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

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Abstract

Under skill-biased technical change, jobs are becoming less physically demanding whereas require increasing cognitive abilities. However, existing research pays insufficient attention on the role of cognitive health in retirement, nor on the heterogeneous retirement effects of physical and cognitive health across occupations. Upon motivating facts, this paper proposes and estimates a dynamic structural model of individual retirement and saving decisions. It incorporates both physical and cognitive health and allows their retirement effects to differ across occupations via four channels respectively: disutility of working, wage, medical expenditure and life expectancy. The model is estimated with the U.S. Health and Retirement Study data by Indirect Inference. We find cognitive health has little retirement effect for manual workers. However, for clerical workers the effect is as large as physical health. We also reveal the different underlying mechanisms through which physical and cognitive health lead to retirement. Our counterfactual experiments find, contrary to common concern, manual workers would have larger delay in retirement if retirement age increased. Nevertheless, they would suffer larger welfare loss than professionals due to the rigidity of deciding when to retire, especially by interacting with their poorer physical heatlh.

Key Words: Cognitive Health; Cognition; Physical Health; Occupation; Retirement; Social Security; Public Pension

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- HRS, databook, health capacity to work

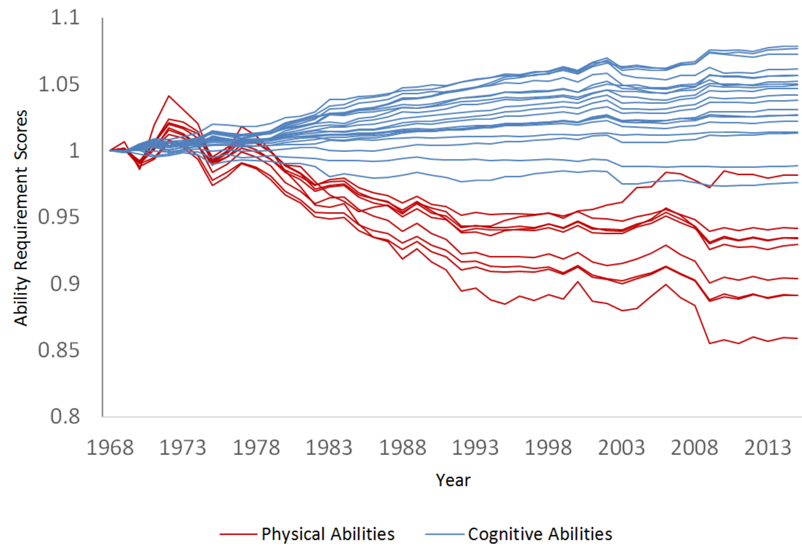
1 Introduction

On top of those economic variables, health is an important concern among studies on retirement. Under population aging, the role of health receives increasing focus. As proposed policy reforms consider delaying older people's retirement to high ages, people worry about the elderly's health capacity to work longer. [1] Existing literature on retirement focuses mostly on the physical dimensions of health. While skill-biased technical change drives jobs to be less physically demanding but more intellectually demanding, ignoring the role of cognitive health may lead to increasing misunderstanding on retirement and biased policy evaluation. Meanwhile, different types of health may have distinct impacts on retirement, depending on which occupation the individual works, as different occupations have distinct ability requirements. This paper explores facts about physical health, cognitive health and retirement across occupations. Based on these facts, we propose and estimate a dynamic structural model of retirement and saving decisions of US males, seeking to understand the heterogeneous roles of physical and cognitive health in occupational retirement, as well as their implication for labor supply, benefits and welfare under Social Security reforms.

Population aging is placing the public pension system under stress, and increasing the retirement age is a focal policy reform considered by many countries, such as U.S., China, Japan and the European countries. For a recent 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. Under this background, we concern about older people's responsiveness to delay their retirement, which may depend on individual's health as well as how demanding the job is. Moreover, it may depend on the interaction between the different dimensions of worker's health with the job's specific ability requirement. This paper proposes and estimates a dynamic structural model of retirement and saving decisions of US males, seeking to understand the heterogeneous roles of physical and cognitive health in occupational retirement, as well as their implication in labor supply, benefits and welfare under Social Security reforms.

[1] Cutler, Meara, and Richards-Shubik (2013)

Figure 1: Changes of Physical and Cognitive Ability Requirements of the average US Jobs



Each line represents how much of an ability is required by the average US job. The trends are calculated by combining the fixed ability requirements of each occupation measured in O*NET in 2016, with time-varying employment share of occupations from the Current Population Survey (CPS), 1968-2015. The measures are normalized to 1 in 1968. Details of the calculation is in the Empirical Facts section.

Under skill-biased technical change, jobs are becoming less physically demanding and they require increasing cognitive abilities as shown in Figure 1. However, there is limited research focuses on the specific role of cognitive health in retirement, nor the one distinguishes the different effects of physical and cognitive dimensions across occupations (Wallace and Herzog 1995). In reality, the ability requirements across occupations differ remarkably, and therefore physical and cognitive health can affect labor supply heterogeneously across occupations. For instance, construction workers may be unable to carry heavy materials due to physical health deterioration, whereas teachers may come across hardship in teaching if they have poor memory. Policymakers and previous studies have mainly focused on the physically demanding occupations. As the proportion of cognitively demanding jobs increases, ignoring the cognitive dimension of health may underestimate the retirement impact of health for a nontrivial group of people.

