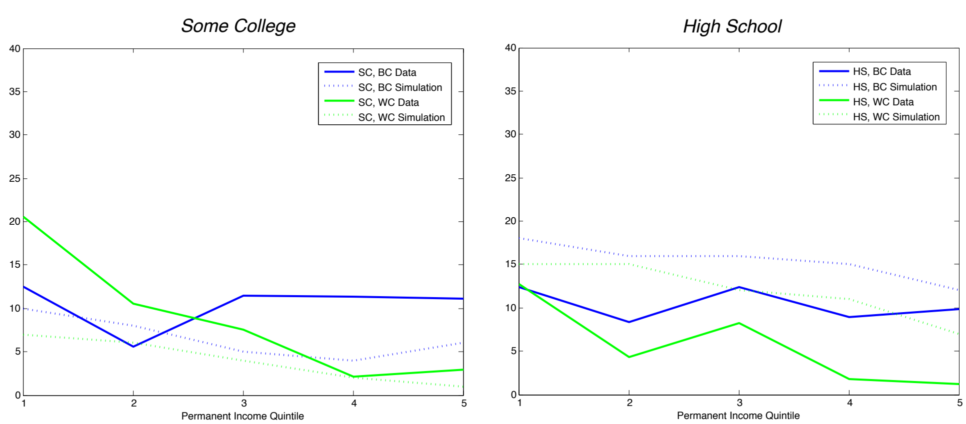


Figure 7: *Data and Simulated DI Decisions*



collar jobs due to the higher risk of income loss through bad health shocks or disability, this is not observed in the data. This is especially the case when looking at the assets for blue- and white-collar workers in the right panel. One explanation is that this risk is insured against to a large extent through SSDI, and observed savings decisions are made in this context. Another factor, discussed further when looking at counterfactual exercises below, is that savings decisions should depend not only on occupation but also the degree of risk aversion; as seen in the Table 9 estimates, the occupations have different compositions of workers in terms of risk preferences.

Labor supply behavior by age category is shown in four graphs in Figure 6. The upper two graphs shows actual and simulated behavior for skilled and unskilled blue-collar workers; the lower two graphs show behavior for white-collar workers. For both occupations, the observed proportion working full time is somewhat lower than the predicted or simulated rate of full-time work. Though not shown here, the proportion working is to a degree sensitive to the consumption floor, which is not estimated within the model.

Disability outcomes in the HRS data and simulated disability decisions are shown in Figure 7 for skilled and unskilled workers ages 55-59. In the model, a person receives disability after he experiences at least one functional limitation, he chooses to apply for DI benefits while stopping work, and, finally, his application is approved. This is similarly sensitive to the consumption floor, though changes in it cannot account for the poor match here on disability episodes.

7. Effects of Health and Disability Risks: Counterfactual Evidence

I use the estimated parameters of the model to generate behavior under several counterfactual scenarios in order to approximate the effects of health and disability risks and SSDI on welfare and occupational choice. The first two counterfactual scenarios allow us to assess the differences in the utility costs arising from the differences in the probabilities of such risks between blue- and white-collar occupations and how this affects the value of Social Security Disability Insurance (SSDI) in each occupation, shown in subsection 7.1, and the effects of this differential risk on initial occupational choice, which is illustrated in subsection 7.2. The third scenario, presented in subsection 7.3, allows us to measure the extent to which the presence of SSDI affects choice of occupation, in particular determining whether fewer individuals would choose blue-collar jobs in the absence of SSDI. The fourth and final counterfactual experiment addresses the question of whether the greater income risk in blue-collar jobs affects later-life participation rates among those who do not experience disability and is presented in subsection 7.4.

7.1. The Utility Costs of Health Risks and the Value of SSDI Across Occupations

In this first counterfactual exercise I measure the utility costs of health and disability risks and the value of SSDI for individuals of different parameter preference types working in either of the blue- and white-collar occupations in this model. These costs are measured in terms of the percent of lifetime consumption one would be willing to forgo to eliminate the risk to income and remain equally well off. Specifically, let compensating variation $\mathcal{CV}_{\mathrm{I}}^{n,j}$ by the value person of Type n, occupation j, and characteristics $(A_t, p_t, h_t, d_t, \varsigma_t, t)$ places on avoiding income loss due to poor health or disability. Equivalently, $\mathcal{CV}_{\mathrm{I}}$ is the amount, expressed in terms of the percent of lifetime consumption in Table 10, that would make this person as well off as he would be in a world where neither declining health with age nor disability affect earnings.

