Occupational Retirement and Social Security Reform: the Roles of Physical and Cognitive Health

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This version: January 30, 2020
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Abstract

Skill-biased technical change leads jobs to be less physically demanding whereas require more cognitive abilities, but existing research on retirement pays little attention on the cognitive dimension of health. This paper first explores occupational facts in ability requirements, multiple dimensions of health, and their interactive relationship in retirement. Based on these facts, this paper proposes and estimates a dynamic structural model of individual retirement and saving decisions, incorporating both physical and cognitive dimensions of health and allowing their retirement effects to differ across occupations via four channels respectively: leisure, wage, medical expenditure and life expectancy. I use indirect inference for estimation, using variants of auxiliary models to exploit either pooled variations or only within-individual variations to identify the model. The counterfactual results suggest cognitive health has little retirement effect for manual workers, whereas for clerical workers it is as vital as physical health. Leisure and life expectancy are more important channels. When retirement age increases, manual workers would actually delay retirement more than professionals. This is not due to their health capacity but instead to their financial rigidity in deciding when to retire.

Key Words: Aging; Cognitive Health; Pension; Physical Health; Occupation; Retirement; Social Security.

1 Introduction

Skill-biased technical change is a fundamental shift to the labor market during the past decades. A notable consequence of this change is that the average job requires less physical abilities whereas becomes more intellectually-demanding, as shown in Figure 1. Meanwhile, health has long been regarded as an important factor in affecting older people's labor supply, and it is becoming more concerning under population aging and the universal background that many governments encourage

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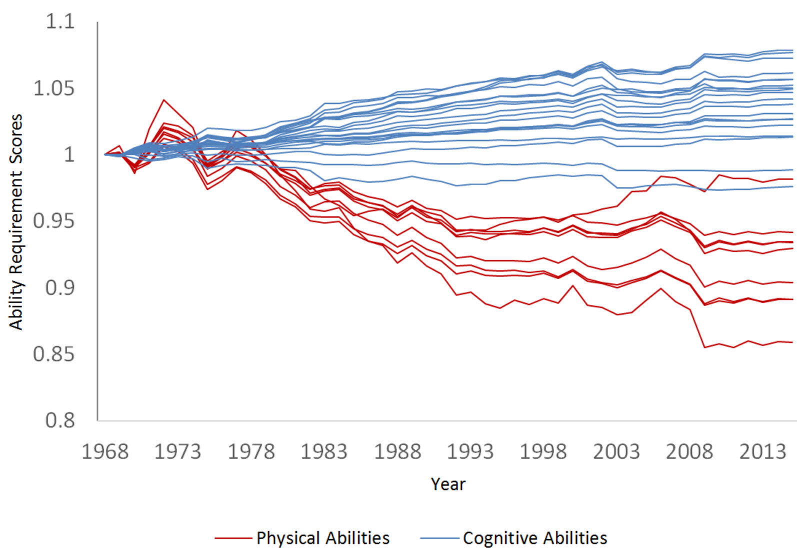
older people to work longer. However, existing literature on older people's labor supply is mostly based on traditional definitions of health, mostly related to the physical dimension. As modern jobs' ability requirements undergo dramatic changes, ignoring the cognitive dimension of health may lead to increasing misunderstanding on older people's labor supply and biased policy evaluations. This paper first explores the empirical facts about physical health, cognitive health and retirement across occupations. Then based on these facts, I propose and estimate a dynamic structural model of individual retirement and saving decisions of U.S. male household heads. The model takes into account not only the physical health but also the cognitive health, and it allows each dimension of health to affect retirement via different occupation-dependent channels. Based on this model, I examine the occupation-specific mechanisms of the retirement effects of physical and cognitive health. Then I quantify the heterogeneous changes in labor supply, savings and welfare across occupations under a counterfactual experiment that increases the retirement age.

Figure 1: Trends of Physical and Cognitive Ability Requirements of The Average US Job



The vertical axis is the score measures how much an ability is required by the average US job. Each line represents one specific type of ability under the physical or cognitive category, defined by O*NET data set. Given a specific ability, the trend is calculated as this ability's requirement by each occupation, measured in O*NET in 2016, weighted by time-varying employment shares of all occupations obtained from the Current Population Survey (CPS), 1968-2015. The scores are normalized to 1 in 1968. Details of the calculation is provided in the Empirical Facts section.

Population aging places the public pension system under long-term stress. Increasing the retirement age is a focal policy reform considered by many countries, such as the U.S., China, Japan and European countries. For instance, the US Congressional Budget Office examines the options to increase the full retirement age (hereafter referred as FRA) respectively to 68, to 70, and by one month per birth year. [1] Under this background, whether the older people would have enough health capacity to delay their retirement? How responsive the labor supply of older people would be when financial factors, health factors, as well as their complex interactions are taken into account? What would be the distributional effects of increasing the retirement age on older people's labor supply, savings and welfare? These are crucial questions needed to be considered when design related policies. Notably, the ability requirements across occupations differ remarkably, which suggests the importance to look at the interaction between individual's occupation and the different dimensions of health. For instance, construction workers may be unable to carry heavy materials due to physical health deterioration, whereas researchers may find it more challenging in a seminar when unable to recall details of their research, or human recourses may assume higher stress when they miscalculate employees' benefits more frequently due to the cognitive decline. In particular, as cognitively-demanding jobs grow and even dominate, omitting the cognitive dimension of health may underestimate retirement and welfare impacts of health for a nontrivial group of people and lead to misleading policy proposals. Moreover, as policy-targeted ages are higher, e.g. FRA increases to 68 or 70, the overlap with high incidence of cognitive malfunctioning such as Alzheimer Disease brings extra concern on the cognitive dimension of older people's health.

This paper first explores some empirical facts about the ability requirements, the multiple dimensions of health, and their relationship with labor supply at older ages. I explore the heterogeneity in physical and cognitive ability requirements across occupations, using the O*NET dataset with detailed information for hundreds of occupations in the U.S. Combined with the Current Population Survey (CPS) data, I document secular trends of the physical and the fcognitive ability requirements of the average U.S. job since 1968, which follow distinct directions. Then estimating reduced form regressions of the labor force participation on the Health and Retirement Study (HRS) data, I find motivating facts about the occupation-dependent effects of the physical and cognitive health on older people's labor force participation.

Motivated by these empirical facts, this paper then develops a structural dynamic programming model of labor supply and saving decisions of male household heads in the United States to capture the dynamic and nonlinear interactions between different dimensions of health, financial conditions and occupations. The model incorporates two dimensions of health: the physical health and the cognitive health. Occupations are grouped into three categories: manual, clerical, and professional.[2]

[1] Social Security Policy Options 2015.

[2] This paper abstracts from modeling the change of occupations and provides a lower bound for the negative impact of poor physical or cognitive health on older people's labor market decisions. Detailed discussion is provided in the Data section.

Consistent with literature based on the general health, as Blundell, French, and Tetlow (2016) and Capatina (2015), the model allows four underlying mechanisms to affect individual's labor supply decision for both physical and cognitive health respectively. Disutility of working and the wage penalty due to poor physical or cognitive health are allowed to be occupation-dependent. In addition, both dimensions of health are allowed to shift the medical expenditure and the life expectancy. The model also captures rich heterogeneity in various dimensions at the individual level: labor earnings, assets, public pension, private pension, health insurance, physical and cognitive health conditions, life expectancy, education, unobserved individual types etc. In the data, the joint distribution and the transition of these variables are also different across occupations.

I use indirect inference to estimate the model based on the Health and Retirement Study (HRS) data from 1996 to 2012, an individual level longitudinal data set covers people older than age 50 in the United States. By indirect inference, I make use of the flexibility of choosing auxiliary models to exploit different data variations to identify the structural parameters. Previous studies based on the simulated method of moments (hereinafter SMM), such as French (2005) and French and Jones (2011), essentially use a mixture of the within-individual and the between-individual variations in labor supply and health to identify the retirement effects of health. For previous research based on indirect inference, the identification strategy is similar when choosing the pooled regression model as the auxiliary labor supply model, as Van der Klaauw and Wolpin (2008) and Haan and Prowse (2014). In this study, I choose regression models with individual fixed-effects to exploit the within-individual variations to identify the retirement effects of health. The approach here aligns with Fu and Gregory (2019), who use regressions under a regression-discontinuity setting as the auxiliary models. The estimates are robust using only within-individual variations.

Based on the structural estimates, the first counterfactual experiment quantifies the importance of physical and cognitive health in affecting older people's labor force participation (hereafter referred as LFP) across occupations under the current Social Security rule. It finds that, if individuals are assumed to maintain good physical health always, the LFP rate between age 65 and 69 would increase by 27% for manual workers, compared to 13% for clerical and 15% for professional workers. On the contrary, if persistent good cognitive health is assumed, the LFP rates would increase respectively by 10% and 4% for clerical and professional occupations, whereas there would be no increase in manual occupations. Moreover, if both physical and cognitive health are assumed good, the increase in LFP rate is found larger for clerical and professional occupations (13.7 and 10.5 percentage points respectively) than manual occupations (8.8 percentage points). This finding, contrasting the usual opinion that poor health mainly matters in physically demanding jobs, suggests the need to pay more attention to health issues under a broader scope for older workers, especially for those in intellectually demanding occupations.

The first counterfactual experiment also evaluates the relative importance of the underlying mechanisms through which physical and cognitive health affect retirement. The results suggest the channel of disutility of working is the most influential for both physical and cognitive health. Moreover, disutility of working caused by poor physical health is the largest for the manual occupation whereas the one caused by poor cognitive health is the largest for the clerical occupation. Occupation-dependent effects are not found in the rest channels. While poor physical health also has a notable effect on retirement by shortening the life expectancy, this effect cannot be found for cognitive health. Finally, the effects of both physical and cognitive health on retirement through the medical expenditure and wage channels are small.

The first counterfactual experiment is based on the current Social Security rule. Under policy changes, a quick thought about the heterogeneous response in retirement may be that workers with poor physical (cognitive) health from physically (cognitively) demanding occupations will be less responsive in postponing their retirement. This effect will also lead to larger reduction in retirement benefits for these people. [3] However, the interaction between occupations and health will further interplay with individual's income and wealth, which also lay large disparity across occupations. For occupations in which workers have lower income and savings, the reduction in retirement benefits induced by policy changes will generate larger income and substitution effects. As a result, workers from these occupations are more financially rigid to choose when to retire based on their health status. These people may have to work longer even if they had poor health. This will cost them nontrivial disutility of working and lead to large welfare loss.

The second counterfactual experiment quantifies the changes in LFP at older ages across occupations when the FRA increases to 70. Manual workers are found the most responsive in delaying their retirement to this reform. Although workers in this occupation have worse physical health and are more affected by poor physical health, which constrain their ability and willingness to postpone their retirement, small effects of cognitive health and the strong income and substitution effects induced by the reduction in retirement benefits contribute to the larger response. Correspondingly, I find manual workers are also subject to larger retirement benefits reduction and larger welfare loss than professional workers. The present discounted welfare loss for a manual worker is equivalent to 20,900 dollars, compared to 21,000 dollars for a clerical worker and 15,900 dollars for a professional

[3] Conditioning on retiring at age 62, retirees can receive 80% of the full benefits when FRA is 65, and this percentage declines to 70% when FRA is 67. If FRA were to increase to 70, this percentage would further decline to 55% according to the current formula.

worker. The fact that manual and clerical workers are more responsive in delaying retirement under the increased FRA, in together with their worse average health, leads to larger disutility of working and larger welfare loss than the professionals.

An increasing number of studies on retirement are based on the dynamic structural models not only to capture the dynamics in financial and health variables but also to implement counterfactual experiments to evaluate potential policy reforms. Building on early works as Gustman and Steinmeier (1986b) and Rust and Phelan (1997), more recent research enriches this type of model by introducing endogenous savings (e.g. French (2005) and Van der Klaauw and Wolpin (2008)), medical expenditure risks (French and Jones (2011)), endogenous medical expenditure (Blau and Gilleskie (2008)), joint decisions of couples (Van der Klaauw and Wolpin (2008)) etc. Bound, Stinebrickner, and Waidmann (2010) examines the effect of health carefully by dealing with the measurement bias in self-reported health within a dynamic structural framework. Capatina (2015) focuses on the effect of health on life-cycle employment and accounts for the importance of four underlying channels: leisure, wage, medical expense and life expectancy. Health variables in these studies are mainly single broad measures, such as the self-reported health. The main goal of these studies is to evaluate the potential impacts of public pension reforms on older people's retirement, savings and reforms. The simplification of health and the missing of interaction with occupations may lead to biases in estimating these impacts, especially under the background of more intellectually-demanding jobs and the overlap between policy-targeted ages and high incidence of cognitive-malfunctioning. For reduced-form studies which focuses more on estimating the retirement effect of health over policy evaluations, a notable study by Blundell, Britton, Costa Dias, and French (2017) include cognition into the labor supply equation. Their estimated effect of cognition is significant but contributes to little explanatory power. Results of this paper highlights the importance to explore the effects by occupations. To the best of my knowledge, this paper is the first to specifically focus on the cognitive dimension of health and examines the occupation-dependent roles of multiple dimensions of health in older people's retirement and saving decisions.

When evaluate the effects of potential public pension reforms, existing research mainly focuses on the aggregate effects, such as French and Jones (2011). Capatina (2015) explored the heterogeneous effects by education, while Bound, Stinebrickner, and Waidmann (2010) by health and Blau and Gilleskie (2008) by health and health insurance type. This paper makes contribution by studying the heterogeneous effects from another angle: the occupation. This is vital not only because of the substantial gap in socio-economic status across occupations but also due to the welfare implication that poor physical and cognitive health interact with occupation's heterogeneous ability requirements.

This paper also speaks indirectly to recent literature studies the health capacity to work at older ages, such as Cutler, Meara, and Richards-Shubik (2013) and Coile, Milligan, and Wise (2016). The counterfactual result that manual workers would be more responsive in delaying their retirement under increased retirement age suggests older people have sufficient health capacity to work, consistent with the related literature. Nevertheless, the continuation of working is mainly driven by the dominance of financial incentives and it masks nontrivial welfare loss resulted from the disutility of working under poor health.

The contributions of this paper are mainly threefold: First, this paper considers the particular role of cognitive dimension of health in retirement, which has growing importance as works are more intellectually-demanding and the high incidence of cognitive malfunctioning overlaps with policy-targeted ages. Second, this paper models the particular interplay between different dimensions of health and occupations and explores the underlying mechanisms of the labor supply effect of poor physical and cognitive health for the older people. Third, this paper makes use of the flexibility of indirect inference to exploit different data variations to identify the effect of health on older people's labor supply, which is the first under a structural framework.

The rest of this paper is structured as follows. The next section presents the empirical facts about occupation, health and retirement. Section 3 is devoted to the structural model and section 4 to the solution and estimation methods. Section 5 describes the data. Section 6 presents the estimates and counterfactual experiments are implemented in Section 7. Section 8 concludes.

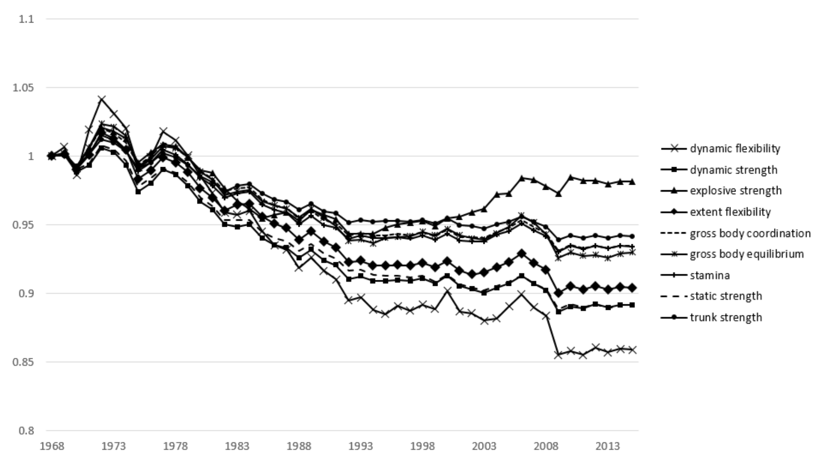
2 Empirical Facts

2.1 Ability Requirements by Occupations

In the past decades, job requirements have been going through a remarkable change: more and more jobs require cognitive instead of physical abilities. To see this, I calculate the trend of how each physical or cognitive ability is required by the average U.S. job from 1968 to 2015. The physical and cognitive abilities are defined by O*NET, a data set provides detailed information about more than 900 occupations in the US. This data set provides scores about how each specific ability is required by each occupation. These ability requirement scores of each occupation are cross-sectional, measured only in 2016. Therefore the data does not allow us to keep track of the ability requirement change within occupation. Instead, I merge the ability requirement scores of each occupation in 2016 from O*NET with the longitudinal employment shares of occupations from the Current Population Survey

(CPS) 1968-2015. [4] As presented in Figure 2, the requirements for all abilities defined by O*NET as physical category have been declining since 1968. On the contrary, Figure 3 reveals that out of the twenty-one abilities under cognitive category, requirements for eighteen have increased .