If the FRA increases, the occupation-dependent roles of physical and cognitive health may imply heterogeneous responses in delaying retirement as well as unequal welfare changes: workers with poor physical (cognitive) health from physically (cognitively) demanding occupations are less likely to be responsive in postponing their retirement, which will lead to a larger reduction in retirement benefits.[2] However, the effects of physical and cognitive health will also interplay with income and

[2]Conditional on retiring at age 62, retirees can receive 80% of the full benefits when FRA is 65, and this percentage

wealth, which are involved with large disparity across occupations. For occupations in which workers have lower income and savings, the reduction in retirement benefits due to the increased FRA will generate larger income and substitution effects. Workers from these occupations may thus be more rigid to choose when to retire and may have to delay their retirement even if they had poor health. This will induce them sizable disutility of working and welfare loss.

To address the above concerns, this paper develops a structural dynamic programming model of labor supply and saving decisions of male household heads in the United States. The model incorporates two dimensions of health: physical health and cognitive health. Occupations in this paper are grouped into three categories: manual and service, sales and clerical, as well as professional and managerial.[3] As one of the main contributions, the model captures the interaction between the occupation and the different dimensions of health by allowing the disutility of working due to poor physical and cognitive health to be occupation-dependent. It also allows the wage penalty due to poor physical and cognitive health to depend on occupations. In addition, both dimensions of health are allowed to shift medical expenditure and survival probabilities. These four channels through which poor physical and poor cognitive health affect utility are captured by corresponding structural parameters. I estimate these parameters by Indirect Inference using the U.S. Health and Retirement Study (HRS) data from 1996 to 2012.

Based on the estimates, the first counterfactual experiment quantifies the importance of physical and cognitive health on labor force participation (hereafter referred as LFP) across occupations under current Social Security rules. 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 good cognitive health is assumed, the LFP rates would increase respectively by 10% and 4% for clerical and professional occupations, whereas there will 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 only matters in physically demanding jobs, suggests a need to pay more attention to health issues under a broader scope for older workers in the intellectually demanding occupations.

The first counterfactual experiment also evaluates the relative importance of the underlying

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.

[3]This paper abstracts from modelling the change of occupations due to its low frequency in the data. Therefore observations that have changed occupations at older ages, which account for only a small fraction of the full sample, are excluded from the estimation sample. Detailed discussion is in the Data section.

channels through which physical and cognitive health affect retirement: disutility of working, wage, medical expenditure and life expectancy. The results suggest the channel of disutility of working is the most important for both physical and cognitive health. Moreover, the disutility of working with poor physical health is the largest in manual occupations whereas the one with poor cognitive health is the largest in clerical occupations. I don't find the occupation-dependent effects in the rest channels. While physical health also has a notable effect on retirement by shifting 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.

This paper then 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 these occupations have worse physical health, which may constrain their ability and willingness to postpone their retirement, little effect from cognitive health and the strong income and substitution effects induced by the reduction in retirement benefits contribute to this larger response. Correspondingly, I found the manual workers are also subject to larger retirement benefits reduction and larger welfare loss than those 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 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.

The rest of this paper is structured as follows. The next section reviews the literature related to this paper. Section 3 presents the empirical facts about occupations and physical and cognitive health. Section 4 is devoted to the structural model and section 5 to the solution and estimation methods. Section 6 describes the data. Section 7 presents the estimates. Counterfactual experiments are implemented in Section 8. Section 9 concludes.

2 Literature Review

An increasing number of studies on retirement have relied 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 the early fundamental works such as Gustman and Steinmeier (1986b) and Rust and Phelan (1997), recent research has enriched 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. These studies, while carefully model the financial variables such as wage, Social Security benefits, health insurance etc., also incorporate demographic variables such as health and life expectancy. However, the curse of dimensionality limits the number of state variables, and the health variable in these studies is usually a single broad measure, such as the self-reported health. Bound, Stinebrickner, and Waidmann (2010) have a particular focus on the role of health in retirement. This is the first paper deals with measurement bias in the self-reported measure of health within a structural dynamic programming model 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. However, these two papers are also based on a single comprehensive measure of health. To the best of my knowledge, my paper is the first one incorporates not only physical but also cognitive dimensions of health and examines their occupation-dependent roles in retirement and savings. As cognitive abilities are in increasing demand by modern jobs, the effects of cognitive health on older people's labor supply should receive more attention.

The existing studies evaluate the retirement effects of Social Security reforms have mostly focused on the aggregate level, with a few exceptions explore the distributional effects by income and health. This paper explores the heterogeneity in individuals' labor supply, savings and welfare changes induced by reforms from a particular perspective: occupations. Different occupations have distinct ability requirements and therefore different dimensions of health should have effects on retirement directly depending on individual's occupation. A notable exception in existing studies is Gustman and Steinmeier (1986a), which study the heterogeneous response in retirement over health and occupations. However, it is also based on a single measure of health, and occupations are classified as whether they are physically demanding or not. As suggested by our guiding evidence in the next section, while LFP of manual workers are more associated with their physical health, cognitive health has a higher correlation with LFP for professional and clerical workers. Given the large disparity in wealth and income across occupations, the inequality across occupations should also deserve policymakers' attention. This paper reveals that the retirement effects of health, under the traditional definition, are underestimated for workers from professional and clerical occupations. This finding encourages policymakers to reevaluate Social Security's progressivity and the welfare implications of Social Security reforms.

