Occupations and Work at Older Ages: Varied Responses to Social Security Policy

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Abstract: Increases in life expectancy over the past century coupled with the "pay-as-you-go" design of Social Security old-age benefits have led to the program facing projected deficits. Social Security claiming ages have increased from age 65 to 67 in the recent past, and further increases are one conceivable approach towards ensuring the program's continued solvency. While not a consideration in current policy design, there are many notable patterns across occupations in retirement, disability, and saving behavior that mean such policy changes will be responded to differently by people in different occupations. In this paper, I take a life-cycle perspective to estimate a number of effects that would occur with further increases in Social Security "Early" and "Normal" claiming ages across people in blue- and white-collar occupations, broadly defined. In particular, I find that increasing the Early Retirement Age has large labor supply and disutility effects for blue-collar workers, and results in greater DI application for this group. This is driven primarily by those in blue-collar work having more steeply declining productivity with age and less margin on which to respond to policy changes. Increasing the Full Retirement Age affects the labor supply of white-collar workers but not blue-collar, however it does increase the savings somewhat for the latter group. Finally, I show the effects of a more occupation-neutral Social Security policy design, which considers longer years of work history in benefit calculations.

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1. Introduction

Increases in average life expectancy, better health in older ages, and work becoming less physically demanding have all contributed to a greater number of working years and postponed retirement. However, this is not uniformly the experienced across the population, as there are many patterns across occupations in the timing of retirement, disability rates, and OASI claiming behavior. Generally, compared to people who have worked in "white-collar" jobs, those in "blue-collar" jobs tend to retire earlier, save less, claim Social Security OASI benefits earlier, and are more likely to apply for and receive SSDI benefits; this is the case even controlling for income.

Sharp increases in life expectancy, declines in fertility, and the "pay-as-you-go" design of Social Security OASI have led to the program facing deficits in the coming decades. To improve the solvency of the program, increases to the Full Retirement Age (FRA) for claiming OASI benefits have already been implemented; further increasing the FRA—or even the Early Retirement Age (ERA)—is one conceivable way of ensuring the program's continued solvency. What would be the effects of such policy changes? A person can respond to increases in these claiming ages by saving more before leaving work to fund more non-work years before claiming FRA, claiming early and reduced benefits, and working longer. Because of differences in productivity and labor supply patterns at older ages for people in blue-collar and white-collar occupations, however, we might expect the response to this policy change to differ among these groups.

This paper takes a life-cycle perspective to study how the interactions among labor supply decisions, health, and OASDI vary across occupations through both descriptive statistics and structural econometric methods. The descriptive component uses data from the Health and Retirement Study (HRS) and O*NET data on occupational tasks to capture patterns in labor supply, saving, and OASDI program behavior for two broadly defined occupations. These features of the data motivate a dynamic model of decision making in later life. The structural analysis component involves finding the parameters of the model that allow simulated agents to most closely replicate the behavior of real people observed in the data.

By constructing a parameterized model of behavior, we can estimate what behavior would look like under counterfactual scenarios and policies and decompose the channels through which declines in health affect the decisions of a heterogeneous set of individuals—decisions which constitute any larger trends of interest. Predicting responses to policies that have not yet been implemented cannot be readily done through non-structural methods, which are better equipped to assess responses to in-place policies. The counterfactual policies addressed in this paper are increases to the OASI ERA, which is currently 62, and the FRA, which is between 65–67 depending on one's year of birth) The simulated behavior of interest under these scenarios are (1) differences between people in blue-collar and white-collar jobs in the labor supply and utility responses to changes in the claiming ages, and (2) the interaction between increases in claiming ages and SSDI applications in different occupations.

2. Related Work

This work aims to address three distinct but interrelated questions, all taking a dynamic, life-cycle approach emphasizing the role of occupations in later-life labor supply and the impact of

Social Security OASI and DI. Accordingly, the literature this study builds on fall under three broad topic categories.

The first set of literature looks primarily at labor supply and utility responses to changes in the OASI claiming age structure, including Behaghel and Blau (2012), Gustman and Steinmeier (2015), van der Klaauw and Wolpin (2008), and Staubli and Zweimuller (2013). Because the emphasis in this paper is how these responses vary by occupation, I will incorporate literature on the capacity to work at older ages Coile and Milligan (2017), and Cutler et al. (2013)) as well as work on later-life occupational differences in productivity (Chirikos and Nestel (1991), Hayward et al. (1989) , Hirsch et al. (2000), and Modrek and Cullen (2012)). My aim is to enhance existing research by measuring the variation in effects across the population by studying the welfare effects of the existing increases in OASI claiming ages and predicting how labor supply changes in response for people across occupations,

Several papers, including Rust and Phelan (1997) have noted and sought to explain through structural models the large spike in both retirement from work and OASI claims at age 62. I find that this is ERA claiming is especially common for blue-collar (BC) workers. Gustman and Steinmeier (2015) explain this through time preferences, but another aspect when considering occupations as in this paper is that BC workers, even with the same time preferences, face more steeply declining productivity (which is captured here).