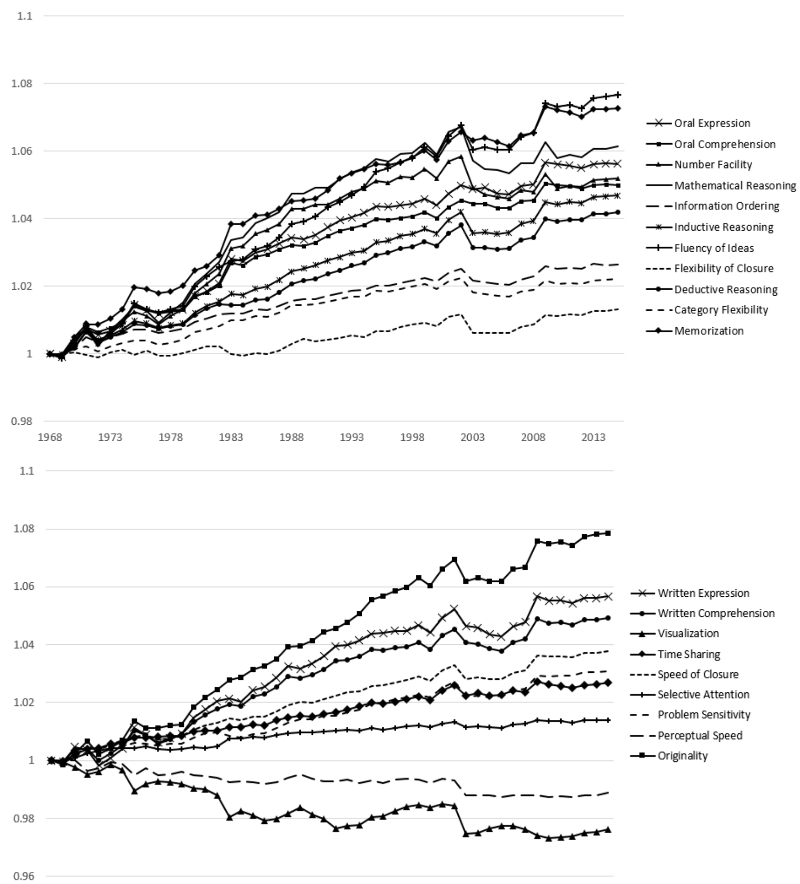
Figure 2: Trends of Physical Ability Requirements of The Average US Job since 1968



This figure presents the scores of physical ability requirements averaged across U.S. occupations, weighted by the employment shares of occupations. The scores in 1968 are normalized to be one.

[4] I first construct a sample consisting of six-digit occupations from the 964 eight-digit occupations in O*NET data set to match with the employment share data from CPS. The constructed sample includes 773 six-digit occupations. To obtain the ability requirement scores for these six-digit occupations, I simply compute the mean of those occupations with eight-digit sub-occupations. To calculate the ability requirement score in a given year averaged over these 773 occupations, the score of each six-digit occupation is weighed by employment shares of all occupations in that year obtained from CPS. Notice that the calculated trends of ability requirement scores are only driven by the compositional change of occupations, as the O*NET data set does not capture variations within occupation.

Figure 3: Trends of Cognitive Ability Requirements of The Average US Job since 1968



This figure presents the scores of cognitive ability requirements averaged across U.S. occupations, weighted by the employment shares of occupations. The scores in 1968 are normalized to be one. The ability "spatial orientation" has gone through a big decline, dropping from 1 in 1968 to 0.82 in 2015. It is not shown in the graph for the scale reason.

Given this systematic change, while physical dimension of health still remains important, the cognitive dimension may become an increasingly relevant factor when the elderly make their retirement decisions. Noticeably, the above trends reflect ability requirements of the average U.S. job. When examining those cognitively-demanding occupations, the impacts of poor cognitive dimension of health can be more concerning. This is mostly important if governments want to understand the distributional effects induced by policy changes. Existing focus is purely on workers from physically-demanding occupations, as they may have limited health capacity to work at old ages, such as the discussion by Vermeer, Mastrogiacomo, and van Soest (2014) for the Netherlands and the heavy labor pension in Austria started from 2007. [5]. When cognitive dimension of health is not considered, the health capacity of workers from cognitively-demanding occupations, especially those at high ages, may be overestimated and their welfare loss can be underestimated.

[5]Key Policies to Promote Longer Working Lives in Austria, OECD 2018

In this paper, occupations are grouped into three categories. The first category includes manual and service occupations. The second category covers clerical and sales occupations. The third category consists of professional and managerial occupations. For simplicity, these three categories will be referred as manual, clerical and professional occupations hereafter. As this paper intends to highlight the implication of the multiple dimensions of health in an occupation setting that people usually focus on, it does not classify occupations into groups based on the ability requirements, although the occupation-dependent pattern of the effects of health is expected to be even sharper.

To reveal the different ability requirements across the occupation groups defined above, I calculate the ability requirement scores for each occupation group respectively. The score of a given ability for a specific occupation group is the sum over the scores of all six-digit occupations under that occupation group, using the employment shares from CPS as the weights. Table 1 suggests large gap in the required abilities across occupation groups. The physical abilities are more required by the manual occupation group as compared to the clerical and professional groups. In particular, scores for the professional group are all less than 0.5 compared to the manual group. On the other hand, most of the cognitive abilities are more required by the professional and clerical groups than the manual group, which is clearly shown in the last column of Table 1 for cognitive abilities. Indeed, the gap in terms of cognitive and physical ability requirements is substantial across occupation groups. For instance, the professional group requires 35% more memorization than the manual group, but only requires 43% of the explosive strength. Comparatively, the importance of memorization relative to explosive strength is as much as 314% for the professional group as opposed to the manual group. [6]

[6] The comparative importance is calculated as $1.35/0.43 \approx 314\%$.

Table 1: Ability Requirement Scores by Occupation Groups

	Manual	Clerical	Professional	Prof./Man.
Physical Abilities				
Dynamic Flexibility	7.1	0.9	0.7	0.09
Dynamic Strength	33.7	10.5	9.4	0.28
Explosive Strength	10.5	2.2	4.5	0.43
Extent Flexibility	42.4	13.8	11.1	0.26
Gross Body Coordination	36.0	12.4	11.7	0.33
Gross Body Equilibrium	27.5	9.3	9.3	0.34
Stamina	40.8	14.4	13.6	0.33
Static Strength	44.7	17.2	13.5	0.30
Trunk Strength	49.0	23.0	21.6	0.44
Cognitive Abilities				
Oral Expression	58.3	71.2	76.0	1.30
Oral Comprehension	60.8	71.9	75.5	1.24
Number Facility	29.8	41.5	44.5	1.49
Mathematical Reasoning	28.8	41.7	47.2	1.64
Information Ordering	53.2	55.6	63.6	1.20
Inductive Reasoning	49.6	52.5	66.5	1.34
Fluency of Ideas	34.8	40.3	55.8	1.61
Flexibility of Closure	40.8	38.5	48.6	1.19
Deductive Reasoning	52.9	54.7	69.1	1.31
Category Flexibility	45.7	50.4	56.8	1.24
Memorization	30.2	35.5	40.8	1.35
Written Expression	42.0	58.3	68.3	1.63
Written Comprehension	48.4	62.7	72.8	1.50
Visualization	41.8	30.3	41.5	0.99
Time Sharing	40.1	39.5	43.3	1.08
Speed of Closure	32.3	32.1	40.1	1.24
Spatial Orientation	21.9	3.4	5.1	0.23
Selective Attention	48.8	49.0	52.4	1.08
Problem Sensitivity	58.9	57.6	70.5	1.20
Perceptual Speed	41.7	39.5	44.2	1.06
Originality	33.3	38.8	53.5	1.61

This table presents ability requirement scores for the occupation groups defined in the paper. The score for a given occupation group is the sum of the scores of the six-digit occupations under that group, weighted by the employments in 2014 from the CPS data .

2.2 Physical and Cognitive Health

From the demand side, the above subsection reveals notable discrepancy in ability requirements across occupation groups. This subsection explores the empirical facts in the physical and cognitive dimensions of health from the supply side.

While physical ability relates to body's capacity to perform activities that require strength and endurance, cognitive ability refers to brain's competence to process information, including memory, numeracy, fluency, orientation, logic, reaction etc. This paper distinguishes the cognitive health from the mental health. The latter is more related to individual's happiness, confidence, resilience etc.[7] Depending on the life-cycle transition, cognition has been commonly classified into crystallized and fluid categories, as defined by McArdle, Ferrer-Caja, Hamagami, and Woodcock (2002). While crystallized cognition remains stable over the life-cycle, fluid cognition has a clear declining pattern as age increases. This declining feature, similar to the physical dimension of health, raises more concerns for its impact on people's life, especially at very old ages. Instead of constructing a comprehensive measure from all dimensions of cognitive abilities, this paper focuses on a crucial dimension of fluid cognition: memory. Another reason to focus on memory is that there are longitudinal and direct measures for memory from HRS. While there are multiple dimensions of cognition, variables for every dimension are not available in this micro longitudinal data set. In terms of the measure of memory that this paper adopts, interviewer reads a randomized list of words and then asks the respondent to recall these words. This exercise is carried out twice in each interview, one right after reading the list and another one after several subsequent questions. Two variables recording the number of words recalled by each respondent are thus provided in each wave. I construct a single variable by summing them up, which has been commonly used in psychological literature. Other studies in economics, such as Smith, McArdle, and Willis (2010), also adopts this measure to examine the relationship between cognition and individual behavioral outcomes.

Based on the primary sample used in this paper, Table 2 shows ample variation in the level of memory by education and by occupation. [8] Figure 4 shows the age profiles of memory from age 51 to 75 by education and occupation. With respect to education, the number of words recalled at age 51-53 by people dropped out from high school averages 8.82, while the one by people with high school degree averages 10.17. The number recalled by those with some college averages 10.70 and with college and above averages 11.68. In terms of occupation, individuals aged 51-53 in manual and clerical occupations respectively recall 9.97 and 10.74 words on average. Individuals in professional occupations recall 11.51 words, which is notably higher. [9] According to the literature in psychology, while some researchers argue fluid cognition starts to decline as early as age 20-30 (e.g. Salthouse

[7] This paper controls for the mental health in reduced form regressions. The structural model does not further include the mental dimension specifically. The main focus of this paper is the occupation-dependent roles of health, particularly motivated by the heterogeneous skill requirements across occupations. Although there may be heterogeneity in mental heath between occupations, the discrepancy may not be mainly driven by skill requirements, and the concern about poor mental health is less clear along the occupation dimension. For these reasons, I abstract it from the model and leave it for future studies.

[8] My primary sample consists of male household heads aged 51-61 in their first observed waves in the 3rd to 11th waves of HRS data. This sample is used for the subsequent structural estimation. Detailed sample definition is in the Data section.

[9] I include observations that have already retired in order to keep track of the whole transition until age 75. The occupation for retired observations are defined by their previous occupation while working. Notice that, the primary sample is restricted to individuals who did not change occupations.

(2009)), even the conservative opinions point out that it starts around the middle of age 50s (e.g. Rönnlund, Nyberg, Bäckman, and Nilsson (2005)). As the following table shows, cognitive decline from 51-53 to 70-72 is around 2 words, approximately 65% of the standard deviation at age 51-53. Moreover, I can see cognition does decline more rapidly after the early retirement age 62, which is the period retirement occurs and policy reform targets. [10]

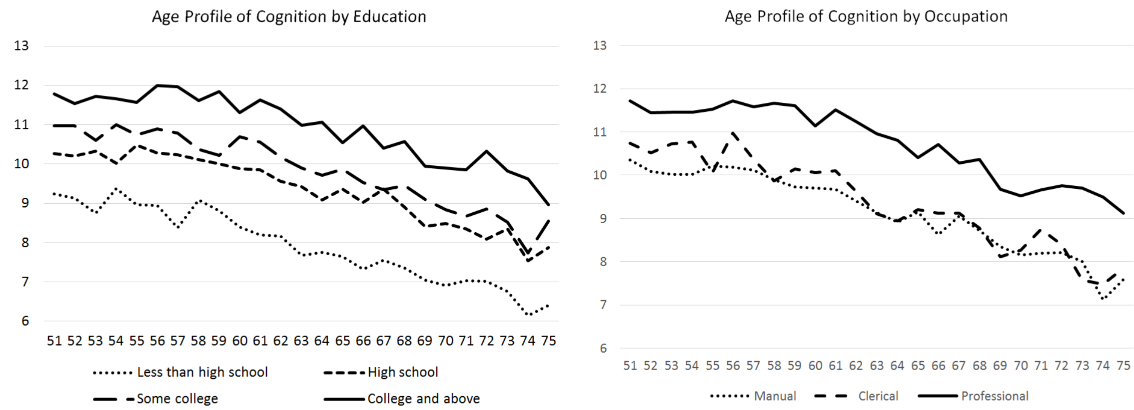
Table 2: Variation in Cognitive Health by Education and Occupation

	LH	HS	SC	CA	Manual	Clerical	Professional
Age 51-53							
Mean	8.82	10.17	10.70	11.68	9.97	10.74	11.51
Standard deviation	3.13	2.72	2.70	2.79	2.87	2.86	2.78
Observations	211	568	531	597	853	194	573
Age 60-61							
Mean	8.51	10.09	10.84	12.01	9.71	10.92	11.88
Standard deviation	2.89	2.99	3.12	2.94	3.05	3.20	2.95
Observations	580	1,208	940	1,124	1,713	358	1,008
Drop from 51-53							
With controls	-0.57	-0.36	-0.36	-0.09	-0.45	-0.56	-0.12
Raw	-0.31	-0.08	0.14	0.34	-0.26	0.18	0.37
Age 70-72							
Mean	7.16	8.71	9.63	10.73	8.25	9.55	10.29
Standard deviation	2.76	2.93	3.10	2.93	2.90	2.91	3.17
Observations	288	568	324	420	671	136	408
Drop from 51-53							
With controls	-2.05	-1.96	-2.05	-1.66	-1.97	-2.19	-1.89
Raw	-1.66	-1.46	-1.07	-0.95	-1.72	-1.19	-1.22

This table presents the mean and standard deviation of number of words recalled by education and occupation for the primary sample. The raw drop is computed as the difference between the means in middle and above panel. The drop with controls is calculated by a regression of words recalled on age dummies and controls. Control variables include race, education, birth year, birth place. LH: less than high school; HS: high school; SC: some college; CA: college and above.

[10] For the results by occupation, one caveat should be kept in mind that the sample does not include individual who has been out of labor force in all waves, because the occupation is unidentifiable. Since This sample restriction systematically excludes observations with old ages and with poor memory, which tends to underestimate the cognitive decline.

Figure 4: Age Profiles of Cognitive Health



These figures are produced based on the primary sample from the HRS data. Cognition is measured by the number of words recalled variable. Race, gender, education, birth year and birth place are controlled.

The measure of physical health used in this paper is a health index constructed as the predicted value from a regression of self-reported health on more specific health-related variables. Following research such as Bound, Schoenbaum, Stinebrickner, and Waidmann (1999), this approach intends to construct a health measure free of the justification bias. Justification bias is a main concern in previous studies about the retirement effect of health, which rises from that retirees tend to report worse health to justify their early retirement. More specific health-related variables are arguably less subjective to this bias and therefore are used as instruments. Specifically, I estimate a ordered probit model of self-reported health on the more specific variables, which include: the summary measure of Activities of Daily Living (ADL), of Instrumental Activities of Daily Living (IADLs), of Mobility, of Large Muscle, of Gross Motor and of Fine Motor, as well as seven indicators about whether the individual ever had each specific type of disease.[11]

The variations in the measure of physical health are presented in Table 3 and Figure 5.

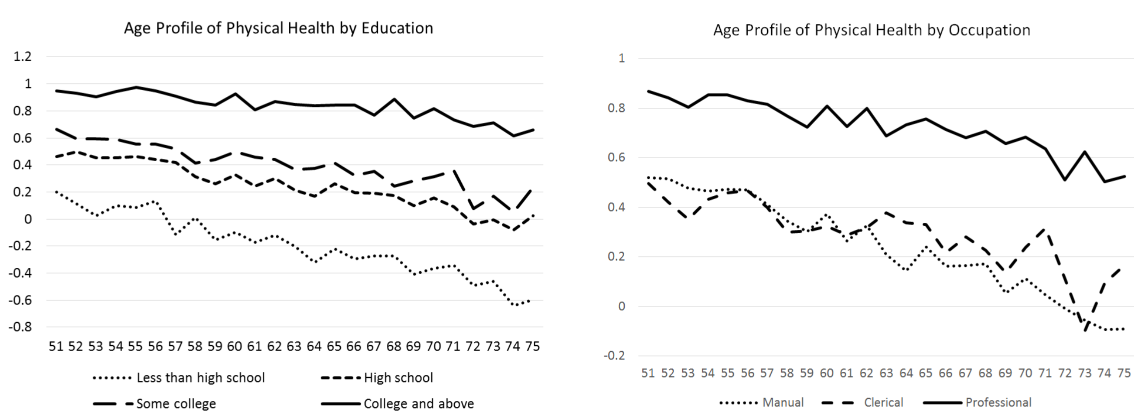
[11] Each of these disease is: 1) high blood pressure or hypertension; 2) diabetes or high blood sugar; 3) cancer or a malignant tumor of any kind except skin cancer; 4) chronic lung disease except asthma such as chronic bronchitis or emphysema; 5) heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems; 6) stroke or transient ischemic attack (TIA); 7)arthritis or rheumatism.