Finally, this paper is related to the recent studies about health capacity to work, such as Cutler, Meara, and Richards-Shubik (2013), Milligan and Wise (2015) and Coile, Milligan, and Wise (2016).

Motivated by the concern that older individuals may have difficulty to change their labor supply facing Social Security reforms, these studies ask how much is their health capacity to work. Cutler, Meara, and Richards-Shubik (2013) and Coile, Milligan, and Wise (2016) simulate the LFP rate for older individuals, based on their actual health at older ages and a reduced form relationship between health and LFP at younger ages. This simulated LFP rate is interpreted as the health capacity to work of individuals at older ages. This exercise provides a simple approach to measure health capacity to work, which has been already applied to many other countries. In my paper, the counterfactual experiments shed light on how individuals' ability to work is constrained by their physical and cognitive health, and how does this effect differ across occupations. Under a structural framework, this paper is explicit about the underlying channels through which health constrains older people's labor supply, and is allowed to relax some strict assumptions. For example, the reduced form relationship between health and LFP used in the above studies implicitly assumes that individuals at older ages had the same expectation for future health and lifespan as at younger ages with the same health. This assumption may lead to an overestimate of older people's capacity to work.

3 Empirical Facts

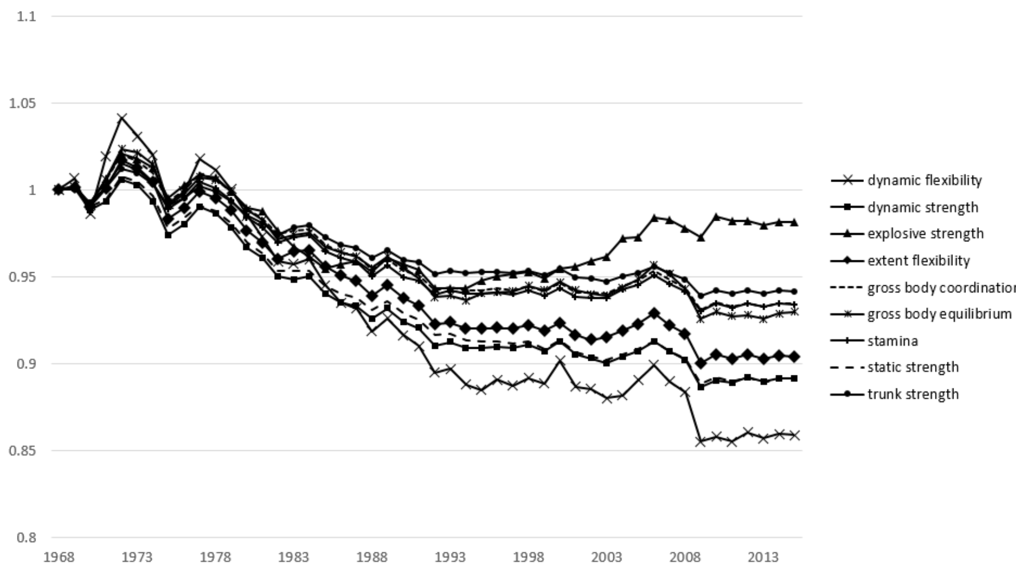
3.1 Changes of Ability Requirements of US Jobs

During the past decades, as skill-biased technical change happens, job requirement has been going through a remarkable change: more and more jobs require cognitive abilities, whereas on average they are becoming less physically demanding. To see this, I calculate how each ability under the physical and cognitive categories are required by the average US job from 1968 to 2015. The physical and cognitive categories are defined by O*NET, a data set provides detailed information about more than 900 occupations in the US, including the scores of specific abilities required by each occupation. I combine the fixed ability requirements of each occupation measured in O*NET in 2016 with the time-varying employment shares of occupations from the Current Population Survey (CPS) 1968-2015 to calculate the trends. [4] As shown in Figure 2, all 9 abilities defined by O*NET

[4]From 964 8-digit occupations in O*NET dataset, I construct a sample based on 6-digit occupations to match the employment data from CPS. This sample includes 773 6-digit occupations. To obtain the ability requirement scores for these 6-digit occupations from those with several 8-digit sub-occupations, I simply compute the mean. To calculate the ability requirement score averaged over these 773 occupations, each 6-digit occupation is weighted by its employment in each given year obtained from CPS. Notice that the ability requirement score for each occupation in O*NET is not longitudinal. For this reason, there is no information about the changes in required abilities over time conditional on each 6-digit occupation. Therefore, the variation in the calculated trends comes from solely cross-occupation employment changes.