In studying work SSDI utilization across broad occupations at older ages, this component will additionally draw on past work looking at the role of occupation in the dynamics of health and working behavior (Hudomiet et al. (2018), Engelman and Jackson (2015), and Rutledge et al. (2017)). Methodologically, this work will model older-age dynamic decisions similarly to French (2005) and French and Jones (2011), with the added dimension of occupations and disability.

Though the simulated counterfactual policy, I predict what the effects within the model will be on SSDI utilization for people in different occupations if the OASI claiming age were to change. One hypothesis of this paper is that while the aggregate change in DI utilization may be small, the response is potentially significant for those in more physically intense, blue-collar jobs. Because productivity in their work declines on average more quickly with age, they are less able to bridge the gap between when they otherwise would have stopped working and the new, higher ERA and FRA by working more years. Because that channel is less feasible for them, DI looks even more attractive to those blue- collar workers compared to white-collar workers. Many researchers have studied the interaction between the OASI FRA and SSDI, including Coe and Haverstick (2010), Duggan et al. (2007), and Li and Maestas (2008). This study will be novel in two ways: Firstly, it will focus on the differential interaction effect over occupations. Secondly, this research will use structural modeling methods to address the question. Using this approach, this project will tell us the relative magnitude and identify the mechanisms through which responses vary for people in different occupations. Making these mechanisms clear can inform design of policy and expectations about how well policy changes are received among different populations.

3. Data and Descriptive Statistics

The primary data source here is the Health and Retirement Study (HRS). The HRS is a biennial panel data set of Americans over age 50, with rich information on health, savings and income, work, program participation, family, and many other factors. Its panel aspect is useful particularly for the understanding the dynamic processes of health, savings, and labor supply decisions central to the work proposed in this study. I also make use of the variables (of restricted access) on detailed occupations and Social Security earnings records to calculate expected OASI and SSDI benefits. The detailed occupations are then linked with O*NET data on occupational tasks to separate occupations in to more physically intense, *blue-collar*, and less physically intense, *white-collar* occupations. In particular, through linking the detailed occupational data in the HRS to O*NET, I can create an indexed measure of the degree to which physical input is required for an occupation, which is a primary dimension along which retirement timing and OASDI program participation vary.[1]

The subset of the HRS respondents studied here includes 5,631 males born between 1924–1947, observed ages 44–90 between 1992 and 2014.[2] Nearly all respondents are observed for more than one interview or wave of the data, resulting in 45,866 person-years, with an average age of 65.5 when surveyed. Table 1 gives a summary of of some characteristics of the sample.

TABLE 1: *HRS Sample Respondents*

Variable:	
Sample Size	5,631
Person-Years	45,866
Birth Years	1924–47
Average Age Observed in HRS	65.5
Marital Status (first observed)	84.6%
If married, % Spouse Working	54.3%
Occupation	53.3% BC, 46.7% WC
Education Category	
Less than HS	23.4%
HS or GED	35.5
Some College	19.6
College and Above	21.5

The main focus of this paper, and what the modelling seeks to explain, is the many outcomes the differ for those in blue-collar and white-collar work. These include differences in labor supply at older ages, the timing of OASI claiming, savings behavior, and rates of disability.

To begin with the labor supply differences, the HRS interviews, for the majority of the sample respondents, span both working and entry into retirement given the average age at interview of 65.5. Figure 1 presents labor force behavior of the sample by broadly defined occupation. Overall, labor

[1]More details in Appendix ??.

[2]The rationale behind restricting the sample to males has two related rationales. The first is that, when estimating a model of behavior, the more similar the individuals are in preferences, the more precisely the model can be estimated. The men and women, especially of the birth-year cohorts analyzed here, have very different labor supply patterns suggests that their preferences might differ enough to justify separate models of decision making or joint household decisions with bargaining, for instance (e.g., Cassanova 2014). A related reason is that a large enough portion of married males have spouses who are not working when first observed in the HRS data, making the male respondent's decisions in essence a household decision. Of those who are married 54.3% have a spouse working FT when first observed (and are excluded from the parameter estimation).

force participation, defined as "working for pay" at the time of the interview (as well as reporting positive earnings and working for more than five hours per week), declines rapidly from age 60 on. Also striking is the difference in work behavior between those in blue-collar and white-collar jobs. For all ages, the percent of those working whose career is in blue-collar work is lower at all ages, and by age 66, for instance, those in white-collar occupations are about 50 percent more likely to be working for pay compared to those in blue-collar jobs (around 45 versus 30 percent).[3] While some of this difference in work behavior is due to earnings levels across the occupations (those with lower earnings levels have somewhat earlier retirement regardless of job type), what will be analyzed here is the extent to which this is driven by more steeply declining productivity in blue-collar work, as well as potentially greater disutility from working in blue-collar jobs with age or poor health.