Then $\mathcal{CV}_{\mathrm{I}}^{n,j}$=$\mathcal{C}_{\mathrm{I}}^{n,j}\ (A_t, p_t, h_t, d_t, \varsigma_t, t)$ solves:

$$\begin{aligned} V_t(A_t + \mathcal{CV}_{\mathrm{I}}^{n,j}, p_t, h_t, d_t, \varsigma_t, \text{status quo}) \\ = V_t(A_t, p_t, h_t, d_t, \varsigma_t, \text{income not affected by health/disability})\,. \end{aligned}$$

Similarly, $\mathcal{CV}_{\mathrm{II}}^{n,j}$ is the compensating value for a person of Type n, occupation j, and characteristics $(A_t, p_t, h_t, d_t, \varsigma_t, t)$ places on avoiding income loss due to poor health or disability; i.e., $\mathcal{C}_{\mathrm{II}}$ is the amount that would make this person as well off as he would be in the status quo world where there is SSDI. Here $\mathcal{CV}_{\mathrm{II}}^{n,j}$=$\mathcal{C}_{\mathrm{II}}^{n,j}\ (A_t, p_t, h_t, d_t, \varsigma_t, t)$ solves:

$$V_t(A_t, p_t, h_t, d_t, \varsigma_t, \text{status quo}) = V_t(A_t + \mathcal{CV}_{\mathrm{II}}^{n,j}, p_t, h_t, d_t, \varsigma_t, \text{no SSDI})\,.$$

When health and disability risks are present, a risk-averse agent will accumulate savings beyond that which he would accumulate solely to smooth consumption over a planned retirement or reduction in hours. I measure the cost of health and disability risks as the difference in lifetime utility for the consumption path with precautionary saving and utility with the optimal consumption path when there are no health and disability risks. This is calculated with the assumption that there is no change in occupation that accompanies the change in scenario; the counterfactual experiment in subsection 7.2 addresses the question of whether occupational choices are affected. In the context of this model, this is a baseline setting, referred to as Scenario 7.1.1, in which earnings are not affected by worsening health or disability.

We should expect the degree of precautionary saving to be greater for more risk averse agents, as well as those in blue-collar jobs who face a greater loss of income when poor health and disability arise. This distortion in the savings path when this risk is present relative to the baseline scenario, then, should be greatest for these individuals, whom we

Table 10: *Results from 7.1 Counterfactuals*

	Equivalent in % Reduction in Lifetime Consumption Willing to Forgo Under:	
	Scenario 7.1.1	*Scenario 7.1.2*
	Value of Counterfactual Absence of Health and Disability Risks	Value of SSDI
High Risk Aversion		
(Types A, B)	16.1%	15.7%
Blue-Collar	22.3	19.6
White-Collar	11.0	10.8
Low Risk Aversion		
(Types C, D)	8.0%	3.2%
Blue-Collar	8.8	3.3
White-Collar	6.2	2.7
All Types	12.6%	10.4%
Blue-Collar	15.4	12.0
White-Collar	9.5	7.3

then expect would be willing to pay more to avoid this distortion. The first column of Table 10 shows the magnitude of these effects in terms of the percent reduction in lifetime consumption an agent of each of the predicted four preference type would be will to forego to avoid the health and disability risk.[30] Indeed, simulated agents with higher degrees of risk aversion (Types A and B), have a consumption path that is more highly distorted by the precautionary savings necessary when health and disability risks to income are present, as measured by the large amount of consumption individuals would be willing to forgo to avoid these risks, which is 22 percent for a blue-collar occupation and 11 percent in white-collar occupations. The less risk averse types, on the other hand, would be willing to forgo about 9 and 7 percent to eliminate the health and disability risks in blue- and white-collar jobs.