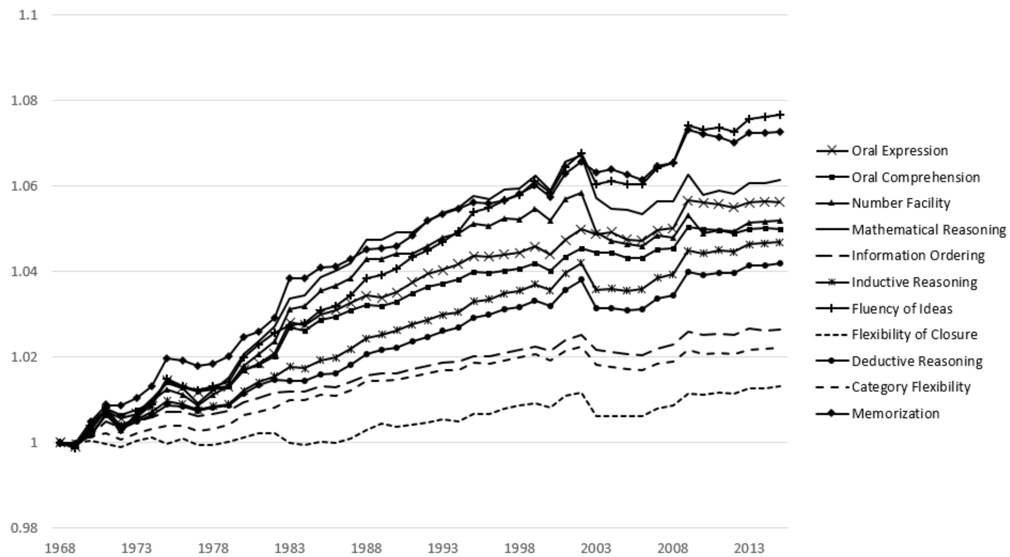
as physical ones have been declining in demand since 1968. On the contrary, Figure 3 reveals that out of the 21 abilities under cognitive category, requirements for 18 abilities have increased .

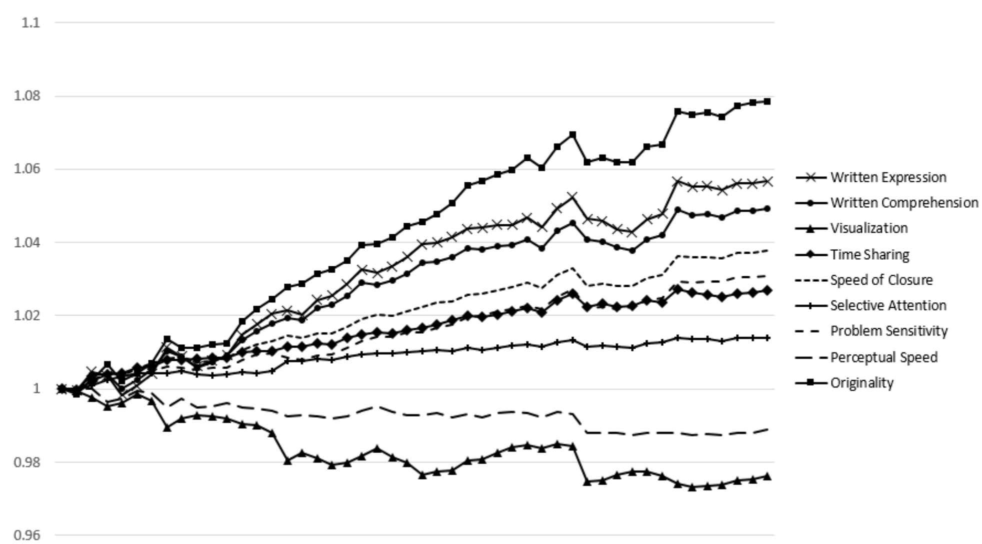
Figure 2: Trends of Average Physical Abilities Required by US Jobs since 1968



This figure presents the scores for required physical abilities averaged across U.S. jobs, weighted by their employment shares. For comparing the trends across abilities, the scores in 1968 have been normalized as one.

Figure 3: Trends of Average Cognitive Abilities Required by US Jobs since 1968





These figures present the scores for required cognitive abilities averaged across U.S. jobs, weighted by their employment shares. For comparing the trends across abilities, the scores in 1968 have been normalized as 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 striking change, while physical health may still remain crucial, cognition may become an increasingly important factor correlated with individual's labor supply at older ages. Most of the existing research about retirement uses health measure such as the self-reported health. This single measure does not allow us to disentangle the roles of different dimensions of health. Moreover, this self-reported health arguably reflects limited information about individual's cognition. It seems unlikely that a respondent will rate himself/herself as unhealthy just because of, for instance, the difficulty in recalling details.

In this paper, occupations are grouped into three categories, mainly based on whether jobs are physically or cognitively demanding. [5] 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.

For the occupation categories used in this paper, I also calculate their ability requirement scores for the abilities under the physical and cognitive categories defined by O*NET. The results in Table 1 and 2 suggest a large heterogeneity in the required abilities across occupations. Moreover, it is clear that the physical abilities are more required by manual occupations than by clerical and professional occupations. In particular, the scores of physical ability requirements for professional occupations are all less than 50% of the ones for manual occupations. On the other hand, most of the cognitive abilities are more required by professional and clerical occupations than manual occupations.

Table 1: Physical Abilities Required by Occupation Categories

	Manual	Clerical	Professional	Professional/Manual
dynamic flexibility	7.05	0.88	0.65	0.093
dynamic strength	33.65	10.54	9.39	0.279
explosive strength	10.49	2.21	4.53	0.431
extent flexibility	42.42	13.77	11.07	0.261
gross body coordination	35.95	12.40	11.69	0.325
gross body equilibrium	27.52	9.27	9.25	0.336
stamina	40.79	14.43	13.56	0.332
static strength	44.69	17.23	13.54	0.303
trunk strength	48.98	22.95	21.57	0.440

This table presents the average required physical abilities for the occupation categories used in this paper, weighted by the employments in 2014.

[5] David and Dorn (2013) also classify occupations by their required abilities, but with a particular focus on the routineness of activities, i.e. whether jobs are regular to be substitutable by machine.