Table 3: Variation in Physical Health by Education and Occupation

	LH	HS	SC	CA	Manual	Clerical	Professional
Age 51-53							
Mean	0.07	0.47	0.58	0.91	0.47	0.49	0.82
Standard deviation	0.56	0.43	0.44	0.33	0.48	0.60	0.39
Observations	211	568	531	597	853	194	573
Age 60-61							
Mean	-0.06	0.27	0.43	0.82	0.26	0.40	0.70
Standard deviation	0.64	0.61	0.61	0.49	0.63	0.66	0.56
Observations	580	1,208	940	1,124	1,713	358	1,008
Drop from 51-53							
With controls	-0.25	-0.19	-0.15	-0.07	-0.19	-0.12	-0.09
Raw	-0.13	-0.20	-0.15	-0.09	-0.21	-0.09	-0.12
Age 70-72							
Mean	-0.25	0.10	0.27	0.71	0.00	0.31	0.56
Standard deviation	0.77	0.74	0.69	0.56	0.74	0.70	0.67
Observations	288	568	324	420	671	136	408
Drop from 51-53							
With controls	-0.51	-0.40	-0.37	-0.18	-0.45	-0.20	-0.23
Raw	-0.32	-0.37	-0.31	-0.20	-0.47	-0.19	-0.26

This table presents the mean and standard deviation of the physical health measure by education and occupation for the primary sample used in this paper. The raw drop is computed as the difference between the means. The drop with controls is calculated by a regression of the physical health measure on age dummies and controls. Control variables include race, gender, education, birth year, birth place. LTHS: less than high school; HS: high school; SC: some college; CA: college and above.

Figure 5: Age Profiles of Physical Health



These figures are produced based on the primary sample from the HRS data. Physical health is measured by a "health stock" predicted by detailed health. Race, gender, education, birth year and birth place are controlled.

2.3 Occupation-dependent Effects of Physical and Cognitive Health

Given the fact that jobs are more and more cognitively demanding and that cognition does decline during the period that retirement occurs, I would like to ask how is cognition related to

Table 4: Add caption

	Cognitive Health			Physical Health		
Slf. Health	0	1	Total	0	1	Total
0	1,219	2,710	3,929	1,219	2,710	3,929
1	2,764	14,673	17,437	2,764	14,673	17,437
Total	3,983	17,383	21,366	3,983	17,383	21,366
Correlation		0.42			0.15	

older workers' retirement in the data. I are particularly interested in whether and how do physical health and cognitive health correlate with retirement across occupations differently. As a guiding exercise, I estimate a hazard model of the labor force continuation on physical and cognitive health by each occupation separately.[12] Based on the primary sample used in this paper, the sample is further restricted on being in the labor force in last wave under the hazard framework. Occupation is defined as the one in last wave when individual was in the labor force. The dependent variable is a binary indicator equal to 1 if the individual remains in labor force.

One comment on the following exercise is that the effects of health are estimated under the current Social Security rules. Social Security rules may dominate the timing of labor force exit and the effects of health may be dampened. Quantifying the effects of health under different Social Security rules can be achieved by the structural model, which will be explored in the subsequent part of this paper.

Table 5: Heterogeneous Effects of Physical and Cognitive Health across Occupations

	Manual	Clerical	Professional
Physical health	0.0803***	0.0627***	0.0497***
	(0.0105)	(0.0194)	(0.0125)
Cognitive health	0.00139	0.00174	0.00327*
	(0.00167)	(0.00309)	(0.00178)
observations	5,525	1,700	4,282
R-squared	0.305	0.294	0.256

Standard errors in parentheses. Results are estimated with the primary sample. Occupations are defined as the ones in last wave while in the labor force. Log asset, log household income, mental health, health insurance, sex, race, region, education, marital status, birth place and cohort are also controlled. Dependent variable is a binary indicator of labor force participation.

The results in Table 5 show that the coefficients of cognition are statistically significant only for professional occupations. In terms of the magnitudes, cognition is also associated with the labor force participation mostly in these occupations but least in manual occupations. On the contrary, physical

[12] For research about labor force transition in the hazard model setting, see Disney, Emmerson, and Wakefield (2006) as an example. In Wen (2017), I provide more reduced form evidence based on different econometric models, such as fixed-effect regressions. The main conclusions do not change.

health has the largest magnitude in manual occupations but least in the professional occupations.

To summarize the above empirical facts, jobs are becoming less physically demanding and require increasing cognitive abilities during the past decades. Cognition experiences a notable decline during the period when the proposed reforms target. From the reduced form exercise, heuristical evidence suggests that physical health and cognitive health have heterogeneous correlations with retirement across occupations. Physical health is associated with retirement in all occupations, but mostly in the manual ones. On the contrary, cognitive health correlates with retirement only in the professional occupations. The occupation-dependent correlations with retirement of the multiple dimensions of health may suggest distinct response in delaying retirement when the FRA increases. Workers from different occupations, also differing significantly in socioeconomic status, may thus incur unequal welfare loss. Moreover, ignoring the retirement impact of poor cognitive health may overestimate professional workers' capacity to work and underestimate their welfare loss when FRA is increased.

3 Model

Motivated by the above empirical facts. I develop a dynamic structural model of labor force participation and saving decisions for the U.S. male household head. The main features of this model are the physical and cognitive dimensions of health and their effects on the older people's decision making through four channels: leisure, wage, medical expenditure and life expectancy. Structural parameters related to the disutility of working, the extra disutility of working due to poor physical/ cognitive health, the wage penalty caused by poor physical/ cognitive health are allowed to be occupation-dependent. Moreover, individuals from different occupations also differ in many aspects due to the rich individual-level heterogeneity, such as physical health, cognitive health, education, labor income, earnings history, Social Security benefits, private pension benefits, health insurance, life expectancy, unobserved individual type etc.

3.1 Choice Set

The model assumes each individual belongs to one of the three occupation groups: The first group $j = 1$ includes manual and service occupations. The second group $j = 2$ consists of sales and clerical occupations, and the third group $j = 3$ covers managerial and professional occupations. The model abstracts from occupation changes across the group, but implicitly allows for changes within the group. Imaging poor health have three potential consequence: occupation change within the occupation group, occupation change across the group, and dropping out from the labor force.

This study essentially allows for the first, though not specifically modeled, and the last behavioral change. As a result, this study provides a lower bound for the effect of poor health, as it captures the effect in extensive margin, the dropping out from the labor force, and implicitly allows for parts of the effect in intensive margin, the occupation change within occupation group.

At each age, the individual chooses whether to participate in the labor force. The LFP decision at age t is denoted by d_t, which equals to 1 if the individual is in the labor force. Being out of the labor force is assumed as an absorbing state. Besides the LFP decision, the individual also chooses how much to consume. Consumption is a continuous decision. The consumption optimization is subject to an upper bound imposed by the borrowing constraint, and a lower bound which is a consumption floor insured by the government. The consumption floor reflects the public transfer such as the Supplemental Insurance Income (SSI) for very poor people. Individuals make their LFP decisions up to age $A^* = 75$ and consumption decisions until age $A^{**} = 90$.

This paper refrains from modelling individual's Social Security application separately, as French (2005), Blau and Gilleskie (2008) and Bound, Stinebrickner, and Waidmann (2010). There are several alternative assumptions about the timing of the collection of Social Security retirement benefits. This paper follows Blau and Gilleskie (2008) and Bound, Stinebrickner, and Waidmann (2010), which assume individuals start to collect Social Security benefits in their first year after exiting the labor force beyond the early retirement age 62. [13]

3.2 Utility Function

The utility function consists of pecuniary and non-pecuniary component, which are additive. Pecuniary utility has the constant relative risk averse (CRRA) form with the coefficient of risk aversion ν. Non-pecuniary utility L_t depends on individual's LFP status d_t and occupation j, as well as the interaction with his physical health h_t^p and cognitive health h_t^c, which equals one if the status is poor and zero otherwise. There is disutility λ_{1j}^{type} when the individual participates in the labor force, when he has good health. Moreover, there is extra disutility of working due to poor physical or cognitive health, which is captured by the parameters λ_{2j} and λ_{3j}, as workers with poor physical or cognitive health can suffer from working differently across occupations. This is the first channel that poor physical/ cognitive health can affect older people's labor force participation decision.

Imposing a finite mixture structure as Keane and Wolpin (1997) and several subsequent studes,

[13] One limitation of this assumption is that individuals who claimed Social Security benefits but remain in the labor force are assumed not receiving benefits yet. As a result, they are not subject to the Social Security earning test by construction. This assumption may reduce the incentive to retire immediately after age 62.

individuals have different unobserved types, reflected in their disutility of working λ_{1j}^{type}. The type captures unobserved individual heterogeneity and helps match the persistence in individual's LFP decisions. Each individual's type is given by the type probability functions, which associate individual's type with observed state variables in the initial wave, such as his occupation, education, etc.

$$U(C_t, d_t) = \frac{1}{1-\nu} C_t^{1-\nu} + L_t \tag{1}$$

where

$$L_t = \lambda_{1j}^{type} d_t + \left(\lambda_{2j} h_t^p + \lambda_{3j} h_t^c\right) d_t + \varepsilon_t^{d_t} \tag{2}$$

The non-pecuniary utility is also subject to a choice-specific idiosyncratic preference shock $\varepsilon_t^{d_t}$. It is assumed following an i.i.d. extreme type one distribution. The structural interpretation of this shock is that it captures those state variables unobserved to researchers but observed to individuals in the model. Notice that the preference shock is assumed additive to the consumption, which implies the consumption decision is independent of this shock once conditional on the LFP decision. Therefore, conditioning on the observed state variables in the model, the choice-specific preference shock ε introduces stochasticity to the discrete LFP decision. To further allow for the stochastic consumption decision, the model needs an extra unobserved state variable attached to consumption C_t. I introduce this unobserved state variable into the total income, which will be specified below.

3.3 Budget Constraint

The individual's asset accumulates according to the following formula, where A_t is the asset at the beginning of period t, Y_t is the total income, C_t is the consumption, ME_t is the out-of-pocket medical expenditure, A_{t+1} is the asset at the beginning of next period t+1, and r is a fixed interest rate:

$$(1 + r)A_t + Y_t = C_t + A_{t+1} + ME_t \tag{3}$$

The asset transition is subject to a borrowing constraint $A_{t+1} = (1+r)A_t + Y_t - ME_t - C_t \geq A_{min}$, where A_{min} is the minimum asset required. Meanwhile, there is a consumption floor C_{min}, which captures the government transfer such as Supplement Security Income(SSI) and Medicaid for individuals in deep poverty. Therefore, in each period the individual can choose his consumption between the range $[C_{min}, C_{Max}]$, where $C_{max} = (1 + r)A_t + Y_t - ME_t - A_{min}$. The government transfer takes place in the extreme case when individual's asset and income are too low, the out-of-pocket medical expense is too high and the borrowing constraint is binding, which implies $C_{max} <= C_{min}$. The amount of government transfer thus can be captured by $max\{0, C_{min} - ((1+r)A_t + Y_t - ME_t - Amin)\}$.

3.4 Income

The total income consists of individuals' labor income W_t^j, Social Security benefits SS_t, private pension P_t, his spousal income Y_t^s, the income from Social Security Disability Insurance $SSDI_t$, and a total income shock ζ_t:

$$Y_t = W_t^j \mathbf{1}(d_t = 1) + (SS_t + P_t)(1 - \mathbf{1}(d_t = 1)) + Y_t^s + SSDI_t + \zeta_t \tag{4}$$

The labor income is a product of the skill rental price r^j and the index of human capital. Aligned with the Mincer earnings function, the human capital index depends on experience, education, physical and cognitive dimension of health, which are allowed to have different returns across occupations. Poor physical and poor cognitive health are allowed to reduce the labor income differently across occupations, which serves as the second mechanism that poor health affects the decision.

$$W_t^j = r^j \cdot \exp\left(\kappa_1^j + \kappa_2^j X_t + \kappa_3^j X_t^2 + \kappa_4^j E + \kappa_5^j h_t^p + \kappa_6^j h_t^c\right) \tag{5}$$

In the model, I calculate the Social Security retirement benefits SS_t closely following the rules of the Social Security Administration. According to the rules, the retirement benefits are calculated as following steps: First, individual's highest 35 years earnings are included to calculate the Average Indexed Monthly Earnings (AIME). The earnings before age 60 are adjusted by the national average wage index to reflect the real wage increase. In the second step, Primary Insurance Amounts(PIA) is a piecewise linear function of AIME, with three separate percentages of the portions of AIME. It functions as a progressive taxation. Finally, to obtain the Social Security benefits, the PIA is multiplied by an adjustment factor, which depends on the age at which the individual claimed the benefits. For example, when the FRA is 65, an individual who claimed his benefit at age 65 receive the amount as much as 100% of the PIA, while the individual claimed at age 62 can only receive 80%. AIME serves as a state variable. In the empirical part of this paper, it is calculated from the administrative earnings history data from SSA. Then I calculate the PIA as well as the Social Security benefits based on this state variable.[14]

Based on the formula how AIME is computed, the transition of AIME takes the following form, where W_t denotes the current labor income and $\dot{W}_{t-1}$ denotes the earnings history until age t-1:

$$AIME_{t+1} = AIME_t + \max\{0, W_t - \min(\dot{W}_{t-1})\}/35$$

Notice that the AIME is updated only when the current labor income is higher than the lowest labor income among the existing 35 years included for previous AIME calculation. If the individual hasn't accumulated 35 working years, $\min(\dot{W}_{t-1})$ is 0 and working always contributes to improving the AIME. Modelling the transition process precisely requires us to keep track of the whole earnings history of the individual to calculate the $min(\dot{W}_{t-1})$, which is intractable. French and Jones (2011) use a fraction of the current AIME as a proxy for the $min(\dot{W}_{t-1})$. Specifically, they use the product of current AIME and an age-dependent coefficients α_t, i.e. $\alpha_t AIME_t$, as the proxy for $min(\dot{W}_{t-1})$. They then estimate the coefficients α_t by simulating the earnings history as close as to the data. Instead, French (2005) simply uses the current AIME as the proxy for $min(\dot{W}_{t-1})$, in which case the coefficients α_t is set as 1. This paper follows the assumption with $\alpha_t = 1$.

This paper also considers Social Security Disability Insurance (SSDI) by allowing its benefits to shift the budget constraint. I refrain from adding another decision variable of the SSDI application and assume the eligibility for SSID is a function of age and both dimensions of health. However, conditional on being eligible, SSDI benefits are calculated based on individual's AIME, following the rules of SSA.

For the rest income sources, the spousal income is predicted by a set of demographic variables following French (2005) and French and Jones (2011).[15] Private pension is difficult to model because the plans vary with each individual. Bound, Stinebrickner, and Waidmann (2010) solves the dynamic programming model by each individual, at the expense of having a sample with only 196 individuals. Van der Klaauw and Wolpin (2008) restricts the sample to individuals with private defined benefit

[14] My application for the Social Security administrative data of earnings history is under review, which is expected to be approved shortly. The results of the current version paper are based on the AIME calibrated to the observed Social Security benefits in the HRS data.

[15] To avoid adding extra state variables, I assume spousal income depends on individual's age and education. Instead, French (2005) assumes spouse income is a function of individual's own income and age.

pension from previous job. Alternatively, French (2005) and French and Jones (2011) approximate private pension benefit as a function of state variables existing in the model. To maintain reasonable sample size and have a sample without strong sample selection for the sake of across-occupation comparison, this paper approximates the private pension following the last two studies. Appendix provides details on the modeling of private pension.

3.5 Health, Medical Expense and Health Insurance

Physical and cognitive health transit jointly with stochasticity. The transition of joint health from period t to t+1 depends on individual's age t, education E, occupation j and labor force participation d_t, as well as joint health status h_t. The transition is also subject to a stochastic component u_t with normal distribution. The joint health status is a vector of physical health h_t^p and cognitive health h_t^c , which takes 4 states: both physical and cognitive health are in good status $\{h_t^p = 0, h_t^c = 0\}$, only physical/ cognitive health is in good status $\{h_t^p = 0, h_t^c = 1\}$ or $\{h_t^p = 1, h_t^c = 0\}$, and both are in poor status $\{h_t^p = 1, h_t^c = 1\}$.

$$h_{t+1} = H(t, E, j, d_t, h_t, u_t) \tag{6}$$

The out-of-pocket medical expenditure ME_t is a function of the joint health status h_t and the insurance type H_t^*.

$$ME_t = g(h_t, H_t^*) \tag{7}$$

As the common modeling of health insurance in previous literature, the health insurance H_t^* has 4 types. The first three types are employer-provided insurance when the individual is younger than 65. When the individual is above age 65, he receives the coverage of public health insurance Medicare.