The value of the certain income provided as SSDI benefits should result in an individual's utility being somewhere in between that which he would experience in the baseline, no-risk Scenario 7.1.1 and the status quo reality in which health and disability risks exist. In Scenario 7.1.2, I measure the value of SSDI through the precent reduction in lifetime

[30] For this exercise, $\mathcal{CV}_{\mathrm{I}}^{n,j}$ and $\mathcal{CV}_{\mathrm{II}}^{n,j}$ are calculated for approximately the modal observation in this sample, who is a high school graduate with \$130K in housing and non-housing assets at age 50, working at age 50 in good health with no functional limitations, who has a permanent income of about \$45,000. In general, $V_t(\cdot, \textit{no SSDI}) < V_t(\cdot, \textit{status quo}) < V_t(\cdot, \textit{no risk})$. To calculate both $\mathcal{CV}_{\mathrm{I}}^{n,j}$ and $\mathcal{CV}_{\mathrm{II}}^{n,j}$, I assume that the 1.8% of FICA taxes that are dedicated to financing SSDI are not taken out of income for the counterfactual value function.

consumption in the no-risk case that would leave an individual indifferent between this and a scenario in which he faces health and disability risks with SSDI benefits in the event of disability.[31] The second column of Table 10 gives the value of SSDI by risk-aversion type and occupation. The less risk-averse types value it at 3 percent of consumption, while the more risk-averse types place a much higher value on the SSDI benefits—which greatly reduce the portion of income exposed to risk—with it being worth on average almost 16 percent of lifetime consumption. The fact that these values are quite close to the amount one would be willing to give up in lifetime income to avoid disability risks entirely suggests that the risk of disability is greater than the effects of worsening health on earnings. As we saw in Table 9, however, high risk aversion types, Types A and B, are far less likely to select blue-collar jobs, with 66 percent choosing white-collar jobs versus 17 percent of the low risk aversion Types C and D. Not taking this into account may overstate the overall value of SSDI, then, to a degree.

7.2. Effects of Health and Disability Risk on Occupational Choice

In the next exercise, I look at how sensitive the initial choice of occupation is to differences in later-life health and disability risks. Most studies estimating life-cycle models understandably make the simplifying assumption that individuals retire at a fixed age—typically 65. There is, however, a great deal of variety in health and labor force decisions in later life, with clear differences between the behavioral tendencies of those in the more physically intense blue-collar jobs and those in white-collar jobs. As we saw in Section 6, at older ages, the wage declines more for blue-collar workers when health declines or functional limitations arise; productivity does not decline with health—which declines with age—in white-collar jobs to the extent that it does in blue collar jobs. This difference is in part what drives the differences in later-life labor force participation between blue- and white-collar workers. This counterfactual scenario allows us to consider how much these differences matter to agents when making their initial occupational decision.

The equilibrium aspect of the model is most relevant in this counterfactual exercise since, as we saw in the previous counterfactual exercises, all preference types exhibit some degree of risk aversion, making a white collar job with lower health and disability risk more appealing, all else equal. In equilibrium, however, as more people go into white-collar jobs, earnings in white-collar jobs fall while earnings in blue-collar jobs rise up to the point where the marginal individual would not choose the white-collar job. Without such effects, we would certainly expect to be overestimating the proportion of individuals who would choose white-collar occupations.

[31] The value will depend on the rate at which the disability insurance replaces lost earnings, which decreases with income. Here, calculations are made for the median earner, for whom the replacement rate of disability insurance would be only about 40 percent of income lost.

Table 11: *Results from Counterfactuals 7.2 and 7.3*

	% Choosing BC Occupation by Type		
	Scenario 7.2 With no risk:	Scenario 7.3 No SSDI:	With Risk (original simulation)
All Types	60.4%	51.3%	54.8%
Type A (high η, low φ_{BC})	64.8	52.1	59.0
Type B (high η, high φ_{BC})	35.4	21.6	26.7
Type C (low η, low φ_{BC})	91.1	86.5	88.2
Type D (low η, high φ_{BC})	33.7	29.9	31.2
	(I)	(II)	
All Types	12.1%	8.1%	
Type A (high η, low φ_{BC})	8.4	7.8	
Type B (high η, high φ_{BC})	6.8	14.1	
Type C (low η, low φ_{BC})	19.0	1.5	
Type D (low η, high φ_{BC})	15.2	3.3	

Column (I): Wage premium with no risk (Scenario 7.2)
Column (II) How much higher wages would need to be in the absence of SSDI for the same proportion to choose blue-collar jobs.