Another way in which those in BC versus WC jobs differ is in their timing of Social Security OASI benefits. The *Early Retirement Age* (ERA) is 62 for all birth years, while the *Normal* or *Full Retirement Age* (FRA) is exactly 65 for much of the sample (born before 1938) and between 65 and 66 for those with later birth years.[4] Monthly benefits—the *primary insurance amount* or PIA—are determined based on earnings histories and are relative to the FRA. The PIA is lower the earlier one claims. Figure 2 presents the OASI behavior of the sample by occupation and earnings. Claiming at the earliest age possible is more common for those in blue-collar jobs, where as claiming at the FRA is significantly more common for white-collar workers. This may be for a number of reasons, including liquidity constraints, differences in risk aversion or patience levels, earnings paths, disutility form work with age, and mortality expectations—all of which would have slightly different implications for counterfactual policies and with many being of primary interest here.

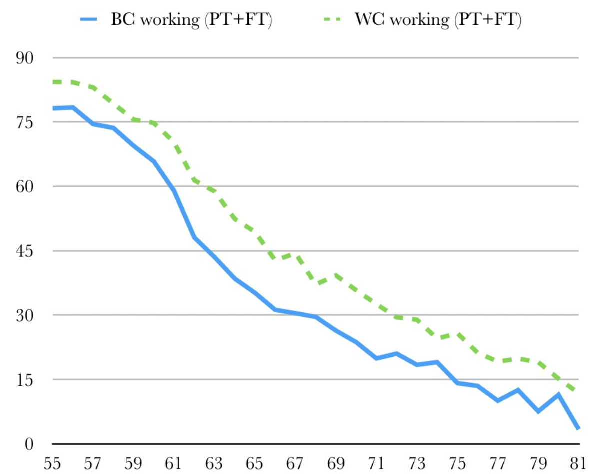
Another difference to note among those whose work is in blue- versus white-collar jobs is the difference in assets held. Overall, even controlling for typical income, those working in white-collar jobs have significantly higher levels of savings. Table 2 specifically presents the savings behavior of the sample by occupation and earnings. As is typical for measures of wealth, the distribution is highly skewed, leading to the mean being much greater than the median. With BC workers in the upper and WC workers in the lower panel, the table shows the mean, median, and median level relative to typical income of non-housing financial assets when aged 55-59. It is divided up by typical income quintiles over all sample respondents, which is determined by annual income from work while observed as a respondent in the HRS while ages 50-59. Focusing on the middle (Third) quintile, for instance, despite blue- and while-collar workers having the same range of typical income, mean financial assets are about \$71K versus \$96K, and the median assets similarly differ at \$17K versus \$29K. These differences conditional on income suggest that there may perhaps be very different average time preferences, levels of risk aversion, or other preferences across the two groups.

Another aspect of the data which differs between those in different broad occupations is in limitations to work due to health as well as SSDI application and receipt. Table 3 shows these patterns. For a given age, BC workers are far more likely to say that their health limits their work. In the first row of the table we see that among those ages 55-59, 27.3 percent of BC workers say

[3] Also, while not shown in this graph, of those who are working at all, the share who report working part-time hours increases from about 5 percent at age 50 to well over half working part-time beyond age 70. The proportion of those who are working working part-time is roughly the same across occupations.

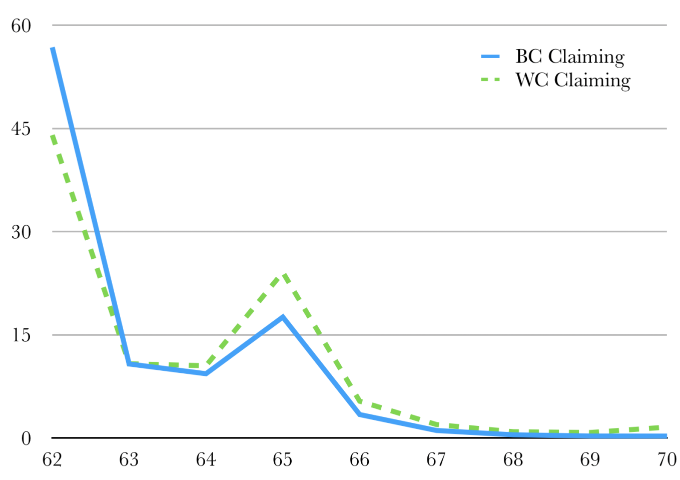
[4] Please see Appendix **??** for more discussion of claiming ages and how benefits are calculated.