1. $H_t^* = 0$: not employer-provided health insurance;
2. $H_t^* = 1$: employer-provided health insurance without retiree coverage;
3. $H_t^* = 2$: employer-provided health with retiree coverage;
4. $H_t^* = 3$: with public health insurance Medicare.

The insurance without retiree coverage requires the individual working for the employer to be insured, whereas the one with retiree coverage provides insurance until age 65 regardless of the individual's employment. I assume that individual expects the insurance type in next period by the following transition rules:

- If $t \geq 65$, $H_t^* = 3$;
- For $H_t^* = 2$, $H_{t+1}^* = 2$ until $t+1 \geq 65$;
- For $H_t^* = 1$, $H_{t+1}^* = 1$ if $d_t = 1$ and $H_{t+1}^* = 0$ if $d_t = 0$;
- For $H_t^* = 0$, $H_{t+1}^* = 0$

3.6 Value Function

Taking all factors aforementioned into account, the individual makes his LFP and consumption decisions at each age to maximize the current utility plus the present discounted utility from the future. Ω_t represents the union of all state variables, both observed and unobserved.

$$V_t(\Omega_t) = \max_{d_t, C_t} \Big\{ U(\Omega_t, d_t, C_t) + \beta \int \big(p_t V_{t+1}(\Omega_{t+1}) + (1 - p_t) B(\Omega_{t+1}) \big) dF_t(\Omega_{t+1} | \Omega_t, C_t, d_t) \Big\} \tag{8}$$

Dependent on survival, the continuation value is either the value function in next period $V_{t+1}(\Omega_{t+1})$ or the utility from bequest $B(\Omega_{t+1})$. Aligned with Van der Klaauw and Wolpin (2008), I assume the bequest utility is linear in the asset left to the next period: [16]

$$B(\Omega_{t+1}) = \iota A_{t+1} \tag{9}$$

Utility in the future is discounted by the subjective discount factor β and the survival rate p_t. The survival rate depends on age and the joint status of physical and cognitive health h_t. s_t is the indicator for survival at age t. Poor health may shorten the life expectancy and thus change the LFP and saving decisions, which is the fourth channel through which poor health can shift individual's decisions.

$$p_t = Pr(s_{t+1} = 1 | s_t = 1, h_t) \tag{10}$$

[16] Estimating more sophisticated form of the bequest utility function, such as De Nardi, French, and Jones (2010), requires fitting the percentiles of assets distribution over the life cycle. This paper targets the expectation of life-cycle assets only. If the targets are the percentiles of assets, the structural estimation by indirect inference requires solving multiple quantile regressions, which complicates the computation excessively.

To summarize, the union of state variables Ω_t in the model are : age, education, occupation, AIME, physical health, cognitive health, asset, Social Security application status in the last period, health insurance type, labor force participation in the last period, the random components to total income and to the non-pecuniary utility.

4 Solution and Estimation Methods

4.1 Model Solution

I solve the finite horizon life-cycle model by backward induction. The policy functions of the model, which include the discrete LFP choice and the continuous consumption decision, has no closed form and are obtained numerically. The solution process follows the steps stated as below.

1. Calculate the choice-specific value $CSV_t(d_t, C_t, X_t, \zeta_t, \varepsilon_t^d)$, which is the current payoff plus the expected value function in the next period. The latter component needs the solution in the next period, which requires solving the model backward. Notice that the choice-specific value is a function of the LFP d_t and the consumption C_t, conditional both on the observed state variables X_t and the unobserved state variables ζ_t and ε_t^d.

2. Given each LFP choice, search for the optimal consumption that maximizes the choice-specific value function evaluated at each possible value of the union of state variables, both observed and unobserved. Notice that the consumption optimization given each LFP choice is independent of the shock ε_t^d due to the additivity between pecuniary and non-pecuniary utility. In this step, for each LFP choice, I obtain the optimal consumption $C_t^*(d_t, X_t, \zeta_t)$ and the corresponding optimal value $CSV_t^*(d_t, X_t, \zeta_t, \varepsilon_t^d)$.

3. Compare the choice-specific value $CSV_t^*(d_t, X_t, \zeta_t, \varepsilon_t^d)$ across the LFP choices. The optimal LFP choice is deterministic conditional on ζ_t and ε_t^d. Conditional on ζ_t only, the LFP decision rule follows the standard form of conditional choice probability, as as in Rust and Phelan (1997). The model solutions are eventually characterized by the LFP decision and the optimal consumption decision conditional on each LFP choice. They are deterministic functions of the observed state variables X_t and the unobserved state variables ε_t^d and ζ_t. However, conditional only on X_t, the decisions are stochastic.

In particular, I search for the optimal consumption for each LFP choice in the second step. Because the choice-specific value function $CSV^d(C_t, X_t, \zeta_t, \varepsilon_t)$ may be unsmooth in consumption due to the consumption floor and borrowing constraint, it is inappropriate to use derivative-based optimization methods to search for the optimal consumption. Instead, I discretize the consumption into finite grid points and search over these points. I use the method by French and Jones (2011) to facilitate the search process. In particular, I only search over all the grid points in the final stage during the backward induction. For earlier stages, with a given set of observed state variables X_t, I start the search from the optimal value of consumption in period t+1 evaluated at the same states as X_t, except the age t. That is, the search in period t starts at the value of C_t same as $C^*_{t+1}(d_{t+1}, X_{t+1}, \zeta_{t+1})$, where $\{X_{t+1}, \zeta_{t+1}\}$ are identical as $\{X_t, \zeta_t\}$. Based on this initial point, I then search over a neighborhood instead of the whole consumption space. I compared the results with the full search results, and the bias is small.

The appendix section shows how the policy function of LFP varies with respect to several main state variables.

4.2 Estimation

Upon solving the model, structural parameters are estimated in two steps. Parameters in the medical expenditure equations, health transition equations, survival probability functions and wage equations are estimated in the first step. Preference parameters and parameters in the type probability functions are estimated jointly in the second step by indirect inference.

Indirect inference is a simulation-based estimation approach, essentially a generalized simulated method of moment (SMM). It searches for structural parameters that simulate the data as close as to the observed data. SMM adopts a set of moments as the criteria for the comparison between simulated data and actual data, whereas indirect inference is based on the parameters of auxiliary models. The auxiliary models can be reduced-form regressions, of which parameters are easy to estimate. Parameters of the auxiliary models are estimated using the actual data and the simulated data respectively. Notice that the parameters of the auxiliary models estimated on the simulated data are functions of the structural parameters. Indirect inference thus searches for the values of the structural parameters that minimize the distance between these two sets of estimated parameters. Whether the auxiliary models are correctly specified does not affect the consistency of the structural estimates, but a set of well-chosen auxiliary models improve the efficiency. Analogous to the hypothesis test of Wald, LR and LM, there are three metrics to construct the objective function by indirect inference. Detailed discussion can be found in Bruins, Duffy, Keane, and Smith Jr (2018). This paper adopts the metric analogous to Wald to construct the objective function. It is numerically the same as the one based on LM metric with the weighting matrix chosen by this paper, which is the variance-covariance matrix of the auxiliary model parameters estimated on the actual data under homoskedasticity.

Guided by the reduced form evidence presented in section 2.3 as well as the structural decision rules, I choose the following auxiliary models to help identify the parameters in preference and type probability functions:

- Linear probability models that regress the LFP binary indicator on physical health, cognitive health, asset, insurance type, last Social Security status dummy, age, separately estimated by each occupation.
- Linear regression of the asset in period t+2 on the asset in period t, age, and their interaction.
- Linear probability model that regresses the LFP binary indicator on physical health, cognitive health, occupation, asset, insurance type, dummy of the Social Security status in last period, using data from the first observed wave of each individual.

In addition, I also estimate the structural model based on another sets of auxiliary LFP models: regressions of LFP controlling for individual fixed-effects. The motivation is to identify the model only based on within-individual variations. Details are discussed in the following subsection.

4.2.1 Identification

This subsection provides the basic intuition for the identification of structural parameters in the model.

For parameters of the pecuniary utility component, the coefficient of risk aversion is identified by relationship between the saving rate and the uncertainty in health, survival, total income and preference in the future. For instance, ceteris paribus, if individuals with higher uncertainty in their future health on average accumulate more assets, this positive correlation will identify individuals as risk-averse, and the strength of this correlation identifies the magnitude of the coefficient of risk-aversion. Similarly, direction and strength of the correlation between the saving rate and the uncertainty in life expectancy identify the bequest motive.

For parameters of the non-pecuniary utility component, in the first-step estimation, the effects of physical and cognitive health on wage, medical expenditure and survival are identified by the variations of corresponding outcome variables against the variation of health. These estimated parameters in wage, medical expenditure and survival functions are held fixed in the second-step estimation. Then the variation of LFP, net of the variation driven through wage, medical expenditure and life expectancy, against the variation of physical and cognitive health pins down the disutility of working due to the poor physical and cognitive health λ_{2j} and λ_{3j}. In particular, holding all others equal, the heterogeneous gradients of LFP over physical and cognitive health across occupations identify the occupation-dependent disutility of working due to the multiple dimensions of health. The baseline LFP probability of each occupation identifies the occupation-dependent disutility of working λ_{1j}.

I also use a different set of auxiliary LFP models that control for the individual fixed effects to exploit only within-individual variations for the estimation. In the auxiliary LFP models based on the pooled regression model, the coefficients of physical health and cognitive health capture the correlations between health and LFP identified by a mixture of the within- and between-individual variations. For between-individual variations, the negative effect of poor health is identified by the comparison between a healthy individual who stays in the labor force and another unhealthy individual who is out of the labor force. In terms of within-individual variations, only if a given individual stayed in the labor force when he had good health and exited when his health turned bad can identify this negative effect. Both variations can lead to the positive coefficients of physical health and cognitive health in the pooled LFP regression. And then these variations are used for the identification of the extra disutility of working due to poor physical/ cognitive health. However, if there is no within-individual variations in LFP and health, the coefficients of physical and cognitive health of the individual fixed-effects LFP regression will be insignificant, and the corresponding structural parameters will not be identified.

Finally, parameters of the type probability functions are identified by the comparison between two sets of auxiliary models: the regressions of LFP using all data and the regressions of LFP using only the data of the initial wave. Take the coefficient of physical health in the type probability functions as an example. As different types of individuals differ in their disutility of working, everything else equal, suppose the type-I individuals are more likely to participate in the labor force than the type-II. That is, they have smaller disutility of working $\lambda_{1j}^{type=1} < \lambda_{1j}^{type=2}$. If individuals at the age 5

The initial labor force participation is endogenous, and we assume the

For the regressions of LFP using all data, the parameters estimated on simulated data should be very close to the ones estimated on actual data, as these regressions are the main targets the structural estimation wants to fit. First consider a hypothetical situation without sample selection.

5 Data

The model is estimated on the data from the third to eleventh wave of Health and Retirement Study.[17] The data are biennial and cover the years from 1996 to 2012. Besides the variables about labor market outcome and individuals' financial conditions, HRS also provides detailed measures for health. Wave 1 and wave 2 are excluded because the measure of memory is inconsistent with the subsequent waves .[18] My primary sample consists of male individuals aged 51-61 in their initial observed waves. Individuals who have never been in the labor force through all observed waves are excluded. The primary sample also drops observations which have changed occupations from period t-1 to t, as well as occupations return to the labor force.[19] Also, observations with missing value in any state variable are dropped. Finally, this sample includes 21,370 observations and 5,698 individuals.

Based on this sample, LFP, wage and assets are simulated. Extra sample restrictions are imposed during the estimation of auxiliary models. For the approximate labor force participation equation by occupation, since the occupation is defined as the one in last period when the individual was in the labor force, the sample is restricted to observations that were in the labor force in last period. For approximate wage equations, the sample is restricted to observations in the labor force, whose wages are observed.

This primary sample is used to generate the simulated sample, which serves as the input to the estimation of preference and wage parameters by indirect inference in the second stage. For the first stage estimation, namely, the estimations of health transition equation, mortality equation and medical expenditure equation, an expanded sample is utilized following French (2005). Because the HRS data used in this paper cover a span of 16 years, from 1996 to 2012, the oldest cohort in the primary sample were aged 61 in 1996 and aged 77 by 2012. However, the structural model requires the health transition equations, the mortality equations and the medical expenditure equations to cover until age 90. For this reason, the first stage estimation is based on the full sample of males

[17] I use the data product cleaned by Rand company.

[18] For the word recall test, the first two waves use a list of 20 words whereas the other waves use a list with 10 words. I refrain from re-scaling the measures in the first two waves because I found the mean words recalled in the first waves are very different from twice the means in the subsequent waves .

[19] These two sample restrictions are imposed because the structural model abstracts from the occupation change and assumes retirement is an absorbing state. By this simplification, this paper does not capture the potential effects of health on occupation changes. For example, individuals with cognitive decline may change to less cognitively demanding occupations and continue working. If this was the case, this paper would underestimate the impacts of health on individuals' labor market outcome. Without imposing these two restrictions, there are 21,759 observations and 5,729 individuals. Notice that I do not drop all the observations of an individual who has ever changed his occupation or returns to the labor force. Instead, I only drop those observations with occupation changes and return to the labor force. If all observations of an individual who has ever changed occupations or has re-entered the labor force were excluded, the sample would be reduced to 4,892 individuals and 17,545 observations.

from the third to eleventh waves of HRS, without the above sample restrictions imposed.

Table 6 presents the descriptive statistics for the main variables used in this paper. Statistics are presented by the LFP status and occupations. The LFP variable is constructed from the current job status variable in HRS. It equals to 1 if the individual is working, unemployed and looking for work, or temporarily laid off, and it equals to 0 if individual is disabled, retired, homemaker, on sick or in other category.[20] Occupation variable is obtained from the current job information in HRS, which provides two-digit occupation codes consistent with U.S. Census. If individual is in the labor force, the occupation is classified into three categories as described in Section 3. In terms of the financial variables, there is a large disparity across occupations. Individuals from the manual occupations have much less assets (housing included) than those from professional occupations, while those from clerical occupations fall in the middle. People from professional occupations have 3.1 times assets as much as those from manual occupations on average. Similarly, individuals from manual occupations also earn much less than those from sedentary occupations. The average age is slightly lower for people from manual occupations, which reflects the fact that they retire earlier. In model solution and estimation, physical and cognitive health are discretized into binary variables respectively. In the full sample, 29% observations are rated as "fair" or "poor" by the self-reported health variable. I therefore define physical (cognitive) health as poor for those observations below the 29% percentile of the distribution of the original physical (cognitive) health measure. As the statistics show, individuals from the professional occupations are also more educated and healthier in both physical and cognitive dimensions. Finally, for observations younger than 65, professional occupations provide more retiree coverage health insurance, whereas the proportion of no insurance is notably higher for manual occupations.

[20] Whether to focus on labor force participation or on working is dependent on whether the research focuses more on the effect of health from the labor supply perspective or from the labor demand perspective. The only difference is the treatment of individuals who are laid off but still look for jobs. If the main effect of health on retirement is such that poor health lowers the productivity observed by the employer and leads to the layoff, then focus on working or not is preferable. On the contrary, if the main effect of health on retirement is through the supply side: poor health reduces individual's willingness to work and leads to voluntary exit from the labor force, then focusing on labor force participation is more appropriate. My finding suggests health affects retirement mainly through the disutility of working channel, which is supportive to the focus on labor force participation instead of working. Wen (2017) tried both labor force participation and working as dependent variables, the results are similar.

Table 6: Descriptive Statistics of the Main Variables

Panel A

	Manual		Clerical		Professional		Out of Labor Force	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Asset (1000 $)	16.65	49.02	29.67	82.49	51.69	137.02	28.34	55.77
Age	58.81	4.92	59.34	5.31	59.15	5.20	66.03	4.98
Log (Wage/1,000$)	0.96	0.86	1.20	0.91	1.68	0.86	-	-
Observations	7,154		2,186		5,165		6,865	

Panel B

	Manual	Clerical	Professional	Out of Labor Force
Phy. Health (%)				
Poor	14.5	12.4	6.0	29.8
Good	85.5	87.6	94.0	70.2
Cog. Health (%)				
Poor	21.3	12.9	6.7	25.9
Good	78.7	87.1	93.3	74.1
Education (%)				
LTHS	24.2	7.4	1.8	19.1
HS	43.0	27.5	12.1	36.7
SC	24.9	35.5	20.1	22.3
CA	7.9	29.6	66.0	22.0
Observations	7,154	2,186	5,165	6,865
Insurance Type, Age<65 (%)				
No insurance	36.9	37.9	27.8	53.8
Tied insurance	28.6	27.1	30.7	2.6
Retiree covered	34.5	35.0	41.5	43.7
Observations	6,207	1,799	4,331	2,548

Statistics are presented by occupations and LFP status. LTHS: less than high school; HS: high school; SC: some college; CA: college and above.