In the first column in the upper panel of Table 11, we see how occupation selection would change if the effects of health and disability risk on productivity were the same across occupations. When earnings do not depend on health status or the presence of disability, a larger share of all preference types choose blue-collar work as compared to occupation choices in the rightmost column, which shows the percent choosing blue-collar occupations in the original simulation, when health and disability risks affecting income are present. The greatest effect of removing earnings risk is for the higher risk aversion types, especially Type Bs, who have a *higher* fixed cost of performing blue-collar work; this is perhaps because they have such a low proportion working in blue-collar jobs to begin with, leaving a large number on the margin of choosing blue-collar work. There is a much smaller effect for those with lower predicted risk aversion, especially those with Type C preferences, for whom the cost of performing blue-collar work is smaller, with nearly 90 percent already working in blue-collar jobs.

As an alternative to this counterfactual exercise, we can consider how much lower earnings in blue collar jobs could be in the absence of health and disability risks while maintaining the proportion choosing blue-collar jobs (the rightmost column of the upper panel of Table 11); this will give us a sense of the premium in blue-collar earnings arising from the higher risk of disability and declining health in these occupations.

The first column of the lower panel in Table 11 gives the percent reduction in blue-collar earnings without the risk for each preference type that elicits the same proportion choosing blue-collar jobs as in the initial simulation. Those with lower levels of risk aversion, Types C and D, would have the same share choosing blue-collar occupation with a larger reduction in earnings than the higher risk aversion types. Also, within each type, those with lower costs of performing blue-collar work would be willing to maintain their occupational choices with a larger reduction in earnings. Note how these differ from the figures in the first column of Table 10, which holds utility—as opposed to occupation—constant relative to the original simulation.

7.3. Occupational Choice and SSDI

In the previous counterfactual exercises, we saw that agents—to various degrees depending on preference parameter types and occupation—placed a value on the elimination of health and disability risk. In the exercise that follows, I look at the value of SSDI, which insures disability risk. Because those in blue-collar jobs are more likely to receive SSDI at some point, this allows us to answer the extent to which SSDI might, in effect, subsidize such jobs by providing this more highly utilized insurance.

To answer this question question, I measure, analogously to the counterfactual questions in subsection 7.2, (1) how many fewer people would choose the physically demanding blue-collar jobs in the absence of SSDI, and (2) how much higher wages would need to be in BC jobs for the same proportion to select in to them in the absence of SSDI. In the second column of the upper panel of Table 11, we see that in the absence of SSDI, fewer individuals of all types would choose blue-collar occupations. Those especially responsive to loss of SSDI benefits in the counterfactual are, as we would expect, the higher risk aversion types, who already choose blue-collar jobs at lower rates. The proportion of Type A individuals, who also have a lower cost of performing blue-collar work, choosing a blue-collar occupation falls from 59 to 52 percent, for instance, while the share of those with Type C and D preferences choosing blue-collar work falls by less than two percentage points, which is somewhat surprising given the high proportions in those jobs to begin with.

Finally, in the second column of the lower panel of Table 11, we have how much higher earnings would need to be in a scenario in which there is no SSDI insuring disability risk to maintain the same balance of blue- and white-collar workers that the original simulation generates. For all preference types, in the absence of SSDI, earnings would need to be about eight percent higher to generate the same occupation proportions, with high risk aversion types being more sensitive overall, and those with higher costs of performing blue-collar work being more responsive within a given risk aversion type. It should be noted, however, that these estimates are sensitive to assumptions about the timing of the onset of disability.

Table 12: *The Effect of Disability Risk on Labor Force Participation*

	% Working (Ages 60-69)	
	Without Disability Risk:	With Disability Risk (status quo)
All Types	40.3%	42.8%
Type A (high η, low φ_{BC})	41.7	45.2
Type B (high η, high φ_{BC})	41.2	44.0
Type C (low η, low φ_{BC})	39.6	41.0
Type D (low η, high φ_{BC})	38.3	38.9

Note: Full-time and part-time work for blue-collar, HS grads.