Figure 1: *Labor Force Status by Age*



Note: 45,866 person-years.

Figure 2: *OASI Benefit Claiming Age*



Note: 45,866 person-years.

that their health limits their work compared to 15.5 percent of WC workers, which is significant considering there is not a large difference in levels of health between the groups. Furthermore, the health limitation is more likely to prohibit work altogether for BC workers, as only about 34 percent work despite the presence of a health limitation compared to the 46 percent of WC workers who remain in work.

The same differences in health limitations to work also translate to differences in SSDI application and receipt. Nearly a quarter of the sample with a blue-collar occupation have applied for SSDI compared to under 11 percent of those in white-collar occupations.[5] At the time the respondents were age 60–64, about 12 percent of BC workers and 5 percent of WC workers were receiving SSDI benefits. While some of these differences may arise due to SSDI benefits looking relatively more attractive to BC workers, who have somewhat lower earnings overall, the effect, though diminished, remains when controlling for income. In any case, taking into account the differences between these occupations could be useful for projecting SSDI trends into the future or more precisely the effects of policy changes.

4. A Model of Work and Social Security Choices

This section presents a model of behavior in which individuals—who may be in either blue-collar or white-collar occupations—make annual choices about work, savings, Social Security OASI claiming and DI applications. Individuals will differ in number of ways, in both state variables and preferences. After estimating the parameters of this model, the model will be used to measure welfare changes and generate simulated behavior under counterfactual policy scenarios.

TABLE 2: *Savings Behavior*

Non-Housing Assets (quintile mean ages 55-59)	Asset Mean ($)	Asset Median ($)	Rel. to Income
BC:			
Lowest Fifth	$16,998 (80,598)	$30	0.00
Second	32,875 (107,581)	5,932	0.16
Third	71,114 (267,071)	16,949	0.32
Fourth	88,607 (173,630)	33,333	0.45
Highest Fifth	146,572 (659,363)	29,710	0.28
WC:			
Lowest Fifth	81,308 (236,860)	11,276	0.61
Second	77,319 (278,478)	11,111	0.28
Third	96,203 (371,696)	28,813	0.54
Fourth	232,707 (1,390,846)	50,741	0.67
Highest Fifth	455,927 (1,987,947)	111,818	0.80

[5]This does not mean that only fewer than 50 percent of the SSDI applications were successful, as those who are observed in the HRS during ages 60–64 are selected on having survived to that age, which is less likely for someone receiving SSDI.

Table 3: *SSDI Behavior*

SSDI Claiming	BC	WC
Health limits work (ages 55-59)	27.3%	15.5%
Working with health limitation	33.7%	45.6%
SSDI Application Ever	24.8%	10.6%
Current SSDI Receipt, ages 60–64	12.1%	4.9%

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

In this model, each individual begins making decisions annual from age 50 on, with a broad occupation they will remain in while working[6], an income history, and health status. Every annual period t, agents make decisions about:

- Current-period labor supply: Agents may choose to work either part- or full-time if working. This is a modest simplification based on the observation that observed hours worked tend to be clustered around 1,000 and 2,000 hours annually. Participation is notated as $p_t \in \{0, PT, FT\}$.
- Consumption that period, c_t. This is by definition also the savings decision, with $c_t \leq A_t + y_t$, where A_t represents assets and y_t income in period t. Additionally consumption must be at least as great as a consumption floor so that $g_t \leq c_t$. These constraints are imposed to reflect the presumed difficulty in obtaining uncollateralized loans at older ages, given the uncertain stream of income and there being no possibility of garnishing an individual's Social Security benefit payments.
- Whether to begin receiving OASI, if ages 62-70: $OASI_t^{app} \in \{0, 1\}$. OASI benefits depend on past contributions (a proportion of historical earnings) and the age benefits are claimed.
- Whether to apply for SSDI if under normal retirement age: $DI_t^{app} \in \{0, 1\}$, which is received with some probability $p(DI_t^{rec} | DI_t^{app}, OCC_t, d_t) < 1$ that depends on occupation and health status, OCC_t and d_t, respectively (described below).