6 Results

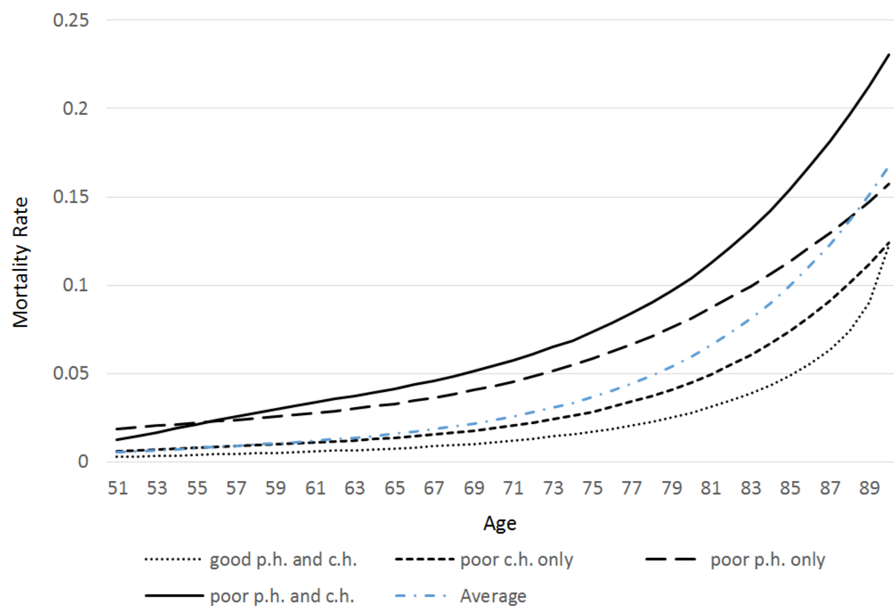
6.1 Mortality Rates

Mortality rates are assumed to depend on age and the joint status of physical and cognitive health. Following French (2005), I use Bayesian rule to calculate the health-dependent mortality rates. Given that both physical and cognitive health have been discretized into two states, there are 4 joint health status: $\{h_t^p = 0, h_t^c = 0\}$, $\{h_t^p = 1, h_t^c = 0\}$, $\{h_t^p = 0, h_t^c = 1\}$ and $\{h_t^p = 1, h_t^c = 1\}$, where h_t^p and h_t^c are the indicators of poor physical and cognitive health respectively. As shown by the formula below, the health-dependent mortality rate can be decomposed into an unconditional mortality rate and an age-specific health shifter. For each joint health states, the shifter depends on the numbers of individuals who are alive at age t and who die between age t and t+1. For instance, most individuals alive at age 51 should have good health, whereas those died between 51 and 52 are very likely to have poor health. This fact will imply a large poor health shifter to the unconditional mortality rate at 51: having poor health at younger ages is rare and it raises the individual mortality rate greatly from the average rate. To compare, most individuals alive at 81 should have poor health, no matter whether they survived to age 82 or not. In this case, having poor health at age 81 will lead to a small poor health shifter. Since most individuals have poor health at age 81, being unhealthy does not change individual mortality rate very much.

$$Pr(s_{t+1} = 0 | s_t = 1, h_t^p, h_t^c, t) = \frac{Pr(h_t^p, h_t^c | s_{t+1} = 0, s_t = 1, t)}{Pr(h_t^p, h_t^c | s_t = 1, t)} \times Pr(s_{t+1} = 0 | s_t = 1, t)$$

The unconditional mortality rate $Pr(s_{t+1} = 0|s_t = 1, t)$ is obtained from Social Security Administration actuarial life tables. I use the HRS data to estimate the health shifter $Pr(h_t^p, h_t^c|s_{t+1} = 0, s_t = 1, t)/Pr(h_t^p, h_t^c|s_t = 1, t)$. It is estimated on the full HRS sample instead of the primary sample, because the primary sample has very few observations at very old ages. To obtain smooth functions, I use quadratic polynomials of age to approximate $Pr(h_t^p, h_t^c|s_{t+1} = 0, s_t = 1, t)$ and $Pr(h_t^p, h_t^c|s_t = 1, t)$. Estimates of the mortality rates by health status are presented below. The mortality rates are the lowest if individual is both physically and cognitively healthy, followed by the ones when individual has poor cognitive health only. The mortality rates are higher when individual has poor physical health only, and they end up the highest if both physical and cognitive health are poor. Appendix provides more details about the estimation.

Figure 6: Estimates of Mortality Rates by Joint Health Status



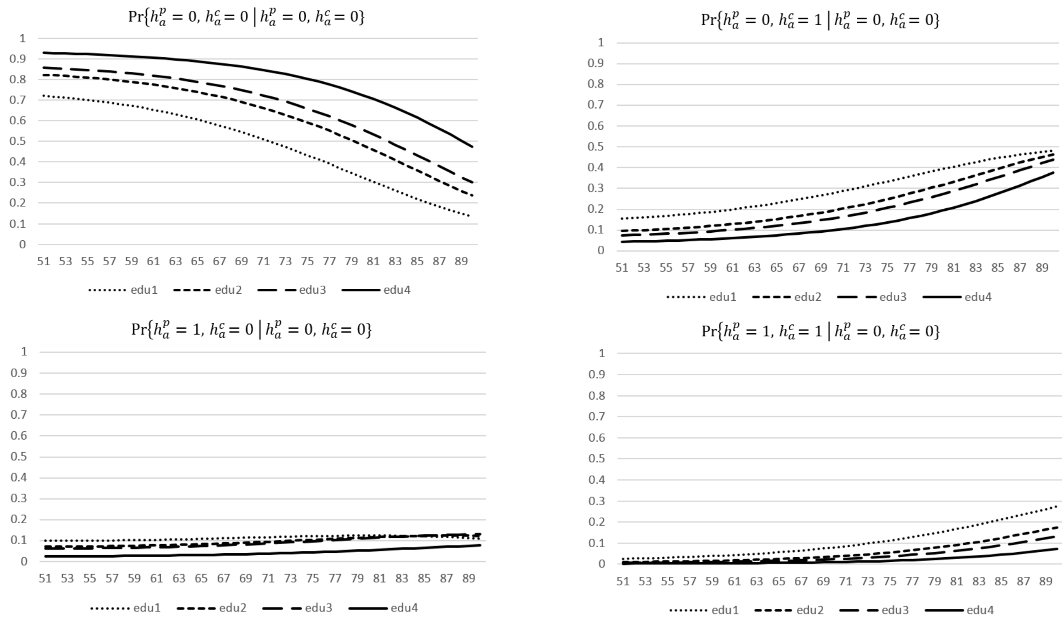
6.2 Health Transition

Health transition is based on the joint status of physical and cognitive health with four states: $\{h_t^p = 0, h_t^c = 0\}$, $\{h_t^p = 1, h_t^c = 0\}$, $\{h_t^p = 0, h_t^c = 1\}$ and $\{h_t^p = 1, h_t^c = 1\}$, where value 1 and 0 denote poor and good health respectively. Joint health state in period t+1 is assumed to be conditional on joint health state, age and occupation in period t, as well as education. Specifically, I estimate multinomial logit regressions of joint health state in period t+1 on quadratic age, education indicators and occupation indicators in period t. I estimate them separately conditioning on each joint health state in period t.[21]

The estimates of health transition probabilities conditional on having both good physical and cognitive health are shown below. The estimates conditional on the rest lagged health states are provided in the appendix. In general, probabilities of getting into a worse health state increase as individual ages. Correspondingly, probabilities of recovering from a worse health state decline with age. People with less education are more likely to transit into worse health states and are also less likely to recover from those states.

[21] I do not estimate the regressions separately by the interaction of education, occupation and joint health states, which has 4*4*4=64 states, because sample sizes are very small under these finer classifications. Education and occupation thus affect health transition probabilities mainly by shifting the constant term, though they also interact with age via the nonlinear logit functional form. According to my exploratory estimates, difference between these two specifications is very small.

Figure 7: Transition Probabilities of Health conditional on $\{h_t^p = 0, h_t^c = 0\}$



6.3 Wage Equation

The occupation-dependent effects of physical and cognitive health are not clear enough for wages. The reductions in wage due to poor physical health are close yet slightly larger in professional occupations than manual occupations, whereas there is no negative effect on wage in clerical occupations. For cognitive health, being unhealthy is associated with lower wages in all occupations. However, the effects of poor cognitive health is much larger in clerical and professional occupations than manual occupations. For the other estimates, wage decreases at older ages, but the decrease is the mildest in professional occupations. Education has the highest return in professional occupations, followed by clerical occupations, with the lowest in manual occupations.

Table 7: Estimates of Wage Equations

	Manual	Clerical	Professional
Skill price and human capital constant κ_1	5.266	5.134	4.824
	(0.3707)	(0.7672)	(0.6697)
Slope of age κ_2	-0.366	-0.372	-0.276
	(0.0023)	(0.0041)	(0.0026)
Education: high school κ_{42}	0.232	0.276	0.314
	(0.0287)	(0.0925)	(0.1207)
Education: some college κ_{43}	0.252	0.233	0.415
	(0.0327)	(0.0922)	(0.1188)
Education: college and above κ_{44}	0.228	0.372	0.609
	(0.0473)	(0.0947)	(0.1170)
Poor physical health κ_5	-0.088	0.021	-0.110
	(0.0314)	(0.0683)	(0.0567)
Poor cognitive health κ_6	-0.084	-0.239	-0.162
	(0.0277)	(0.0651)	(0.0523)

Only κ_{1j} are reported because r_j and κ_{1j} cannot be separately identified. The current version of the model assumes the experience is linear in wage equation. Therefore κ_{3j} are set as 0. Education takes four discrete values in my model, so κ_4 correspond with the premium of three discrete higher education levels (less than high school is omitted as baseline). Standard errors in parentheses.

6.4 Preference Parameters

Preference parameters and parameters of the type probability functions are estimated jointly in the second step by indirect inference. Parameters estimated in the first step, i.e. parameters of health transition equations, mortality equations, medical expenditure equations, wage equations and spousal income equation, are held fixed in the second step estimation. I estimate my structural preference parameters using different auxiliary LFP models to exploit different variations for identification. The estimates of preference parameters using pooled linear LFP regressions as the auxiliary LFP models are presented in Table 8:

Table 8: Estimates of Preference Parameters based on OLS Auxiliary LFP Model

	Manual	Clerical	Professional
Non-pecuniary utility			
Disutility of working (good health) $-\lambda_1$	0.099	-0.051	0.013
	(0.00058)	(0.00031)	(0.00006)
Extra disutility of working (poor p.h.) $-\lambda_2$	0.608	0.290	0.306
	(0.0072)	(0.0112)	(0.0008)
Extra disutility of working (poor c.h.) $-\lambda_3$	-0.201	0.198	0.014
	(0.0025)	(0.0017)	(0.1658)
Pecuniary utility			
Bequest motive ι	0.044		
	(0.00016)		
Coeff. of risk aversion ν	1.835		
	(0.0067)		

Parameters are estimated by indirect inference. Results are from early version where model does not include unobserved individual type. Results based on the model with unobserved individual heterogeneity under finite mixture structure will be updated soon. Auxiliary LFP model is the linear regression estimated by OLS. Standard errors in parentheses.

The estimate of the coefficient of risk aversion ν is 1.835, which is close to the estimates in previous studies, such as 1.591 and 1.678 by Van der Klaauw and Wolpin (2008), 0.960-0.989 by Blau and Gilleskie (2008), 1.07 by Rust and Phelan (1997), 2.565 by Haan and Prowse (2014). French (2005) and French and Jones (2011) have larger estimates close to 5. For the parameters of non-pecuniary utility, I normalize the utility of being out of labor force to be zero. Notice that it is assumed the same regardless of individual's health status. $-\lambda_1$ is the disutility of working if individual has good health in both physical and cognitive dimensions. It is the largest in manual occupations, consistent with the intuition that working in manual occupations are more labored. [22] $-\lambda_2$ and $-\lambda_3$ are the focuses of this paper. $-\lambda_2$ is positive across all occupations, suggesting that poor physical health leads to extra disutility of working in all occupations. However, this extra disutility is the largest in manual occupations (0.61) and much milder in clerical and professional occupations (0.29 and 0.31). On the contrary, poor cognitive health induces extra disutility if working in clerical and professional occupations (0.20 and 0.01), but this extra disutility of working cannot be found in manual occupations.

The estimates of preference parameters using fixed-effects LFP regressions as the auxiliary LFP models are presented in Table 9. For auxiliary LFP models, the coefficients of physical and cognitive health are identified by the change in LFP and the change in health. These variations are used to identify corresponding structural preference parameters. The occupation-dependent pattern of disutility of working is robust. The first type of individuals suffer from working even with good

[22] Notice that the disutility of working is negative in clerical occupations. This suggests working in clerical occupations with good health is more enjoyable than staying at home.

health, while the second type of individuals gain positive utility from working.

Table 9: Estimates of Preference Parameters based on Auxiliary LFP Model Controlling for Individual Fixed Effects

	Manual	Clerical	Professional
Non-pecuniary utility			
Disutility of working (Type1) $-\lambda_1^{type1}$	1.458	1.161	1.361
Disutility of working (Type2) $-\lambda_1^{type2}$	−0.226	−0.523	−0.323
Extra disutility of working (poor p.h.) $-\lambda_2$	0.820	0.440	0.470
Extra disutility of working (poor c.h.) $-\lambda_3$	−0.004	0.732	0.729
Pecuniary utility			
Bequest Motive ι	0.003		
Coeff. of Risk Aversion ν	4.078		

The structural model allows for unobserved heterogeneity under a finite mixture structure. Parameters are estimated by indirect inference. The auxiliary labor supply models are linear regressions controlling for individual fixed effects. Standard errors are still under calculating.

7 Counterfactual Experiment

7.1 Occupational Effects of Physical and Cognitive Health

After obtaining the structural estimates, I implement counterfactual experiments to answer the research questions that this paper is after. The first question is how physical and cognitive health affect older workers' retirement across occupations, and how is the retirement effect of health under the broader scope, which incorporates not only physical but also cognitive dimensions. Following previous literature based on the tradition measure of health, my structural model allows both physical and cognitive health to affect individual's utility via four underlying channels: disutility of working, wage, medical expenditure and life expectancy.[23] The first counterfactual exercise switches off all the 4 channels together of physical or cognitive health to explore how older people's labor LFP rates vary across occupations. Switching off all these channels together is equivalent to assume individual's health is always good through out their rest lifetime.

Notice that the first counterfactual experiment is implemented under the current Social Security rules, and the effects of health on LFP may change when Social Security reform takes place. The structural model helps capture the effects of health under the change of rules, which will be the focus in the next subsection.

The first row of Table 10 presents the baseline LFP rates between age 65 and 69 across occupations. They are simulated based on the estimates in Section 7 and the actual data in each

[23] French and Jones (2017) provides a thorough discussion of the channels through which health may affect retirement.

individual's initial observed wave. As shown in the bottom row, when all the channels through which physical health can affect utility are shut down, the simulated LFP rates increase across all occupations. However, the increase is the largest for manual occupations by 11.8 percentage points and the smallest for clerical occupations by 6.8 percentage points. When the effects of cognitive health on utility are muted, clerical workers raise their LFP rate by 5.4 percentage points, around 79% of the increase in LFP rate when the effects of physical health are turned off. On the contrary, labor force participation rate barely increases for manual workers. Finally, when switch off all the channels of both physical and cognitive health, I find that the increase in LFP rate is the largest for clerical workers, followed by those in professional jobs. Relatively, the rise in LFP rate of manual occupations turns out to be the smallest. One reminder is that these estimated effects are surely dependent on the current Social Security rules, as well as individuals' wealth and income. Nevertheless, workers form clerical and professional occupations, whose retirement is usually considered less affected by poor health, are actually influenced by this broader definition of health nontrivially.

Table 10: Changes in Labor Force Participation Rates between 65 and 69
when the Effects of Different Health are Switched Off

	Physical Health			Cognitive Health			Both Health		
	Man.	Cler.	Prof.	Man.	Cler.	Prof.	Man.	Cler.	Prof.
Baseline	0.439	0.540	0.574	0.439	0.540	0.574	0.439	0.540	0.574
Wage	0.441	0.540	0.577	0.441	0.543	0.579	0.444	0.543	0.583
	[*0.002*]	[*0.000*]	[*0.003*]	[*0.002*]	[*0.004*]	[*0.006*]	[*0.005*]	[*0.004*]	[*0.010*]
Disutility	0.529	0.587	0.640	0.405	0.575	0.576	0.474	0.625	0.643
	[*0.090*]	[*0.047*]	[*0.066*]	[*-0.034*]	[*0.035*]	[*0.002*]	[*0.035*]	[*0.085*]	[*0.069*]
Mediexp	0.435	0.538	0.571	0.439	0.540	0.574	0.435	0.540	0.571
	[*-0.005*]	[*-0.002*]	[*-0.002*]	[*0.000*]	[*0.000*]	[*0.000*]	[*-0.005*]	[*0.000*]	[*-0.002*]
Mortality	0.461	0.564	0.595	0.446	0.542	0.581	0.469	0.566	0.609
	[*0.022*]	[*0.024*]	[*0.021*]	[*0.007*]	[*0.002*]	[*0.007*]	[*0.030*]	[*0.026*]	[*0.035*]
All	0.557	0.608	0.659	0.417	0.594	0.594	0.527	0.677	0.678
	[*0.118*]	[*0.068*]	[*0.085*]	[*-0.022*]	[*0.054*]	[*0.021*]	[*0.088*]	[*0.137*]	[*0.105*]

Man.: manual and service occupations; Cler.: Sales and clerical occupations; Prof.: Managerial and professional occupations. Changes from baseline are in square brackets.