Table 2: Cognitive Abilities Required by Occupation Categories

	Manual	Clerical	Professional	Professional/Manual
Oral Expression	58.28	71.19	76.01	1.304
Oral Comprehension	60.75	71.90	75.49	1.243
Number Facility	29.76	41.45	44.46	1.494
Mathematical Reasoning	28.81	41.66	47.18	1.638
Information Ordering	53.15	55.63	63.62	1.197
Inductive Reasoning	49.61	52.51	66.53	1.341
Fluency of Ideas	34.76	40.34	55.79	1.605
Flexibility of Closure	40.77	38.46	48.59	1.192
Deductive Reasoning	52.94	54.67	69.11	1.305
Category Flexibility	45.73	50.35	56.76	1.241
Memorization	30.24	35.49	40.82	1.350
Written Expression	41.96	58.29	68.25	1.627
Written Comprehension	48.43	62.69	72.76	1.502
Visualization	41.79	30.28	41.53	0.994
Time Sharing	40.08	39.54	43.29	1.080
Speed of Closure	32.34	32.08	40.08	1.239
Spatial Orientation	21.94	3.36	5.14	0.234
Selective Attention	48.75	49.00	52.41	1.075
Problem Sensitivity	58.88	57.59	70.51	1.198
Perceptual Speed	41.66	39.47	44.24	1.062
Originality	33.29	38.79	53.50	1.607

This table presents the average required cognitive abilities for the occupation categories used in this paper, weighted by the employments in 2014.

3.2 Physical and Cognitive Health

While physical health relates to body's capacity to perform activities that require strength and endurance, cognition refers to brain's ability to process information, such as memory, numeracy, fluency, orientation, logic, reaction and so on. It should be carefully distinguished from the mental health, which is more related to individual's happiness, confidence, resilience etc.[6] Depending on the transition over lifecycle, cognition has been commonly classified into crystallized cognition and fluid cognition, such as in McArdle, Ferrer-Caja, Hamagami, and Woodcock (2002). While crystallized cognition remains fairly stable over life cycle, fluid cognition has a clear declining pattern as people age. This declining pattern of fluid cognition, similar to physical health, raises more concern for its impact on people's life at older ages. For this reason, instead of constructing a comprehensive measure for cognition, this paper chooses to focus on an crucial dimension of fluid cognition: memory. Another advantage of focusing on memory is that there are longitudinal and direct measures of

[6]For the reduced form exercises and the auxiliary models used for structural estimation, mental health is controlled for. However, the structural model does not characterize the effect of mental health specifically. While physical and cognitive health are likely to have occupation-dependent effects on retirement because of the different skill requirements, it is unclear whether manual workers or professional workers are more harassed by phycological problems. Introducing mental health to our model not only adds an extra state variable but also may require more delicate classification of occupations. For these reasons, I abstract it from the current model and leave it for future studies.

individual's memory from HRS. For each respondent, interviewer reads a randomized list of words and asks him/her to recall as many as 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 about the number of words by each respondent are thus provided in each wave. I construct a single variable by summing them up, which has been commonly used in phycological literature.

Based on the primary sample used in this paper, Table 3 shows ample variation in the level of memory by education and by occupation. [7] 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. [8] According to the literature in psychology, while some researchers argue fluid cognition starts to decline as early as age 20-30 (e.g. Salthouse (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, we can see cognition does decline more rapidly after the early retirement age 62, which is the period retirement occurs and policy reform targets. [9]

[7] Our 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.

[8] 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.

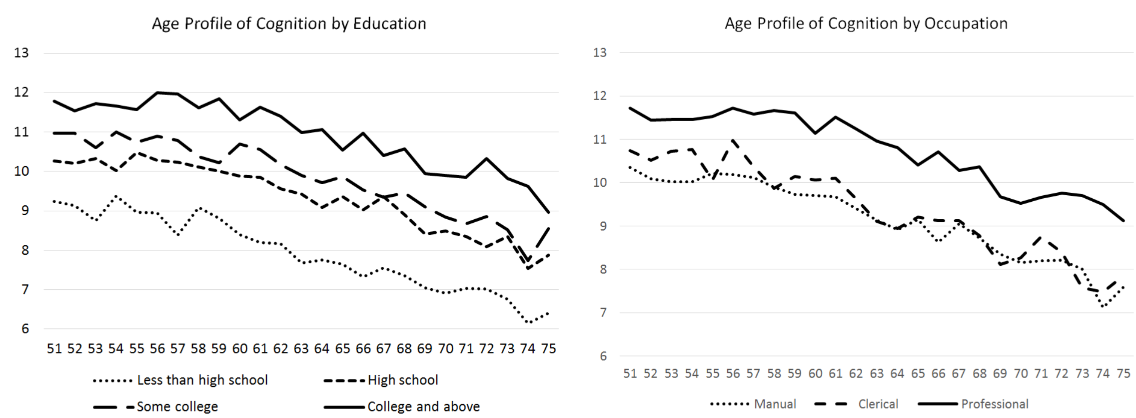
[9] For the results by occupation, one caveat should be kept in mind that the sample does not include individual who has been out of labor force in all waves, because the occupation is unidentifiable. Since This sample restriction systematically excludes observations with old ages and with poor memory,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

Table 3: 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.

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.[10]

The variations in the measure of physical health are presented in Table 4 and Figure 5.