7.4. Effects of Health and Disability Risk on Blue-Collar Participation at Older Ages

In the final counterfactual exercise, I look at whether blue-collar workers *who do not become disabled* exit the labor force earlier than they otherwise would in the absence of disability and health risks. The intuition is that because the presence of such risks prompts precautionary savings, those who do not become disabled will have accumulated enough savings to stop working sooner. Given the structure that the model takes and the estimated parameters of it, we should expect there to be an effect for the more risk-averse blue-collar workers (Types A and B), but because blue-collar workers are much more likely to be Type C (less risk averse with a lower disutility of blue-collar work, φ_{BC}), the overall effect on blue-collar participation at older ages is small. To carry out this counterfactual, I set the effect of poor health and functional limitations on earnings to be zero,[32] and look at the behavior of those who never have a functional limitation arise.

In the rightmost column of Table 12, we have the simulated percent working those in blue-collar jobs working full- and part-time. For all predicted preference types, for ages 60-69, 42.8 percent are working. The types with higher levels of risk aversion, Types A and B, have higher levels of participation, as the higher savings levels are obtained through not only delayed consumption but also through a greater amount of paid work. When we take away exposure to decreased earnings due to disability, we see the largest response in participation among the higher risk aversion types who were saving more for the event of disability in the status quo scenario: Types A and B fall by three or four percentage points, while participation for Types C and D fall by less than two percent at these ages.

There are two mechanisms through which poor health and disability lead to lower

[32] In this model, only productivity, as measured by earnings, is affected by poor health or disability. If a job finding or job destruction rate that depended on health and disability had been incorporated, the dependence would be shut down to carry out this counterfactual.

labor force participation, especially for blue-collar workers. The first is through the effect of poor health and disability on productivity leading to earlier exit, which occurs to a greater extent for blue-collar workers. The second mechanism, as we have seen through this counterfactual exercise, is through the savings that the disability risk induces. Even for those who *do not* become disabled, there is earlier exit because, having saved for an even that never occurred, they find themselves with a level of savings that is high enough to finance their retirement at an earlier age than would be optimal if there were no disability risk.

8. 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. I document these differences and the health and functional limitation transition process with age bringing them about and consider, in the context of a dynamic model, the effects of these processes—especially later in the life cycle—and SSDI on occupation decisions early in the life cycle.

The main contributions of this study lie in literatures on SSDI program evaluation and occupational choice. Through the model estimated here, we can get a sense of the differences in the value of SSDI to heterogeneous individuals. Further, this model is novel in incorporating a richer later-life setting within an occupational choice problem. Through counterfactual exercises, I find that the additional disability risk in blue-collar jobs relative to white-collar jobs is equivalent to an additional six percentage point reduction in lifetime consumption and that the absence of SSDI, which insures some of this risk, would be equivalent to, respectively, a twelve and seven percent reduction in consumption for those in blue- and white-collar jobs.

Furthermore, I find that the presence of SSDI results in three percent more individuals choosing blue-collar occupations, which is comparable to the effect on occupation selection resulting from an eight-percent increase in blue-collar earnings. This overall effect, however, is greatly mitigated by the selection into occupations by those of different risk tolerance levels. Individuals who are less risk-averse, and therefore value insurance relatively less, are also more likely to sort into blue-collar occupations, in which they are more likely to utilize disability insurance. Similarly, risk averse types tend to sort into white-collar occupations, resulting in fewer people being on the margin of the occupation choice. As a result, earnings for the most risk-averse type would, for instance, have to be nearly fifteen percent greater to choose blue-collar occupations in the absence of SSDI.

A technical but possibly impactful issue is the sensitivity of results to the particular asset figures used. There are many ways to measure assets in the HRS; consumption and savings decisions, which estimated off of changes in asset levels between periods along with income, determine risk aversion parameters, which drive many of the counterfactual results estimating the value of insurance, cost of risk, and behavior in response to changes in these measures. While this concern over asset definitions is not unique to this paper, it is in some sense potentially more problematic here as key results depend on asset levels. A related issue is that of the consumption floor in the model, which is intended to capture income received possibly through Supplemental Security Income (SSI) or unemployment insurance (UI) benefits. Many papers studying DI and labor force behavior look at its interaction with other programs like unemployment insurance and Medicare, which is important as some individuals on DI roles might otherwise be counted as unemployed and receive unemployment benefits; DI may replace those benefits indefinitely. Indeed, DI applications increase with unemployment levels. While I do not account for unemployment or incorporate any strategic behavior in the DI application decision; this will be handled in a separate, extended paper. Accounting for this program interaction would provide a more complete picture of the effects of DI in a world where complementary programs are present.