The first counterfactual experiment also quantifies the relative importance of the underlying channels respectively for physical and cognitive health. To achieve this, I switched off the underlying channels one by one and simulate individuals' LFP between age 65 and 69. Then I compare the simulated results with the baseline LFP rates. The results presented in Table 10 suggest that both physical and cognitive health affect individuals' LFP at older ages mainly through the disutility of working. Moreover, the effects via the disutility of working channel depend on occupations.

Physical health is found affecting LFP also through the mortality channel, with similar effects across occupations. Cognitive health has little effect on LFP through this mortality channel. Finally, the channel of wage, which was found important for life-cycle labor supply by Capatina (2015), has very little effect at older ages according the above results.

7.2 Increase in Full Retirement Age

The previous counterfactual experiment reveals the heterogeneous roles of physical and cognitive health across occupations in older individuals' LFP under the current Social Security rules. This heterogeneity is likely to affect people's ability and willingness to delay their retirement under the proposed Social Security reforms. Individuals with poor physical(cognitive) health from physically (cognitively) demanding occupations may be unable or unwilling to postpone their retirements when the FRA increases. These individuals will receive less Social Security benefits due to their early retirement. Individuals in which occupations will be more responsive in delaying their retirement is unclear, because while physical health is important for manual occupations, my above findings also suggest cognitive health plays an important role in clerical and professional occupations.

Moreover, the effects on delaying retirement and the welfare implication across occupations of health may also depend on the financial variables, given the large disparity in wealth and income across occupations. Individuals from manual occupations may have greater incentives to keep working when the FRA increases, because they have less savings to support early retirement. These individuals, who also have worse health as shown in Table 6, may incur larger disutility of working because they are more likely to keep working with worse health.

Accounting for the complex interplay between the multiple dimensions of health, occupations and income and wealth, the second counterfactual experiment simulates individuals' LFP before and after the increase of FRA to age 70 and evaluates the welfare changes across occupations.

I evaluate the welfare changes by two measures. The first measure is the difference in present discounted value (PDV) of utility before and after the increase of FRA. The second measure is the compensating variation, which evaluates the amount of wealth needed to be taken from individuals at age 62 to generate the same utility loss due to the policy reform. The PDV measure has the issue that the same amount of pecuniary loss implies larger utility reduction for poor individuals because the utility function is concave. The measure of compensating variation addresses this concern at the cost of introducing another issue. The same amount of utility loss, such as the disutility of working, will imply larger pecuniary compensation for rich people than for poor ones. For this reason, I report the results based on both measures.

Table 11: Changes in Labor Force Participation Rates between 65 and 69
when Full Retirement Age Increases to Age 70

	Baseline			FRA to 70			Changes		
	Man.	Cler.	Prof.	Man.	Cler.	Prof.	Man.	Cler.	Prof.
LFP 65-69 (p.p.)	0.456	0.563	0.598	0.731	0.790	0.716	0.275	0.227	0.119
PDV SS Benefits (10,000 $)	15.36	14.32	14.24	11.68	11.11	11.61	-3.68	-3.21	-2.63
PDV Utility	-0.57	0.92	2.70	-1.14	0.49	2.53	-0.57	-0.43	-0.18
Compensating Variation (10,000 $)							-2.09	-2.10	-1.59

Man.: manual and service occupations; Cler.: Sales and clerical occupations; Prof.: Managerial and professional occupations. Changes from baseline are in square brackets. PDV SS Benefits and PDV Utility are respectively the present discounted value of SS benefits and utility as of age 62. Compensating variation evaluates the amount of wealth needed to be taken from individuals at age 62 to generate the same utility loss induced by the policy reform

The results are presented in Table 11. Because Social Security retirement benefits are lower when the FRA increases to 70, both the substitution effect and income effect lead to a delay of retirement and increase the LFP rates at older ages. Although policymakers are mostly concerned about the ability to work of workers from physically demanding jobs, the results in Table 11 suggest manual workers' LFP is actually more responsive to this policy change. The first reason is related to the findings about the effect of cognitive health on LFP for clerical and professional workers. Although poor physical health limits individuals' ability and willingness to work in physically demanding occupations, cognitive health also has a larger effect on LFP in clerical and professional occupations. Moreover, when the aggregated effects from both dimensions are considered, health constrains the ability and willingness to work in clerical and professional occupations as least as much as in manual occupations. The second reason for this larger response is workers in manual occupations have less income and savings. Therefore, the reduction in Social Security benefits generates stronger substitution and income effects to them.[24] The two reasons combined explain why the older people from manual occupations are more responsive in delaying retirement to the increase of FRA.

However, although individuals from the manual occupations are shown responsive in delaying their retirement, my welfare analysis suggests that they suffer a large cut in retirement benefits as well as a large welfare loss. The big Social Security benefits reduction is related to the large response in delaying retirements. On top of the reduced retirement benefits, there is another reason for the larger welfare loss in manual and clerical occupations. As mentioned, because individuals from

[24] Gustman and Steinmeier (1986a) also found a larger labor supply response to the increase of FRA by 1983 Amendment for more physically demanding jobs.

manual and clerical occupations are poorer, they therefore have to keep working and retire much later than before due to the larger income and substitution effects induced by the benefits reduction. This larger response, combined with their worse health on average, induces larger disutility of working and thus larger welfare loss.

8 Conclusion

Since 1960s, skill-biased technical change has been placing the requirement of cognitive abilities for US jobs, whereas jobs on average are becoming less physically demanding. Few existing studies have put a particular focus on the effect of cognitive health on retirement, neither do they distinguish the different roles of physical and cognitive health. Because cognitive abilities are becoming more important for modern jobs and they decline notably at older ages, the period on which policy reforms are targeting, the importance of cognitive health calls for more attention. This paper incorporates both physical and cognitive dimensions of health and studies their heterogeneous roles in retirement across occupations. It also seeks to understand its implication on welfare changes across occupations if the FRA increases to 70.

Under the current Social Security rules, I found that while physical health affects retirement across all occupations, the effect is the largest in manual occupations. On the contrary, poor cognitive health has little effect on retirement in manual occupations, but it influences the LFP of workers in clerical and professional occupations notably. Moreover, considering the broader definition of health that includes the cognitive dimension, I find that LFP in clerical and professional occupations are constrained by health as least as much as in manual occupations. This finding contrasts the usual opinions that workers in the physically demanding occupations suffer the most from health issues. This paper then evaluates the importance of underlying channels through which physical and health affect retirement. The channel throgh disutility of working is found the most important.

When the FRA increases to 70, the counterfactual experiment reveals that individuals from the manual occupations increase their LFP rates at 65-69 greatly. Although their ability and willingness to delay retirement is more likely to be constrained by poor physical health, they are also less affected by poor cognitive health than the clerical and professional workers. Moreover, having less income and savings leads to the larger income and substation effects induced by the retirement benefits reduction. Given that manual workers have worse health on average and they have to retire much later when the FRA increases to 70, this policy reform induces larger disutility of working and larger welfare loss for them.

To conclude, this study reveals the heterogeneous roles of physical and cognitive health in occupational retirement. It encourages policymakers to re-examine the distributional welfare impact of Social Security reforms from the perspective of occupations.

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Appendices

Appendix A Reverse Causality

An important concern about the effect of health on retirement is the reverse causality, as many recent studies have suggested that retirement has a statistically significant impact on the cognition of the older people (Rohwedder and Willis (2010); Bonsang, Adam, and Perelman (2012); Mazzonna and Peracchi (2012); Bingley and Martinello (2013)). Based on the same primary sample, I implement two reduced form robustness tests to address this concern. First, I instrument the contemporaneous physical and cognitive health with the lagged physical and cognitive health. Lagged health is measured two years ago and, under the hazard framework, is the one obtained when individuals are still working. Therefore it should not be affected by individual's change of LFP status. Compared with the previous results, the results in the column 2-4 in the following table show that the coefficient of cognition for manual occupations becomes smaller, whereas the one for clerical occupations increases significantly. Although the coefficient of cognition for professional occupations is statistically insignificant now, it is driven by a bigger standard error. In terms of the magnitude of this coefficient, it is also larger compared to the OLS estimate.

Figure 8: Robustness Checks for Reverse Causality

	Labor Force Participation			Expected Prob. of Working		
	Man.	Cler.	Prof.	Man.	Cler.	Prof.
physical health	0.0572***	0.0477**	0.0437***	0.00393	0.0508	0.0213
	(0.0140)	(0.0233)	(0.0160)	(0.0237)	(0.0400)	(0.0272)
cognitive health	0.000885	0.0159*	0.00491	0.000461	0.00585	0.00524**
	(0.00515)	(0.00851)	(0.00579)	(0.00265)	(0.00373)	(0.00234)
IV	Yes	Yes	Yes			
Fixed-effects				Yes	Yes	Yes
Observations	4,702	1,500	3,792	4,675	1,403	3,494
R-squared	0.294	0.294	0.260	0.024	0.069	0.044
Num. of Individuals				2,477	753	1,640

Standard errors in parentheses. Results are calculated with primary sample. Log asset, total household income, mental health, health insurance, sex, race, region, education, matrial status, birth place and cohort are also controlled. Dependent variable for labor force participation regressions is a binary indicator of being in the labor force. Sample of these regressions is conditional on being working in last wave. Health is instrumented with lagged health while working. Dependent variable for Expected Prob. of Working regressions is the subjective probability of working after age 62. Sample of these regressions is conditional on younger than age 61 and working. Individual fixed-effects are controlled. Man.: manual and service occupations; Cler.: clerical and sales occupations; Prof.: managerial and professional occupations.

As a supplementary evidence, in the second robustness test I use a variable measuring the interviewees' subjective probability of continuing working after the age 62 as the dependent variable, following McGarry (2004). Meanwhile, the sample is restricted to those who are working and younger than age 61(included). By focusing on the working sample, the issue of reverse causality should be mitigated [25]. The results are reported in (5)-(7) column. The individual fixed-effects are controlled. The results show that effects of cognitive health are much larger for clerical and professional occupations than manual occupations.

Appendix B Occupation Classification

In HRS, occupations are reported as 4-digit codes consistent with USA Census. The occupations from wave 1 to wave 7 are coded based on Census 1980 whereas since wave 8 the codes of Census 2000 are applied. For confidentiality, the 4-digit codes are masked and classified into 17 groups for Census 1980 codes and 25 groups for Census 2000 codes. Table 12 and 13 list the mapping between the three categories defined in this paper and HRS 2-digit masked occupations.

Table 12: Occupations Classification based on Census 1980

Manual and service occupations:
(10)Farming, forestry, fishing; (11)Mechanics and repair; (12)Construction trade and extractors; (13)Precision production; (14)Operators: machine; (15)Operators: transport, etc.; (16)Operators: handlers, etc.; (5)Service: private household, cleaning and building services; (6)Service: protection; (7)Service: food preparation; (8)Health services; (9)Personal services;
Clerical and sales occupations:
(3)Sales; (4)Clerical, administrative support;
Managerial and professional occupations:
(1)Managerial specialty operation; (2)Professional specialty operation and technical support;

Occupation (17)Member of Armed Forces is excluded from my sample. This classification is applied to HRS wave 1 to 7.

[25] I admit that retirement may still affect the working individuals' cognition by expectation. For example, individuals start to less their work engagement even before retirement. I need to assume that this expectation effect is minimal.

Table 13: Occupations Classification based on Census 2000

Manual and service occupations:
(19)Farming, Fishing, and Forestry; (20)Construction Trades (21)Extraction Workers; (22)Installation, Maintenance, and Repair; (23)Production; (24)Transportation and Material Moving; (12)Healthcare Support; (13)Protective Service; (14)Food Preparation and Serving Related; (15)Building and Grounds Cleaning and Maintenance; (16)Personal Care and Service;
Clerical and sales occupations:
(17)Sales and Related; (18)Office and Administrative Support
Managerial and professional occupations:
(1)Management; (2)Business and Financial; (3)Financial Specialists; (4)Computer and mathematical; (5)Architecture and Engineering; (6)Life, Physical, and Social Science; (7)Community and Social Service; (8)Legal; (9)Education, Training, and Library; (10)Arts, Design, Entertainment, Sports, and Media; (11)Healthcare Practitioners and Technical;

Occupation (25)Member of Armed Forces is excluded from my sample. This classification is applied to HRS wave 8 to 11.

Appendix C Calculation of Social Security Benefits

Given the complexity of the Social Security scheme, there are several modelling issues and simplifications to be discussed:

C.0.1 Eligibility for Social Security benefits

Individuals are entitled to Social Security retirement benefits only after they earned 40 credits. The credits are linked to the annual earnings and each year a maximum 4 credits can be earned. For example, in 2016 one credit is received for each $1260. For most people, this requires them to work at least 10 years to be qualified for the Social Security retirement benefits. Because of the curse of dimensionality, I do not maintain the credits that individual has earned as a state variable in the model. Instead, all individuals are assumed to be qualified as long as they reach the early retirement age. Given that the average work experience at age 62 is very long, this should not be a very strict assumption [26].

C.0.2 State Variables

As described before, AIME serves as a state variable in my model and I calculate PIA and Social Security benefits based on it. The dependence of benefits on the age at which individual begins

[26] As far as I know, the only exception which keeps the earned credit as a state variable is Van der Klaauw and Wolpin (2008).

drawing benefits requires adding this age as another state variable. Given the multiple values this variable can take, adding it as a state variable will significantly expand the state space of current model, which is already tremendously large. Instead, I reflect the adjustment from PIA to real benefits in the transition process of AIME to exclude the starting age of benefit-taking as a state variable. The cost of doing it is to add another binary values state variable: whether the individual is the first or subsequent year taking benefits.

To be specific, take the individual starts to draw benefits at age 66 as an example. By Social Security rule, the benefits individual takes is 1.08 times of his PIA, not only for benefits collected at the age of 66 but also all the subsequent ages. To convert the PIA to real benefits amounts, say, at the age of 68, a variable records that individual began collecting benefits at age 66 is necessary to obtain the adjustment coefficient 1.08. To avoid doing this, at the age of 66 when individual collects the benefits for the first time, in the transition process of AIME, I multiply the AIME by the adjustment coefficient. Notice that the adjustment coefficient is only known at age 66 but not subsequent ages without keeping the age of first-time-benefit-drawing as a state variable. In the all following ages, the adjustment from PIA to real benefits is not needed because it is already reflected in the AIME. However, without modelling the Social Security application as a choice, I assume the first year of not working after age 62 as the beginning time of drawing benefits. In the case that individual reenters working after receiving Social Security benefits, I cannot distinguish whether it is his first time or not if he stops working without the assistance of extra varaibles. Therefore I add a binary state variable to record whether it is the first time of benefit-drawing. This variable, together with AIME, will determine individual's Social Security retirement benefits eventually [27].

Appendix D Private Pension

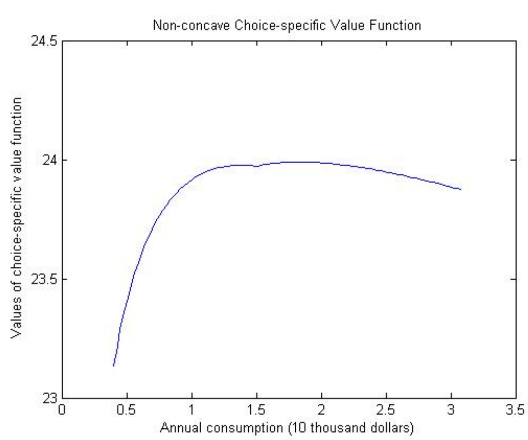
Private pension is an important supplement to Social Security, particularly for people with high income. Coile and Gruber (2007) reveals that private pension has equivalent importance in incentivizing older people to retire. There are two main plans of the private pensions: the defined-benefit pension and the defined-contribution pension (hereinafter DB and DC plans). The DB plan was previously prevalent whereas the DC plan has become popular recently for the sake of alleviating the increasing burden upon employers. The private pension plans are employer-specific and very heterogeneous. Completely modelling this essentially requires solving the model with respect to

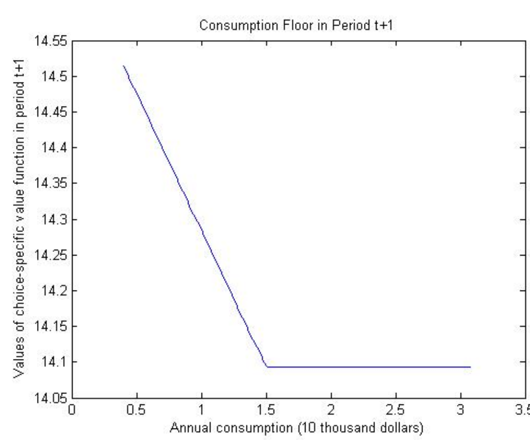
[27] French and Jones (2011) models the Social Security application. Thus whether it is the first time of benefits taking can be determined directly from the choice variable. Van der Klaauw and Wolpin (2008) does not have Social Security application as a choice variable. Nevertheless they add the age at which individual begins drawing Social Security benefits as a state variable.

every individual respectively.[28]. Alternatively, Van der Klaauw and Wolpin (2008) abstracts from modelling the DC plan because it requires adding an extra decision variable similar to saving [29] French and Jones (2011) further abstract from modelling the private pension based on the detailed employer-specific plans. Instead, they construct a complex while reduced-form model to predict the private pension without specifically distinguishing the DB and DC plans. This paper follows the approach adopted by French and Jones (2011).