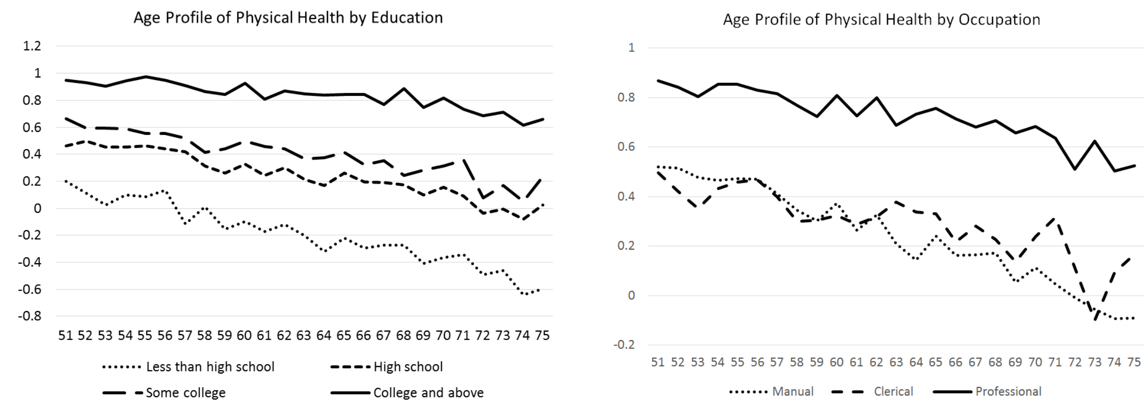
Table 4: Variation in Physical Health by Education and Occupation

	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.

[10] 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.

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.

3.3 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, we would like to ask how is cognition related to older workers' retirement in the data. We 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.[11] 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.

[11]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.

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

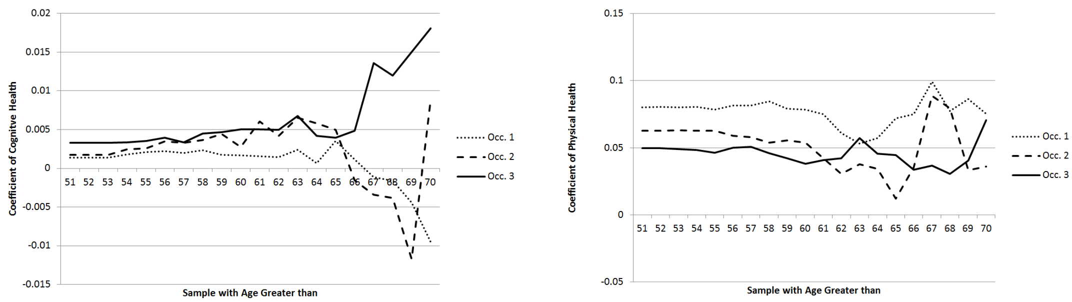
Standard errors in parentheses. Results are estimated with the primary sample. Occupations are defined as the ones in last wave while in the labor force. Log asset, log household income, mental health, health insurance, sex, race, region, education, marital status, birth place and cohort are also controlled. 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 health has the largest magnitude in manual occupations but least in the professional occupations.

Moreover, I also found the correlation between cognitive health and LFP is increasing with age only in professional occupations. Specifically, I re-estimate the above LFP regressions by restricting the sample to observations older than each given age [12]. The left graph in Figure 6 presents the results for cognitive health. An impressive feature from this figure is, the correlation between cognitive health and LFP increases in professional occupations, as the sample is restricted to older ages. At age 51, recalling one less word is associated with 0.327 percentage points decrease in the probability of remaining in labor force. This number becomes 0.5 percentage points at age 62 and increases to 1.20 percentage points at age 68. There is also an increase in clerical occupations, but this trend reverses since age 65. The correlation in manual occupations is almost flat, before plunging after age 65. On the contrary, the right graph shows no particular increasing or decreasing pattern for the correlation of physical health and LFP in all occupations.

[12] Because of the limitation of sample size, the effects by each age $\Pr(P_t = 1 | H_t^p, H_t^c, X_t, \text{age} = a)$ are very noisy. As an alternative, the estimates of $\Pr(P_t = 1 | H_t^p, H_t^c, X_t, \text{age} >= a)$ are estimated.

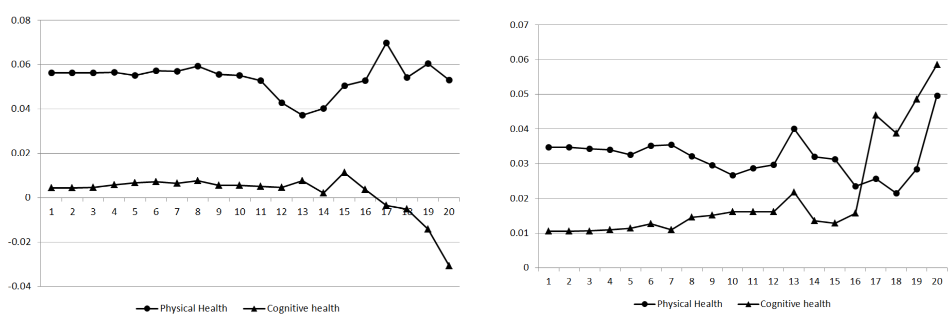
Figure 6: Occupational Effects of Physical and Cognitive Health by Samples with Different Ages



The results are the coefficients of physical health and memory in the labor force participation regressions, estimated on samples restricted to observations older than each given age.