Finally, a prominent feature of SSDI that has now been accounted for in this model is the automatic enrollment of recipients onto Medicare rolls after two years. This increases the value of receiving SSDI perhaps quite significantly for some. This could be incorporated into a similar model either as a large non-pecuniary benefit attached to SSDI, or as a reduction in medical expenses, which I have not modeled here. The way in which I would expect this to affect results would not be related to occupational choice necessarily. There is additionally interaction, possibly, with SSDI and SSOASI claiming ages. As claiming ages increases, receiving SSDI—which gives an amount equivalent to the NRA benefits—should be that much more valuable. Though some studies show it does not increase the number of ERA claimants applying for SSDI—this change in claiming age could help us identify the cost of applying.

A. Appendix

A.1. Supplementary Tables and Figures

Table A.1: *Whether Spouse Works by Education and Income Quantile*

Education Level	Permanent Income Quintile				
	1	2	3	4	5
Less Than HS	.57	.62	.57	.66	.64
GED	.54	.52	.56	.73	.50
HS	.69	.72	.70	.62	.60
Some College	.73	.76	.71	.71	.72
College and Above	.74	.78	.80	.76	.67

Note: Includes 3,752 respondents.

Table A.2: *Whether Spouse Works and SSDI Receipt*

Ever received SSDI?	Spouse Working Initially	
	No	Yes
Never Received	86.94	86.23
Received	13.06	13.77

Observations from 2,505 respondents in the Original HRS and War Babies cohorts, with high school and some college education levels.

Table A.3: *Transitions between BC and WC:*

	Last Occupation	
Longest Occupation	WC	BC
White-Collar	88.16	11.84
Blue-Collar	8.34	91.66

2,804 initial WC person-year observations; 2,697 for BC career respondents.

Table A.4: *Subjective Probability of Working Past Age 65*

	WC Occupation	BC Occupation
Prob. Working 65+		
0-39 percent	57.91	66.65
40-60 percent	17.83	16.20
61-100 percent	24.26	17.15

6,962 WC person years; 6,444 BC person years.

Table A.5: *Age Claiming SS Benefits by Occupation*

	WC Occupation	BC Occupation
Age Claiming SS		
<62	5.23	8.59
62	37.91	49.39
63	10.19	9.63
64	9.24	9.32
65	25.08	16.21
>65	12.35	6.86

15,589 WC person years; 13,731 BC person years.

Table A.6: *Age Claiming SS Benefits by Occupation and Subjective Life Expectancy, Excluding SSI/SSDI Claimants*

		Prob. of Living Past Age 75			
		0-39%	40-60%	61-100%	Total
WC:					
	<62	7.69	6.30	6.33	6.47
	62	46.15	48.01	42.71	44.62
	63	8.97	10.77	8.80	9.39
	64	7.18	7.66	7.17	7.32
	65	22.31	20.85	28.18	25.42
	>65	7.69	6.40	6.80	6.78
BC:					
	<62	16.18	8.57	8.10	9.56
	62	52.31	53.75	54.56	53.92
	63	10.92	9.64	9.13	9.59
	64	8.40	9.25	9.40	9.19
	65	9.45	14.41	15.17	13.99
	>65	2.73	4.38	3.64	3.75

3,568 WC observations; 2,960 BC observations.

Table A.7: *Relationship Between Lifespan and Work Expectations*

	Subjective Prob. of Living Past Age 75		
	0 to 39 percent	40 to 60 percent	60 to 100 percent
Prob. of Working Past 65			
0 to 39 percent	72.9	62.7	55.1
40 to 60 percent	13.7	19.6	16.7
61 to 100 percent	13.5	17.8	28.2

Note: Includes 21,277 person-year observations.