These decisions are summarized as $\mathcal{D}_t = \{p_t, c_t, OASI_t^{app}, DI_t^{app}\}$. All of these decisions are made given the known state space for that period. The state variables are:

- Asset level, A_t, which includes all non-housing financial assets including pension estimates.
- Current income, y_t (varies by whether working part- or full-time).
- 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, which is whether already began receiving in the past or not: $OASI_{t-1}^{rec} \in \{0, 1\}$ and $DI_{t-1}^{rec} \in \{0, 1\}$ as well as Average Indexed Monthly Earnings, $AIME_t$, which is a function of past earnings and determines the OASI and SSDI benefit level for an individual.

[6] In Jacobs (2023), I consider the selection of occupation taking into account differences in later-life productivity, arguing that both the presence of DI and heterogeneous risk aversion levels matter for the early occupation choice, savings, labor supply decisions.

- Occupation, $OCC_t \in \{BC, WC\}$.

Vector $\mathcal{S}_t = \{A_t, y_t, h_t, d_t, OASI^{rec}_{t-1}, DI^{rec}_{t-1}, AIME_t, OCC_t\}$ represents the state space at period t. Agents make these decisions with uncertainty over a number of state variables looking forward, knowing the distribution but not the future outcome. These are:

- Future health, including overall and functional limitations (disability), h_{t+1} and d_{t+1}. Both of these are a function of current health statuses and age.
- Future income from work, y_{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: $p(DI^{rec}_t | DI^{app}_t, OCC_t, d_t) < 1$.

The agent's continuation value for decisions $\mathcal{D}_t$ at time t, given state space $\mathcal{S}_t$ is

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

where $V(\mathcal{S}_t, \mathcal{D}_t)$ includes the current period utility $u(\cdot)$ plus future discounted utility, which depends on survival $s(h_t, t)$:

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

with the future expected continuation value defined as

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

and

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

From equation (2), current period utility, which is specified below, will depend on current consumption, c_t, labor force participation, p_t, health, h_t, and whether one has applied for DI, DI^{app}_t. 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 precise 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 Appendix A. 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, with $Y(\cdot)$ being income that includes income from work and transfers:

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

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

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

where r is interest earned on savings, g_t is a consumption floor,[7] and ø captures the tax structure.

4.2. Preferences

Preference specification. 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 (with $\eta > 0$) 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. A number of utility parameters come through the L_t leisure variable, which is given by

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

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 while in poor health (φ_{BC,h^p}), and working in a white-collar job while in poor health (φ_{WC,h^p}).[8]

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 and Jones (2011). Here, α_B represents the utility weight on bequests and K_0 gives the extent to which bequests are a luxury good.[9]

As will be described further in Section 5 below, agents can differ by type in preference parameters η (risk aversion) and φ_p (the fixed utility cost of performing work). Indeed, this preference heterogeneity plays an important role in matching observed work, savings, and OASI claiming

[7]Following French and Jones (2011) and Hubbard et al. (1995), 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.

[8]As an alternative to the consequences of working while poor health entering through leisure, in Jacobs (2014), the cost comes solely through the 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 $\varphi_{BC,h^p} > \varphi_{WC,h^p}$.

[9]It is difficult to distinguish bequest motives from precautionary savings without K_0, which **?** use to measure the level of wealth at which savings can be interpreted as bequest motives as opposed to precautionary savings.

Table 4: Summary of Variables

	Description
State Variables:	
t	Age at time t
p_{t-1}	Participation decision last period
A_t	Total assets (quintile)
h_t	Health status: good, fair and poor
d_t	Functional limitation (binary)
OCC	Occupation
$AIME_t$	Average Indexed Monthly Earnings (SS Covered Income History)
Choice Variables:	
p_t	Labor force participation (none, PT, FT)
c_t	Consumption/savings
$OASI_t$	OASI benefit claiming
DI_t	SSDI benefit application
Preference Parameters:	
α_c	Consumption weight
β	Time discount factor
η	Coefficient of relative risk
N_t	Fixed utility cost of work, intercept
φ_p	Utility cost of work, with time trend
φ_{BC,h^p}	Utility cost of working in poor health, BC occupation
φ_{WC,h^p}	Utility cost of working in poor health, WC occupation
φ_{DI}	Utility cost of applying for DI
θ_b	Bequest weight
K_0	Bequest shifter

behaviors. Table 4 summarizes the variables included in the model.

The following section will describe the procedure for estimating these parameters and present estimates.

5. Estimation and Results

5.1. Procedure

The preference parameters of the model presented in Section 4 estimated in two main stages as in Gourinchas and Parker (2002), French and Jones (2011), and others. The first-stage estimates are of parameters that are not generated through the model but come from outside. These include the distributions and transition processes for earned income, health and disability, and survival—which are estimated from HRS data—and the rate of return on assets and the discount rate, which are taken from estimated in existing literature. These parameters are then transferred into the second stage of estimation.