Appendix E Grid Search Method for Optimal Consumption

In a few cases, the choice-specific value function is not a concave function of consumption. For example, when the consumption in period t is over a threshold so that the assets left for next period is too low in a certain range such that the individual is hitting the consumption floor in period t+1 in this assets range. This will lead to the situation that expected value function in period t is declining in current consumption and then becomes flat after the assets left for next period is lower than a threshold (i.e. after the current period consumption is higher than a threshold). By widening the searching frame, say set *Cnear* to 10 instead of 5, this issue can be addressed. I also tried another strategy to avoid increasing the search frame which leads to slower searching speed. If the non-concave case happens, in which $U(Cbest + Cnear) > U(Cbest) < U(Cbest + Cnear)$, I reset *Cbest* to *Cbest-Cnear* or *Cbest+Cnear* depending on which provides the higher utility. This leads to slightly higher bias in the optimal consumption if *Cnear* is small, but the bias is trivially small. The following two figures provide the examples of the non-concavity of choice-specific value functions.





[28]Examples include Blau and Gilleskie (2008) and Bound, Stinebrickner, and Waidmann (2010)
[29]The contribution to DC pension is similar to savings through pension wealth.

Appendix F Policy Function of Labor Supply

Individual's labor supply depends on the following observed state variables: (1)Age (2) Pension (3)Insurance type (4)Asset (5)Labor supply in last period (6)Experience (7)Marriage (8)Physical health (9) Cognitive Health (10)Income shock. This appendix section explores the variation of policy function of labor supply with respect to several main state variables.

1. Age: The probability of not working should be increasing in ages. Particularly, there should be two jumps at age 62 and 65. The soar in not working at age 62 should be attributed to the availability of Social Security. First of all the Social Security should have an income effect which gives individual an wealthier outside option of not working. On the other hand, the Social Security earning test should provide extra incentives of not working [30][31]. The jump at age 65 should firstly result from the non-actuarial Social Security benefits after age 65. Then the individuals who have health insurance tied to their work (i.e. not retiree coverage) have incentives to leave their jobs at age 65 because of the universe of Medicare.

2. Insurance type: As mentioned above, the probability of not working should have a jump after age 65 because of the Medicare. First of all, individuals with tied insurance, who are assumed to be insured only if they work in full time, will have the largest increase in the probability of not working. This is because before and after age 65, while the utility of working in full-time do not change significantly (the individual is covered by health insurance whatsoever), the utility of not working (and of working in part-time) will increase greatly. This is because individuals who did not benefit the health insurance are now enjoying the Medicare and pay less out-of-pocket medical expenditure. This should increase the probability of not working (and working in part-imte) of these people after age 65.

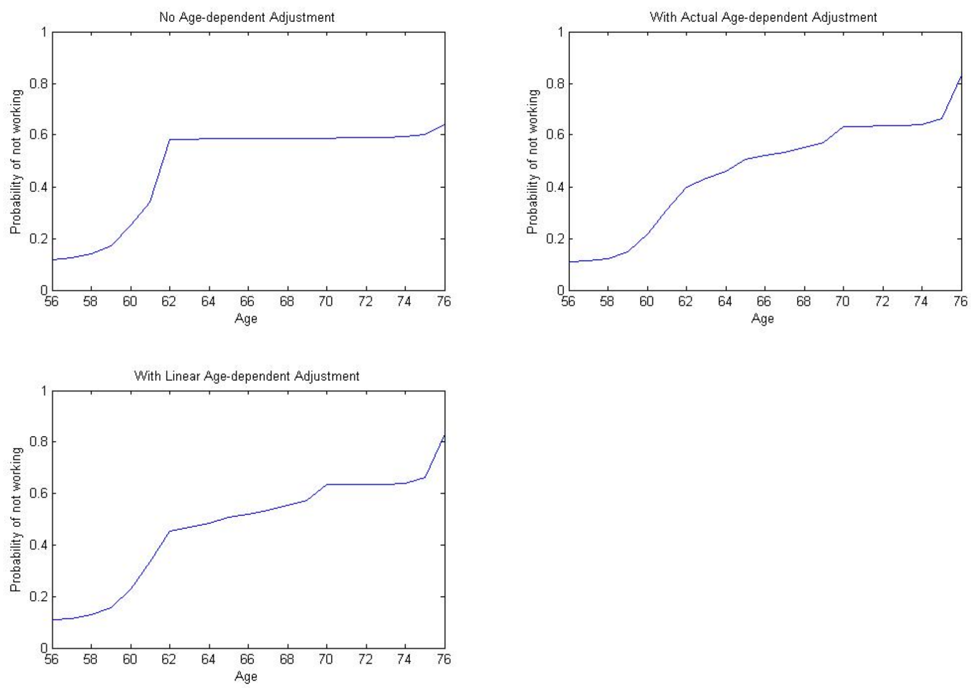
   Another issue is the variance of medical expenses. In the current model the medical expenses is deterministic and it affects individuals' decisions just through the budget constraint. As Rust and Phelan (1997) and French and Jones (2011) pointed out, the uncertainty of the medical expenses together with risk-averse utility plays an important role in shaping individuals' behaviors as well.

3. Adjustment by age of first benefits receipt: To calculate the amount of monthly benefits upon

[30] However if I are going to assume that individuals start to receive Social Security since the first non-working age after 62, the individual is not subject to the earning test by construction.

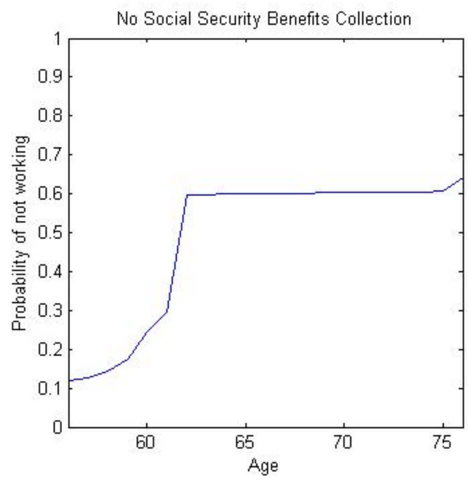
[31] If I want to recalculate the Social Security benefits because the money collected by earning test is refunded in the future, then this gives incentive to not working after age 65 instead of age 62. This is because, thought the earning test is applied since age 62, the recalculation of the benefits makes it actuarial fair between age 62-65 but not the case after 65.

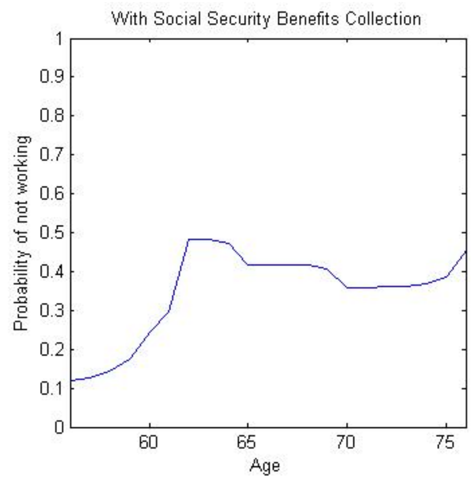
PIA, adjustment is imposed and it depends on the age at which individual starts to draw the retirement benefits. While individuals begin drawing benefits at age 65 receives 100% of his PIA, individuals claim benefits one year earlier than the full retirement age 65 have (1-6.67%) monthly benefits of his PIA. While the reduction is around 6.67% every one year earlier than 65, which is approximately actuarially fair. The increment rate is 5% every one year up to age 70, and it is not actuarially fair. This gives extra incentives for individuals to claim Social Security benefits before age 65. I plot how does the probabilities of not working vary over ages under 3 specifications. Under the first specification, I assume no age-dependent adjustment, so individual always receives 100% PIA as the monthly benefits. In the second specification I have the actual age-dependent adjustment coefficients, which is described above. Finally, linear age-dependent adjustment coefficients are imposed. That is, no matter earlier or later than full retirement age, the change in the portion of PIA as monthly benefits is 5%.



4. Social security earnings test: Individuals with ages above 62 and below 70 are subject to the Social Security earnings test if they receive both labor earnings and Social Security benefits. For those aged 62-64, 1$ of the retirement benefits is withheld for every 2$ earnings higher than a low exempt amount. For individuals aged 65-70, 1$ of the benefits is retained for

every 3$ earnings higher than a high exempt amount[32]. The earnings test is only applied to individuals younger than 65 since 2000. In my model, individuals cannot receive the public pension and keep working in their first year of Social Security benefits collection, because I assume the first year of being out of labor force after age 62 is the initial year that individual starts benefits collection. However, if the individuals decide to return to the labor market once they begin drawing public pension, the earnings test becomes effective. In below, I plot the the probabilities of being out of the labor force over age, conditional on having/ not having Social Security benefits collected in last year.





Appendix G Further Details about Data Treatment

G.1 Work Experience

The HRS records the information of up to three previous jobs the individual has worked for more than 5 years. Available related information includes occupation, industry, starting and fishing time etc. I rely on these information to construct the experience variable. The potential biases may come from the following sources: a). experience in jobs that individual worked less than 5 years is not included. b). If the individual changed his jobs frequently and has more than 3 jobs that he worked for more than 5 years, only the experience from 3 jobs is considered. Another notice related to the definition of work experience is that actually "occupation tenure" rather than "occupation experience" is assumed in my economic model for the sake of computational tractability. If individual worked in occupation A then changed to occupation B and finally worked back in occupation A.

[32]In 1992, the low exempt amount is 9,120$ and the high exempt amount is 14,500$.

The foregone experience in occupation A accumulated in early period is obsolete. When measure this "occupation tenure" empirically, the constructed measure of "occupation tenure" is usually overestimated compared to the definition in the structural model, because I do not observe jobs that individual worked less than 5 years. Specifically, the previous experience in occupation A will be still included in the calculation of "occupation tenure", even though the individual has worked in occupation B before he returns to occupation A again. The reason is that it is impossible for us to know the individual has worked in occupation B between the two experience in occupation A, if he worked less than 5 years in occupation B.

Things have changed seriously. HRS actually does not have all information, particularly information about occupation, up to three jobs with more than 5 years tenures. Instead, HRS have the occupation information only for 1. current job if working, 2. last job if not working, 3. on top of 1 and 2, the most recent job with more than 5 years tenures. This is an even more partial job history. French and Jones (2011) do not need work experience to predict the wage, neither do Blau and Gilleskie (2008) and Bound, Stinebrickner, and Waidmann (2010). Van der Klaauw and Wolpin (2008) is the only paper predicts wage with work experience, and they indeed use the HRS job history information to construct the work experience. However, the reason why they are able to do so is because the work experience in their setting is a general instead of occupation-specific measure. That is, they do not need the information about occupation, which is missing for jobs that were not the most recent one, to construct the general work experience.

Now I have the following solutions: (1) Construct the occupation-specific experience variables using the partial job history information in HRS. Use these variables for the wage equation. That is, for those who work, work experience consists of the one from current job and the one from most recent job held 5 or more years. For those who do not work, work experience consists of the one from last job and the one from most recent job on top of the last job. (2) Construct the same work experience variable with partial job history information. For wage equation, supplement these partial work experience variables with age that also has occupation-specific premium. (3) Abandon the Mincer type wage equation. Assume AR(1) process for wage as French and Jones (2011), Blau and Gilleskie (2008) and Bound, Stinebrickner, and Waidmann (2010) did. The potential issue is that the role of occupation-specific skill rental price is not obvious under this assumption.

G.2 Biennial Data

HRS basically collects data every other year, whereas the individuals in my model make decisions annually. This data structure leads to empirical issues during simulation and estimation.

G.2.1 Simulation

To simulate the decisions, the data of corresponding state variables that the structural decision rules condition on is required. Notice that these state variables are only directly observed in the survey years. While these state variables are missing in non-survey years, they can be updated by simulation based on the state variables and decision variables observed in preceding survey years. Therefore, the decisions can be simulated either only in those survey years based on directly-observed data, or also in non-survey years based on simulation-updated data. To be consistent with the actual data, I am going to simulate the decisions in those survey years only [33].

In a more complex setting, some of the state variables can be non-contemporaneous to the decision variables. To be specific, decisions in period t may condition on some state variables that require information from period t-1 [34]. In this case, even if only the decisions in survey years are going to be simulated, data of related state variables is insufficient. Currently, these kind of state variables in my model include the lagged labor supply and occupation status in period t-1, lagged assets in period t-1 (i.e. the asset at the beginning of period t) and Social Security collection status in period t-1. For assets, I am going to follow French and Jones (2011) and set the values of assets in period t-1 to be the same as in period t-2, under the assumption that assets transit slowly and smoothly.

For the labor supply status in period t-1, there are two alternatives to address this issue. The first approach is similar to the simulation of decisions in non-survey years mentioned previously. Specifically, the missing labor supply status in non-survey period t-1, which serves as a state variable for decisions in period t, will be simulated conditioning on the state variables in period t-1. Notice that the state variables in period t-1 are also unobserved. Instead, they are going to be updated by further simulation based on state variables and decisions observed in surveyed period t-2.

The second approach aims at recovering the labor supply status in non-survey period t-1 by retrospective data collected in survey period t. Specifically, for individuals who are not working

[33] Van der Klaauw and Wolpin (2008) simulate the decisions both in survey years and non-survey years. However, simulating the decisions in non-survey years only help increase the sample size of simulated data whereas the sample size of actual data remains unchanged. Therefore I do not see much necessity to simulate decisions also in non-survey years.

[34] In my context, one period corresponds with one year, being consistent with the theoretical model.

in period t, HRS collected information about their last jobs, such as the last year and month the individual worked, the occupation and industry etc. I assume if individual's last job finished earlier than one year ago, the individual's work status in period t-1 (one year ago) is not working. Instead, if individual's last job ended within one year, the labor supply and occupation in period t-1 take values from last job. For those individuals who are working in period t, I examine the current job tenure at period t. If the current job tenure is longer than one year, the job status in period t-1 is set the same as in period t. The unsure case happens if individual's job in period t started within one year. In this case, in principal I have no information regarding to individual's job status in period t-1. This is because while I do have information about the job in period t-2, I don't know when did that job finish. However, given that these observations account for a very small fraction of my sample, I assume that the job in period t-2 had extended to period t-1. Namely, in this minor case I assume the job status in period t-1 remained the same as in period t-2 [35]. For current version of this paper, I take the second approach to simulate the decisions.

The last state variable requires information from period t-1 is the Social Security collection status in last period (denoted by iss_t). Individuals with age younger than 62 (inclusive) in period t should not have collected Social Security benefits in last period t-1 ($iss_t = 0$). Starting from age 63, the Social Security collection status in last period depends on the work status in last period. Particularly, if individual aged greater than 62 (inclusive) stopped working in period t-1 [36], I assume she started to collect Social Security benefits and have $iss_t = 1$. The Social Security collection status variable is constructed based on the job status variable in period t-1 discussed above. Finally, I assume that once individuals have started benefits collection, it continues until the end of their lives ($iss_t = 1 if iss_{t-1} = 1$).

G.2.2 Estimation of Auxiliary Model

As described above, some of the state variables that decisions in period t condition on require information from period t-1, which is not surveyed by HRS. Two treatments to the missing value issue for simulation were discussed in previous section. Regardless of which approach is taken during the process of data simulation, the biennial data structure also needs to be examined and discussed

[35] There is one possibility to improve this information: HRS has collected more job information besides the current job (if working) and last job (if not working). Particularly, data about previous jobs held by individuals with more than five years are also collected (up to two jobs). Therefore, if the job in period t-2 lasted longer than five years, the end time of that job should be asked by survey in period t. With this end time of job in period t-2, I can determine the job status in period t-1 better. The flaw is that if the job in period t-2 lasted less than 5 years, the information is not covered by HRS.

[36] This is defined by working in last period but not working in current period.

when choosing and estimating the auxiliary models.

The main auxiliary models consist of a bunch of regression functions as "approximate decision rules". Without loss of generality, the dependent variables of these "approximate decision rules" are the decision variables in period t, and the right-hand-side variables are corresponding state variables that the structural policy functions condition on. The parameters in auxiliary models will be estimated with actual data and then they will be used as inputs to construct the estimation criterion for structural estimation. The issue of biennial survey data is again some of the state variables require data from period t-1 which are missing in non-survey years. Importantly, labor supply equations in my auxiliary models will be estimated separately with different subsamples defined by the job status in last period. To address this issue, I revised the "approximate decision rules" by conditioning the decisions in period t on variables in period t-2 instead of in period t-1. For example, assets in period t-2 instead of in period t-1 is added to the right hand side of the labor supply equation of period t. At the expense of lower efficiency for structural estimates, this revised auxiliary model should offer a looser but still valid description of data relationship.