Table A.8: *Among Non-Workers, Percent with Health Problem Limiting Work:*

Age Category	Non-Workers		Workers	
	WC	BC	WC	BC
50-54	50.41	68.33	7.43	9.92
55-59	46.27	69.29	7.70	10.63
60-64	35.42	53.35	9.12	11.56
65-69	30.94	41.56	10.35	13.48
70-74	30.89	42.32	13.11	16.22
75-79	36.18	45.12	15.19	15.33
80-84	41.79	52.38	19.48	24.32
85-89	49.30	55.05	9.38	27.27

Among non-workers, 10,798 WC person-year observations; 14,214 for BC career respondents. Among those working, 14,951 WC person-year observations; 12,464 for BC career respondents.

Table A.9: *Labor Force Status Reported if Receiving SSDI*

Self-Reported Labor Force Status	
Works FT	0.85%
Works PT	0.48
Unemployed	0.71
Partly Retired	3.27
Retired	71.04
Disabled	22.30
Not in Labor Force	1.35

Note: Includes 4,368 person-year observations.

TABLE A.10: *Physical Intensity of Work, Education, and Occupation*

	How Often Job Requires Physical Effort[1]			
	Always	Mostly	Sometimes	Never
White-Collar	8.05	8.77	30.20	52.97
Blue-Collar	32.25	24.10	30.26	13.39

	Level of Education					
	Less than HS	GED	High School	Some College	College	*Total*
White-Collar	13.95	25.85	36.09	59.97	91.35	48.46
Blue-Collar	86.05	74.15	63.91	40.03	8.65	51.54

[1] 14,356 WC person-year observations; 12,451 BC person-year observations.
[2] 57,194 person-year observations.

Table A.11: *Summary of Variables*

	Description
Choice Variables, $\mathcal{D}_t$	
p_t	labor force participation (none, PT, or FT)
c_t	consumption
$OASI_t^{app}$	application for OASI benefits
DI_t^{app}	application for DI benefits
State Variables, $\mathcal{S}_t$	
A_t	total assets (non-housing)
w_t	earnings
h_t	health status
d_t	functional limitation status
$OASI_{t-1}^{rec}$	whether receiving OASI benefits
DI_{t-1}^{rec}	whether receiving DI benefits
$AIME_t$	average indexed monthly income
OCC_t	occupation
Preference Parameters (to be estimated)	
η	risk aversion
α_c	consumption weight
α_X	scales the effect of work preference shock $\epsilon_t(\mathcal{D}_t)$
φ_P	fixed cost of work
$\phi_{H^{Bad}}$	leisure cost of bad health
φ_{BC}	cost of BC work
α_B	scales the bequest
K_0	bequest shifter
Fixed Parameters	
$\boldsymbol{\tau}$	tax structure
L	total leisure hours available
r	interest earned on assets, before taxes
—	
N_t	hours worked

References

Autor, D. H. and M. G. Duggan (2003): "The Rise in the Disability Rolls and the Decline in Unemployment," *Quarterly Journal of Economics*, pp. 157–205.

Benítez-Silva, H., M. Buchinsky, H. M. Chan, J. Rust, and S. Sheidvasser (1999): "An Empirical Analysis of the Social Security Disability Application, Appeal, and Award Process," *Labour Economics*, pp. 147–178.

Berkovec, J. and S. Stern (1991): "Job Exit Behavior of Older Men," *Econometrica*, 59, 189–210.

Blau, D. (1994): "Labor Force Dynamics of Older Men," *Econometrica*, 62, 117–156.

Bound, J. (1991): "Self-Reported Versus Objective Measures of Health in Retirement Models," *Journal of Human Resources*, 26, pp. 106–138.

Burkhauser, R. V., J. Butler, and G. Gumus (2004): "Dynamic Programming Model Estimates of Social Security Disability Insurance Application Timing," *Journal of Applied Econometrics*, pp. 671–685.

Campolieti, M. (2002): "Moral Hazard and Disability Insurance: On the Incidence of Hard-to-Diagnose Medical Conditions in the Canada/Quebec Pension Plan Disability Program," *Canadian Public Policy*, 28, pp. 419–441.

Card, D. and T. Lemieux (2001): "Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis," *Quarterly Journal of Economics*, 116, pp. 705–746.

Casanova, M. (2011): "Happy Together: A Structural Model of Couples Retirement Choices," UCLA Working Paper.

Chandra, A. and A. Samwick (2004): "Disability Risk and the Value of Disability Insurance," Chapter in NBER book Health at Older Ages: The Causes and Consequences of Declining Disability Among the Elderly (2008), David M. Cutler and David A. Wise, editors, pp. 2245–2324).