In the second stage, the utility parameters are estimated along with the preference type prediction parameters through *method of simulated moments*. Through this process, the parameters that generate simulated behavior that aligns most closely, in a *generalized method of moments* sense, with behavior observed in the data for select data moments are found through an iterative process, as described in subsection A.3. The estimation procedure is described in greater detail in Appendix A.

5.2. Data Moments

The moments capture the main behavior the model seeks to explain. Below is a sketch of how the parameters are identified through matching as closely as possible the various simulated and real data moments. The parameters for this model are estimated using a total of 184 data moments, while additional moments may be used to validate the model:

- *Median assets by age category (55-59, 60-64, 75–79), income quintile, and occupation.*[10] This gives $3 \times 5 \times 2 = 30$ 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 working part-time or full-time by age (55-59, 60, 61, 62, 63, 64, 65, and 66-70), occupation, and health status.* This makes $2 \times 8 \times 2 \times 2 = 64$ moments. These moments reflect the primary labor supply decisions of interest, which should be generated by the model. 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 applying for 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. These moments recover the hassle or utility cost parameter of applying for SSDI.
- *OASI claiming status by age (62, 63–64, 65-66, 67-70), occupation, and permanent income quintile.* This gives $5 \times 2 \times 5 = 50$ moments.

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 **??**.

5.3. Discussion of Results

The results from the parameter estimation are presented in Table 5, where preference parameters shared across individuals are in the upper panel and those differing by type are in the power panel. Here I will briefly interpret the estimates, highlighting their sensitivity to specific modelling and data choices when relevant.

Beginning with the consumption weight α_c, it is, at .49, in the range of estimated from other estimated models; this measure might look higher if the behavior of interest was of somewhat

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

Table 5: *Parameter Estimates*

Shared Preference Parameters		*Estimates*			
α_c	Consumption weight	.49			
φ_p	Utility cost of work, time trend	15			
φ_{BC,h^p}	Cost of working in poor health, BC	301 (hours)			
φ_{WC,h^p}	Cost of working in poor health, WC	125 (hours)			
φ_{DI}	Cost of applying for SSDI	298 (hours)			
θ_b	Bequest weight	.01			
K_0	Bequest shifter	212 ($1,000s)			
*Type-Specific Preference Parameters**		*Type 1* (32%)	*Type 2* (15%)	*Type 3* (22%)	*Type 4* (31%)
η	Risk aversion	2.67	2.67	5.02	5.02
N_t	Fixed cost of work (hours)	114	340	114	340
Percent in each Type category		BC		WC	
	Type 1	34		30	
	Type 2	22		12	
	Type 3	17		25	
	Type 4	27		33	

younger men. The utility cost of work that varies with age, φ_p is 15. The interpretation of this is that as one ages, assuming health and other factors are unchanged, it feels *as if* one is experiencing 15 fewer hours of leisure each year. As mentioned earlier, this is one component of the model that brings about increasing exit from the labor force with age.

The utility costs of working in poor health in either occupation, φ_{BC,h^p} and φ_{WC,h^p}, which are identified by moments of exit from work of blue- and white-collar workers by age and health status, show that working in poor health is more costly when the work is in a blue collar job (as if there is 301 fewer hours of leisure to enjoy during the year). This is one part of the model, along with wages, that generates relatively earlier retirement for those in blue-collar jobs, all else equal. These results are most sensitive to the earnings profiles, which differ by occupation.

The bequest function parameter θ_b, the estimated weight placed on bequests, is somewhat lower than expected, though this may be a results of considering only non-housing financial assets, as housing is a major component of realized bequests. The bequest shifter K_0, at about $212,000, represents the baseline level of assets for which assets beyond that can be assumed to be intentional bequests.

As for the shared preference parameters, the agent *Types* are distributed roughly evenly across high and low levels of risk aversion, with 47 percent predicted to have lower levels of risk aversion (η = 2.67) and 53 percent higher (η = 5.02). Risk aversion η levels are in some sense higher than anticipated given that the asset measure they are identified through—non-housing financial assets—would tend to show lower risk aversion than, say, assets with housing included. However this is perhaps less surprising considering the low bequest weight θ_b; less importance is placed on leaving bequests, so more savings is interpreted as precautionary rather than intentional bequests.

Turning to the lower panel of Table 5, we have for each occupation the percent estimated to be of each of the four Type categories.