To compare the magnitudes of the correlation with LFP of cognitive health and of physical health, I calculate the standardized coefficients of physical health and cognitive health. The left graph of Figure 7 shows, for manual occupations, the correlations between physical health and LFP are always larger than the ones of cognitive health. For instance, the correlation with LFP of cognitive health is just 12.6% of the one of physical health for individuals older than 56. For individuals older than 62, this percentage reduces to 10.8%. In terms of the professional occupations, the correlation of cognitive health relative to the one of physical health becomes larger when the sample is restricted to older ages.

Figure 7: Heterogeneous Effects of Physical and Cognitive Health for Manual Occupations (left) and Professional Occupations (right)



The results are the coefficients of physical health and memory in the labor force participation regressions, estimated by the sample restricted to observations older than each given age.

The above findings may suggest memory becomes more disruptive when it depreciates to a certain degree. It may also relate to the Alzheimer whose onset is usually over 65 years old. Given the policy proposals considered by policymakers are focusing on raising the FRA to 68 or even 70, this increasing importance of cognitive health over age may be crucial to be taken into account.

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.

4 Model

4.1 Choice Set

In the model, individuals belong to one of the three occupation categories: Category $j = 1$ includes manual and service occupations. Category $j = 2$ consists of sales and clerical occupations, and category $j = 3$ covers managerial and professional occupations. The model abstracts from the change of occupations. At each age, individual chooses whether to participate in the labor force or not. I assume that being out of labor force is an absorbing state. Individual's LFP decision at age t is denoted by d_t, which equals to 1 if the individual is in the labor force.

Besides the LFP decision, individual also chooses how much to consume in each period. Consumption is a continuous variable, whose optimization is subject to an upper bound due to the borrowing constraint. There is also a consumption floor insured by the government. It captures the public transfer such as the Supplemental Insurance Income (SSI) for very poor people. Individuals in the model make the LFP decisions up to age $A^* = 75$ and the consumption decisions until age $A^{**} = 90$.

For computational feasibility, I refrain from modelling individual's Social Security application as French (2005). 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. One limitation of this assumption is that individuals are not subject to the Social Security earning test by construction, if they have started the benefits collection but remain in the labor force. This assumption reduces the incentive to retire immediately after age 62.

4.2 Utility Function

The utility function consists of a pecuniary and a non-pecuniary component. Pecuniary utility is in the CRRA form with the coefficient of risk aversion ν. Non-pecuniary utility L_t linearly depends on individual's LFP status and occupation j, as well as on his physical health h_t^p and cognitive health h_t^c. When individual is in good health, there is an occupation-dependent disutility λ_{1j} if he chooses to participate in the labor force. Moreover, I also allow the extra disutility of working due to poor physical and cognitive health to depend on the occupation, as captured by the parameters λ_{2j} and λ_{3j},. This is to reflect the intuition that workers with poor physical and/or cognitive health can suffer differently across occupations.

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

where

$$L_t = \sum_{j=1}^{4} \lambda_{1j} d_t^j + \sum_{j=1}^{4} \Big(\lambda_{2j} h_t^p + \lambda_{3j} h_t^c \Big) d_t^j + \varepsilon_t^{d_t} \tag{2}$$

The utility is also subject to choice-specific idiosyncratic preference shocks $\varepsilon_t^{d_t}$. They are assumed following an i.i.d. extreme type one distribution. The structural interpretation of these shocks is that they are state variables unobserved to researchers but observed to individuals in the model. These preference shocks are assumed to be choice-specific, and the joint distribution of these shocks across choices affects individual's LFP decision. Notice that these preference shocks are assumed additive to consumption, which implies the consumption decision is independent of them once conditioning on the LFP decision. Therefore, conditional on the observed state variables in our model, these choice-specific preference shocks εs only introduce randomness to the discrete LFP choices. To allow random consumption decisions conditional on the observed state variables in the model, I assume an extra unobserved state variable attached to the total income, which will be specified below.

4.3 Budget Constraint

Individuals' assets accumulate as the following formula:

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

This asset transition is subject to the borrowing constraint $A_{t+1} = (1+r)A_t + Y_t - ME_t - C_t \geq A_{min}$. A_{min} is the minimum asset required and it is set constant as -5,000 dollars. By this assumption, individuals are free to save but face a constraint to borrow from the future. Meanwhile, I assume that there is a consumption floor C_{min}. The consumption floor captures the government transfer, such as Supplement Security Income(SSI) and Medicaid, for those in extreme poverty. Therefore, in each period the individuals can choose their consumption between the range $[C_{min}, C_{Max}]$, where $C_{max} = (1+r)A_t + Y_t - ME_t - A_{min}$ and C_{min} is assumed constant as 2,000 dollars . The government transfer takes place in the extreme case that individual's asset and income are too low and the out-of-pocket medical expense is too high, which implies $C_{max} <= C_{min}$. In this case, the government provides a basic transfer which equals to $\max\{0, C_{min} - ((1+r)A_t + Y_t - ME_t - Amin)\}$, so that every individual can reach the minimum consumption floor. [13]

4.4 Income

The total income consists of individuals' labor earnings W_t^j, Social Security benefits ss_t, private pension P_t, his spousal income W_t^s, and a total income shock ζ_t:

$$Y_t = \sum_{j=1}^{3} d_t^j W_t^j + d_t^4(ss_t + P_t) + W_t^s + \zeta_t \tag{4}$$

The labor earnings is the product of the skill rental price r^j and an index of human capital. The human capital depends on experience, education and two dimensions of health, which are all allowed to have different returns across occupations:

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

[13] French and Jones (2011) assumes that individual has borrowing constraint $A_t + Y_t - C_t \geq 0$, which is not affected by the medical expense.