De Nardi, M., E. French, and J. Jones (2010): "Why do the Elderly Save? The Role of Medical Expenses," *Journal of Political Economy*, 118, pp. 39–75.

Feldstein, M. and J. Liebman (2002): "Social Security," Chapter 32, Handbook of Public Economics, Volume 4, A.J. Auerbach and M. Feldstein, editors, pp. 295–336).

French, E. (2005): "The Effects of Health, Wealth, and Wages on Labour Supply and Retirement Behaviour," *Review of Economic Studies*, 72, pp. 395–427.

French, E. and J. B. Jones (2011): "The Effects of Health Insurance and Self-Insurance on Retirement Behavior," *Econometrica*, 79, pp. 693–732.

Gallipoli, G. and L. Turner (2011): "Household Responses to Individual Shocks: Disability and Labor Supply," Working Paper.

Gentzkow, M. and J. Shapiro (2014): "Measuring the Sensitivity of Parameter Estimates to Sample Statistics," Chicago Booth and NBER Working Paper.

Gourinchas, P. O. and J. A. Parker (2002): "Consumption Over the Life Cycle," *Econometrica*, 70, 47–89.

Hall, R. (1978): "Stochastic Implications of the Life Cycle–Permanent Income Hypothesis: Theory and Evidence," *Journal of Political Economy*, 86, pp. 971–987.

Heckman, J., L. Lochner, and C. Taber (1998): "Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of Labor Earnings with Heterogeneous Agents," *Review of Economic Dynamics*, 1, 1–58.

Hubbard, R., J. Skinner, and S. Zeldes (1995): "Precautionary Saving and Social Insurance," *Journal of Political Economy*, 103, pp. 360–399.

Johnson, M. and M. Keane (2013): "A Dynamic Equilibrium Model of the US Wage Structure, 1968–1996," *Journal of Labor Economics*, 31, pp. 1–49.

Kantor, S. E. and P. V. Fishback (1996): "Precautionary Saving, Insurance, and the Origins of Workers' Compensation," *Journal of Political Economy*, 104, pp. 419–442.

Katz, L. F. and K. M. Murphy (1992): "Changes in Relative Wages, 1963-1987: Supply and Demand Factors," *Quarterly Journal of Economics*, 107, 35–78.

Keane, M. and K. Wolpin (1997): "The Career Decisions of Young Men," *Journal of Political Economy*, 105, 473–522.

Kimball, M. S. (1990): "Precautionary Saving in the Small and in the Large," *Econometrica*, 58, pp. 53–73.

Kreider, B. (1999): "Social Security Disability Insurance: Applications, Awards, and Lifetime Income Flows," *Journal of Labor Economics*, 17, pp. 784–827.

Lahiri, K., D. Vaughan, and B. Wixon (1995): "Modeling SSAs Sequential Disability Determination Process Using Matched SIPP Data,," *Social Security Bulletin*, 58, pp. 3–42.

Lee, D. (2005): "An Estimable Dynamic General Equilibrium Model of Work, Schooling, and Occupational Choice," *International Economic Review*, 46, pp. 1–34.

Lee, D. and K. Wolpin (2006): "Intersectoral Labor Mobility and the Growth of the Service Sector," *Econometrica*, 74, pp. 1–46.

Low, H. and L. Pistaferri (2010): "Disability Risk, Disability Insurance and Life Cycle Behavior," NBER Working Paper.

Meyer, B. and W. Mok (2013): "Disability, Earnings, Income and Consumption," NBER Working Paper.

RAND HRS Data, Version L (2012): Produced by the RAND Center for the Study of Aging, with funding from the National Institute on Aging and the Social Security Administration. Santa Monica, CA.

Rust, J., H. Benítez-Silva, and M. Buchinsky (2001): "Dynamic Structural Models of Retirement and Disability," Manuscript, presented at the ASSA 2001 Meeting of the Econometric Society.

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

Stephens, M. (2001): "The Long-Run Consumption Effects of Earnings Shocks," *Review of Economics and Statistics*, 83, pp. 28–36.

Weil, P. (1993): "Precautionary Savings and the Permanent Income Hypothesis," *Review of Economic Studies*, 60, pp. 367–383.