5.3.1. Results on correlation between occupation and estimated time preference or risk aversion.

[Panel of graphs of data versus data moments here]

6. Simulated Profiles with Counterfactual Policies

Taking the estimated preference parameters, I use the model to simulate labor supply, Social Security OASI claiming, SSDI application rates, and savings for agents facing alternative two Social Security policy changes. The first involves raising the Early Retirement Age from 62 to 64, keeping the FRA as is (65 to 66 for those in the HRS data over which the model was estimated). The second raises the FRA to age 68, keeping the ERA at age 62.[11]

Two findings highlighted here are that (1) increasing the Early Retirement Age has larger labor supply and disutility effects for blue-collar workers, and results in greater DI application (2) increasing the Full Retirement Age affects the labor supply of white-collar workers more than for blue-collar workers, however it does increase the savings somewhat for the latter group. In Table 6, these and several other responses to counterfactual policy changes are summarized relative to the simulated moments under the policy in the model.

6.1. Responses to Counterfactual Policies

6.1.1. Increasing the Early Retirement Age

The middle column of Table 6 shows the effect of increasing the ERA to 64 on a number of behaviors. The first is the number of years worked between the ages of 60–69. With the existing claiming age structure, those (simulated) in blue-collar occupations worked 4.07 out of those ten years and those in white-collar occupations worked over one year more on average, 5.14 years. When the ERA is raised to 64, BC workers respond primarily by working longer, 5.19 years from 60–69 and save only slightly more at about \$18K versus under \$16K.

Also worth noting is the interaction between SSDI application and increased claiming ages across occupations. SSDI application for those in BC occupations goes up by almost 6 percent while for WC the rate increases by under 2 percent. Regardless of occupation, those applying now for SSDI were disproportionately early OASI claimers under the status quo policy.

Finally, welfare loss resulting from increasing the ERA is lower for those in WC occupations, who experience a welfare loss of 2.1 percent compared to 5.7 percent for those in BC occupations. This is presumably because WC workers can adjust along the lines of labor supply in a less costly way. In summary, raising the ERA seems to be especially costly for the typical blue-collar worker. This is driven primarily by the fact that those in blue-collar work have more steeply declining productivity with age and are also more likely to be the lower η preference type, which wants to hold fewer assets giving less margin on which to respond to policy changes.[12]

[11] For the purposes of simplifying presentation, I show only these two counterfactual policies. Looking at the effects of alternative policies (e.g., increasing both the ERA and FRA, increasing the FRA to 70, etc.) can also be done and is relatively straightforward to simulate.

[12] All counterfactual responses are sensitive to the fact that simulated agents are behaving as if they were aware of the counterfactual policy at age 50. This would overstate welfare loss if in fact the policy were known at an earlier

6.1.2. Increasing the Full Retirement Age

The rightmost column of Table 6 shows behavior when the FRA is raised to age 68. Comparing to labor supply changes when the ERA is raised, the effects for BC workers are quite minimal, and a smaller than the effects for WC workers; the number of years worked while aged 60–69 goes up by only .08 years for BC workers compared to nearly .7 years for WC workers.

Increasing the FRA has the effect for both occupations of decreasing the percent who claim OASI benefits at the ERA, and more so for WC workers than for BC workers. The effect, however, is very small compared to the large *increase* due to raising the ERA. For workers in both occupations, the rate of SSDI application goes up—by 4.6 percentage points for BC workers and by 3.6 percentage points for WC workers, which is a relatively higher increase for the latter.

Generally, for all behaviors, raising the ERA induces more of a response from BC workers, while raising the FRA has a relatively greater response for WC workers.

TABLE 6: *Summary of Counterfactual Policy Results*

			Policy	
		Status Quo	Raising ERA	Raising FRA
Labor Supply: Years worked 60-69				
	BC	4.07	5.19	4.15
	WC	5.14	5.47	5.82
OASI ERA claiming				
	BC	49.5%	65.2	44.4
	WC	37.8	57.7	31.4
SSDI application rate				
	BC	21.2%	26.9	25.8
	WC	11.3	12.8	14.9
Welfare changes*				
	BC	-	-5.7%	-4.4
	WC	-	-2.1	-3.1
Savings (median, age 55-59, in $1,000s)				
	BC	$15.5	17.9	16.1
	WC	30.7	33.2	32.9

*These changes are calculated for age 50 on for average characteristics.

age as agents would have more periods over which to adjust.

Appendices

Table 7: *SS claiming by subjective life expectancy and occupation*

	When claimed SS benefits		
	By age 62	63-64	65 and Older
Physical Intensity of Work			
White-Collar	48.4	17.2	34.4
Blue-Collar	59.0	18.6	22.4
Prob. of Living Past 75			
0 to 39 percent	73.7	12.9	13.4
40 to 60 percent	64.9	16.2	18.9
61 to 100 percent	58.9	16.0	25.1

Note: Includes 2,390 observations.