Appendix H Standard Error

The asymptotic variance of the structural estimates is given the following formula:

$$(G_0^{'}\Omega_0 G_0)^{-1}(G_0^{'}\Omega_0\Lambda_0\Omega_0 G_0)(G_0^{'}\Omega_0 G_0)^{-1}$$

where

$$\Lambda_0 = Var[s_i(\varphi_0)] = E[s_i(\varphi_0)s_i^{'}(\varphi_0)]$$

and

$$G_0 = E[\bigtriangledown_{\varphi} s_i(\varphi_0)]$$

φ is the vector of structural parameters estimated in the second step. $s_i(\varphi)$ is the the simplified notation for the score $s(x_i(\varphi), \widehat{\theta})$, which is evaluated at the parameters of auxiliary models estimated on the real data and at the simulated data based on the structural parameters φ. G is the Jacobian matrix of the derivative of scores with respect to the structural parameters. Ω is the weighting matrix.

Based on the above formula, I obtain the consistent estimator as:

$$(\widehat{G}'\widehat{\Omega}\widehat{G})^{-1}(\widehat{G}'\widehat{\Omega}\widehat{\Lambda}\widehat{\Omega}\widehat{G})(\widehat{G}'\widehat{\Omega}\widehat{G})^{-1}$$

Appendix I Estimation of Mortality Rates

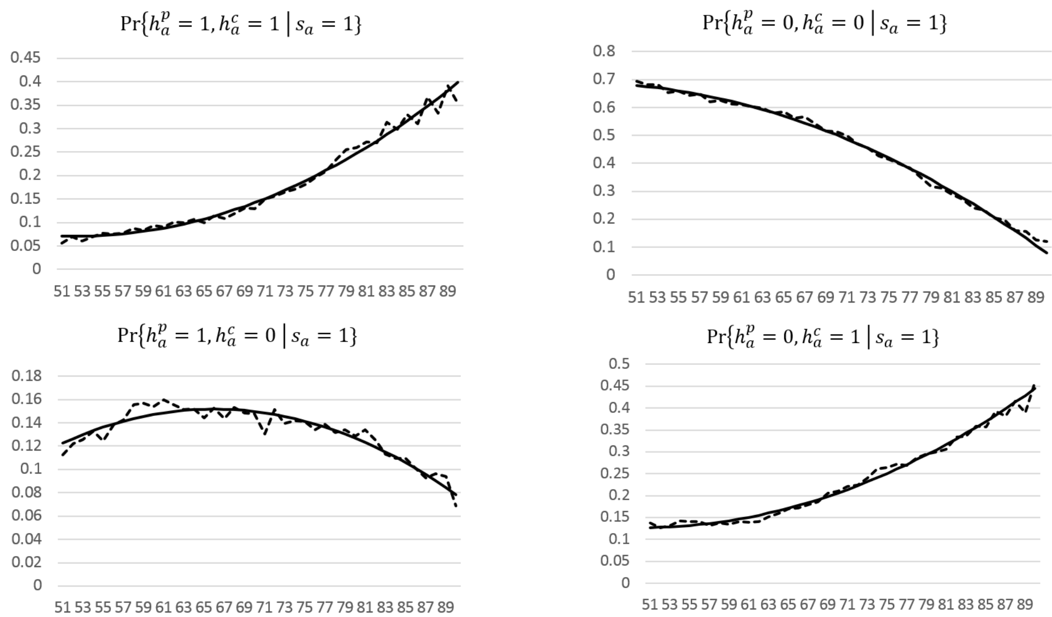
Existing literature usually assumes that mortality depends on health and age. Restricting the sample for the structural estimation to observations alive in last period, mortality rates can be estimated by regressing mortality indicator on health and age polynomials. The limitation of this approach is a high requirement of data quality and sample size. Even if the sample is representative, estimates do not necessarily match the life tables from external sources such as Social Security Administration, because of the statistical noise introduced by small sample size. The advantage of this approach is the sample on which mortality functions are estimated is the same as the sample used for the estimation of structural parameters. Literature based on this approach includes Rust and Phelan (1997), Van der Klaauw and Wolpin (2008). Observations at very old ages are sparse. For this reason, Rust and Phelan (1997) extrapolates mortality beyond sample age while Van der Klaauw and Wolpin (2008) uses subjective probabilities of living as supplementary data.

Alternatively, several studies directly or indirectly cites the data of mortality rates from external source such as Social Security Administration. Gustman and Steinmeier (2005), Haan and Prowse (2014) Haan and Prowse (2014) directly use external mortality data instead of estimating the mortality function. These research basically assumes that health does not shift individuals' mortality rates, because the external mortality rates are not conditional on health. French (2005) use the Bayesian rule to estimate the health-dependent mortality rates based on the external unconditional mortality rates. Bound, Stinebrickner, and Waidmann (2010) assumes a proportional hazard function for mortality rates. They estimate a health shifter on their main sample, and multiply it with the unconditional mortality rates obtained from Social Security Administration.

The limitation of the approach by Bound, Stinebrickner, and Waidmann (2010) is that health is assumed to shift the unconditional mortality rates by a fixed proportion at every age. The unconditional mortality rates, obtained from external sources, are the national average at each age. This probability at age 51, for example, associates with people with good health on average. Therefore, having a poor health should shift individual's mortality rate from the average greatly. On the contrary, the unconditional mortality rate at age 81 corresponds with people mostly with poor health, which already captures the average effect of poor health. At this age, the mortality rate of a individual with poor health should not departure from the unconditional probability greatly.

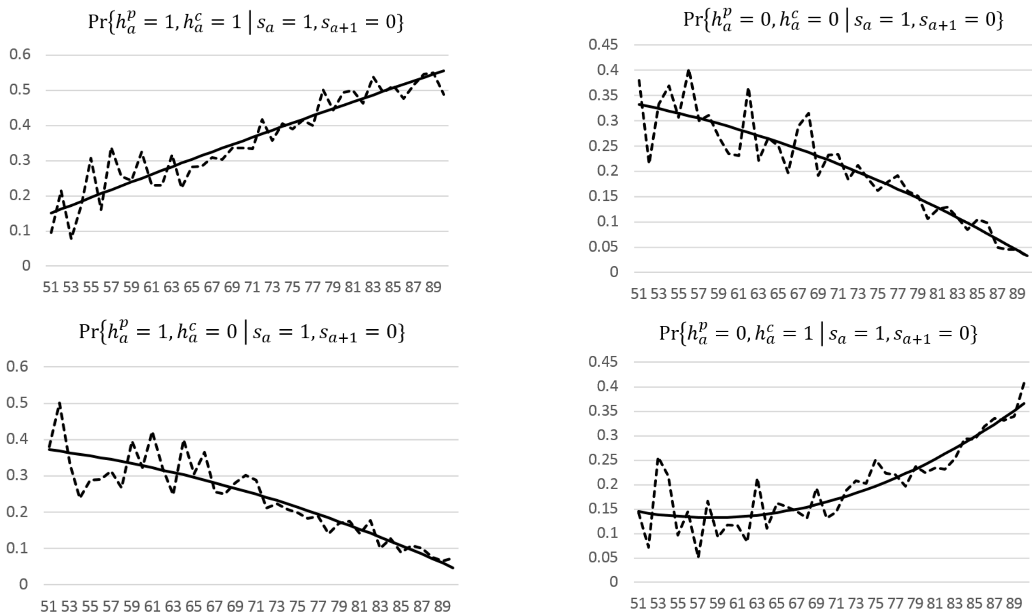
This paper estimates the mortality rates following French (2005). The unconditional survival probability $Pr(s_{t+1} = 0|s_a = 1,)$ is obtained from Social Security Administration actuarial life tables. I use HRS data to estimate the health shifter $Pr(h_t^p, h_t^c|s_{t+1} = 0, s_a = 1)/Pr(h_t^p, h_t^c|s_a = 1)$. It is estimated based on the full HRS sample instead of the sample for estimation of structural parameters, because the estimation sample has very few deceased observations. I use quadratic polynomials of age to approximate $Pr(h_t^p, h_t^c|s_{t+1} = 0, s_a = 1)$ and $Pr(h_t^p, h_t^c|s_a = 1)$ to obtain smooth functions. From the figures below I can see the fitness is very good.

Figure 9: Probabilities of Health States Conditional on Being Alive at Each Age



. Dash lines are the raw probabilities and solid lines are smoothed.

Figure 10: Probabilities of Health States Conditional on Deceasing after Each Age



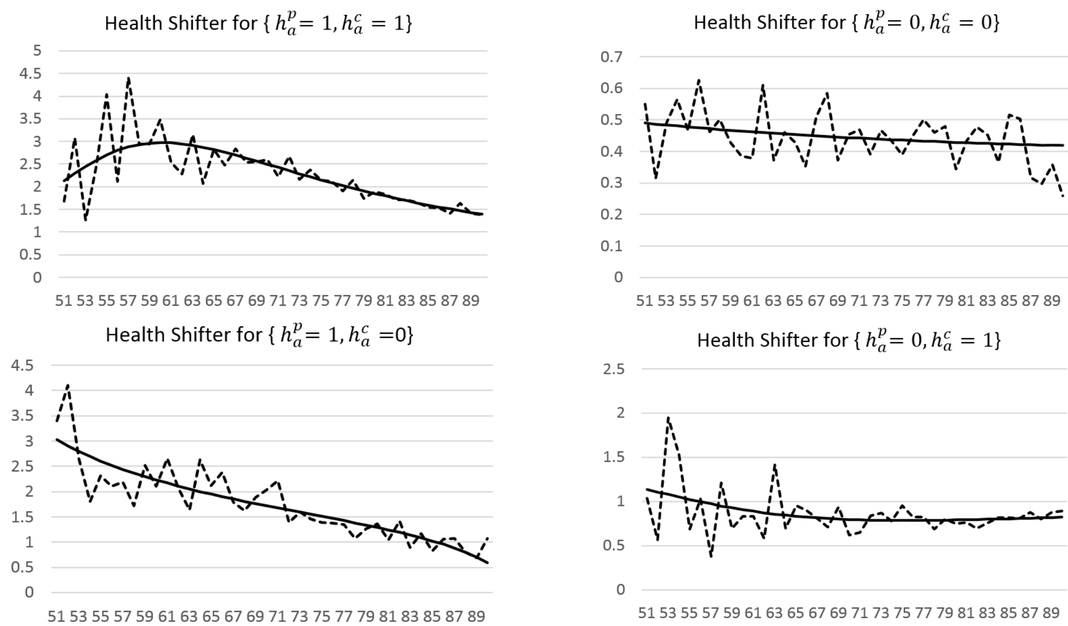
. Dash lines are the raw probabilities and solid lines are smoothed.

Figure 9 and Figure 10 show the probabilities of each health states from age 51 to age 75, conditional on being alive at age a and on deceasing between age a and $t+1$. As people age, both for alive and deceased individuals [37], the probability of having both good physical health and good memory plunges, whereas the likelihood of suffering poor physical and cognitive health rises significantly. Interestingly, while the probability of having only cognitive issue increases with age, the probability of being in poor physical health only does not increase as people get older.

Finally, raw and smoothed shifters of the four joint health states are presented in Figure 11. The health shifter, given by formula $Pr(h_t^p, h_t^c | s_{t+1} = 0, s_t = 1)/Pr(h_t^p, h_t^c | s_t = 1)$, is a health-dependent and age-specific factor which is going to be multiplied with the unconditional averaged survival probabilities obtained from SSA. I can see, at age 61 the mortality of individuals with poor physical health and poor memory $\{h_t^p = 1, h_t^c = 1\}$ is three times as large as the average mortality, and it becomes 1.5 times as large as the average at age 90. This decline is due to the deterioration of average health. On the contrary, individuals with good physical health and memory $\{h_t^p = 0, h_t^c = 0\}$ have a mortality rate 40%-50% compared to the average.

[37] Hereinafter, alive individuals are referred to those alive at age a and deceased individuals are referred to those deceased between age a and $t+1$.

Figure 11: Mortality Shifters for Different Health States



. Dash lines are the raw probabilities and solid lines are smoothed.

Appendix J Estimates of Health Transition

Here are the results of estimated health transition, conditional on other health states in last period.

Figure 12: Transition Probabilities of Health conditional on $\{h_t^p = 1, h_t^c = 1\}$

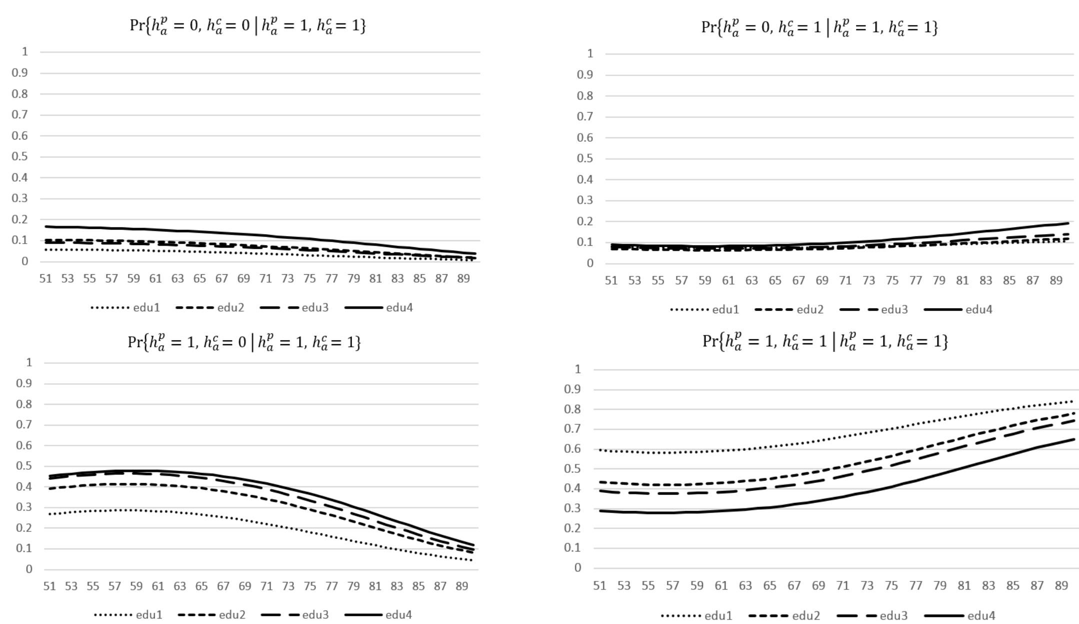


Figure 13: Transition Probabilities of Health conditional on $\{h_t^p = 0, h_t^c = 1\}$

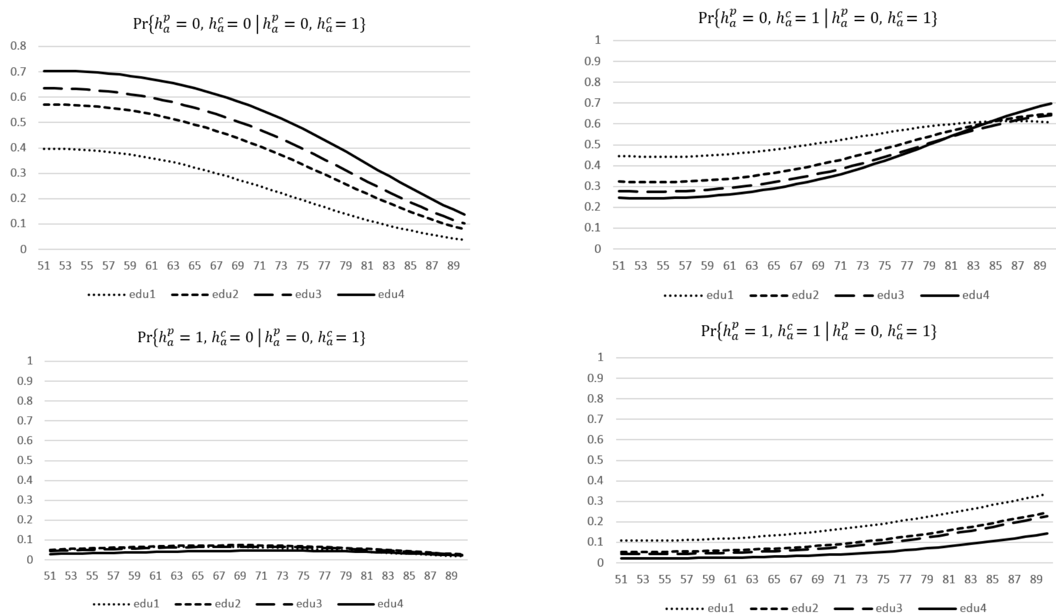


Figure 14: Transition Probabilities of Health conditional on $\{h_t^p = 1, h_t^c = 0\}$