A. Appendix A: Parameter Estimation

A.1. First-Stage Estimates

A.1.1. Health and Disability Transitions

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 8 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. While the distribution of health is somewhat different for those in blue-collar and white-collar occupations, the transition probabilities themselves are not significantly different, at least at the older ages analyzed here. While the transition process faced by individuals does not depend on occupation, we will see in the wage estimates shown in Table 10 that the effects on productivity of worsening health are greater for those in blue-collar occupations.

A.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 9. 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 10.

A.1.3. Wage Estimates

This is an important aspect: BC worked exit earlier due to more steeply declining wages and increasingly greater disutility from physical work.

Estimated wages depend on age, health, and functional limitations interacted with occupation. Specifically,

$$\begin{aligned} \ln w_t = &+ \gamma_0 + \gamma_1 N_t + \gamma_2 \text{Age}_t + \gamma_3 \text{Age}^2 \\ &+ \gamma_4 \mathbb{1}_{\{BC, poor\ H\}} + \gamma_5 \mathbb{1}_{\{WC, poor\ H\}} \\ &+ \gamma_6 \mathbb{1}_{\{BC,\ func.\ lim.\}} + \gamma_7 \mathbb{1}_{\{WC,\ func.\ lim.\}} + \varsigma_t \end{aligned} \tag{6}$$

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

A.1.4. Mortality Profiles

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

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

TABLE 8: *Sample Health Transition Probabilities*

		Next Period Health		
	Current Health	G/VG/E	Fair	Poor
Age=55	G/VG/E	.89	.09	.02
	Fair	.44	.35	.21
	Poor	.15	.35	.50
Age=65	G/VG/E	.85	.13	.02
	Fair	.44	.38	.18
	Poor	.13	.33	.55
Age=72	G/VG/E	.81	.16	.02
	Fair	.40	.38	.22
	Poor	.12	.32	.56

TABLE 9: *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	.47	.53	.72	.28
65	.42	.58	.56	.44

TABLE 10: *Wage Equation Estimates*

Outcome: ln*Annual Earnings*		
Variable	*Coefficient*	*(s.e.)*
Age (years)	.111	(.028)
Age^2	-.001	(.000)
Functional Limitation, f_{it}		
White-Collar	-.006	(.018)
Blue-Collar	-.079	(.019)
Poor Health, h_{it}		
White-Collar	-.015	(.015)
Blue-Collar	-.052	(.017)
Full-Time Work, N_{it}	.740	(.032)
$\widehat{\rho}$ (autoreg. coeff.)	.940 (.019)	
$\widehat{\sigma}^2_{\nu}$ (trans.)	.031 (.009)	

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.

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.[13]

A.2. Preference Heterogeneity

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 performing work (high N_t) parameters: (1) *Type 1* is less risk averse (low η) and has a lower cost of working (low N_t); (2) *Type 2* is less risk averse (low η) and has a higher cost of working (high N_t); (3) *Type 3* is more risk averse (high η) and has a lower cost of working (low N_t); and (4) *Type 4* is more risk averse (high η) and has a higher cost of working (high N_t). Though

[13]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).

η is sometimes determined outside of the model in similar studies,[14] 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 N_t to account for different inclinations to work.

To predict the types, I estimate a multinomial logistic regression within the second stage, where the probability of individual i being *Type n*, $n = 1, 2, 3, 4$, is

$$\Pr(i{=}\textit{Type } n) = \frac{\exp(\mathbf{fi}_n \mathbf{X}_i)}{1 + \sum_{k \neq n} \exp(\mathbf{fi}_k \mathbf{X}_i)} \tag{7}$$

where

$$\mathbf{fi}_n \mathbf{X}_i = \beta_{n,0} + \beta_{n,1}(\text{Assets at 50})_i + \beta_{n,2}(\text{Work Enjoyment})_i + \beta_{n,3}(\text{Income Gamble})_i \,,$$

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

A.3. Computational Procedure

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

$$\widehat{\theta} = \operatorname*{argmin}_{\theta} \; \widehat{\varphi}\,(\theta, \widehat{\chi})' \, \Omega \; \widehat{\varphi}\,(\theta, \widehat{\chi}) \tag{8}$$

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 (8) is obtained by the following procedure

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

[14] For example, **?** set a parameter with roughly the same interpretation as η in this paper to 1.5, while **?** set the coefficient of relative of risk aversion to 3 for their exercises.

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 in Subsection A.2). 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 3,000 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 (8).

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 (8) is found.

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