Following French (2005) and French and Jones (2011), spousal income is predicted by a set of demographics.[14] Social Security retirement benefits ss_t are calculated by formulas strictly following the Social Security Administration, which will be specified in the next subsection. 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, whereas Van der Klaauw and Wolpin (2008) restricts the sample to individuals without private pension. Alternatively, French (2005) and French and Jones (2011) approximate private pension by the model's existing state variables. To maintain reasonable sample size, this paper approximates the private pension following these two studies. Appendix provides detailed discussion about the modelling of private pension.

4.5 Social Security

This paper calculates the Social Security retirement benefits closely following the rules of the Social Security Administration. According to these 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 calculated as a piecewise linear function of AIME, with three separate percentages of the portions of AIME. It functions similarly 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 individual starts drawing the benefits. For example, when FRA is 65, individuals who claim their benefits at age 65 will receive an amount as much as 100% of the PIA, where as those retire at age 62 can only receive 80%. In this paper, AIME is calculated from the Social Security earnings history data and serves as a state variable. I then calculate the PIA as well as the Social Security benefits based on it.[15]

Individuals aged 62 to 69 who are taking Social Security benefits but still working are subject to the Social Security earnings test [16]. The money withheld by earnings test are not lost but credited to the benefits after the individual retires. However, the money withheld between 62-64 are actuarially fair whereas since age 65 this withholding is not the case, which means individuals working after age 64 are essentially taxed by the Social Security earnings test [17]. For this reason, Social Security

[14] To avoid adding extra state variables, we 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.

[15] My application for the Social Security administrative data of earnings history is under review, which is expected to be approved shortly. Therefore, the results in the current version paper are based on a constant AIME which is able to simulate retirement benefits close to the average level in the data.

[16] After 2000, the earnings test for individuals with age 65 and older are abolished

[17] See French and Jones (2011) for detailed discussion

benefit requires a recalculation when individuals eventually exit the labor force. However previous studies usually abstract from this recalculation because of the complexity, which is also followed by this paper.

As mentioned before, we do not model the Social Security application independently. By assumption, individual starts to draw Social Security benefits once they exit from the labor force after age 62. One implication of this assumption is that individuals who continue working after age 62 without interruption are assumed to collect no Social Security benefits until their exit from the labor force. These individuals are therefore not subject to the earnings test by construction.

Based on the formula of how AIME is computed, the transition rule of AIME takes following form:

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

We denote the current earnings as W_t and the earnings history until age t-1 as $\dot{W}_{t-1}$. Basically, the AIME is updated only when the current earnings is higher than the minimum earnings among the 35 years which were used in previous calculation. Notice that if the individual hasn't worked enough 35 years, $\min(\dot{W}_{t-1})$ is 0 and AIME is always contributed by working. Modelling the transition process precisely requires us to keep track of the whole earnings history of the individuals to calculate the $min(\dot{W}_{t-1})$, which is intractable. French and Jones (2011) use a fraction of 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, that is $\alpha_t AIME_t$, 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. French (2005) simply uses the current AIME as the proxy for minimum earnings, in which case the coefficients α_t is set as 1. While the simulation-based estimates of α_t can be developed, this paper follows the simpler assumption with $\alpha_t = 1$.

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

4.6 Health, Medical Expense and Health Insurance

Physical and cognitive health transit jointly with uncertainty. The transition of joint health to period t+1 depends on individual's age t, education E, labor supply and occupation j_t, current joint health status h_t, as well as idiosyncratic shock u_t. The joint health status takes 4 states, which is a combination of physical health h_t^p and cognitive health h_t^c.

$$h_{t+1} = h(t, E, j_t, h_t, u_t) \tag{6}$$

The out-of-pocket medical expense ME_t is assumed as a function of the joint health status h_t and the insurance type H_t^*.[18]

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

The health insurance H_t^* has 4 types. The first three types are associated with the insurance offered by employers when individuals are younger than 65. When individuals are older than 65, they are insured by the public health insurance Medicare.

1. $H_t^* = 0$: not offered health insurance by employers;
2. $H_t^* = 1$: offered health insurance without retiree coverage;
3. $H_t^* = 2$: offered health insurance with retiree coverage;
4. $H_t^* = 3$: with public health insurance Medicare.

We assume that individual expects the insurance type in next period by the following transition rules:

- If $t \geq 65$, then $H_t^* = 3$
- If $H_t^* = 2$, then $H_{t+1}^* = 2$
- If $H_t^* = 1$ and $d_t = 1$, then $H_{t+1}^* = 1$
- If $H_t^* = 0$ or ($H_t^* = 1$ and $d_t = 0$), then $H_{t+1}^* = 0$

[18] This paper abstracts from the uncertainty in medical expenditure, following Van der Klaauw and Wolpin (2008) and Capatina (2015). This tends to underestimate the retirement effect of health through the medical expenditure channel. However, introducing uncertainty to medical expenditure requires adding an extra unobserved state variable to the model. It not only enlarges the state space but also requires integrating out this unobserved component when solve the model. This is exceptionally challenging given that our model has already an unobserved component attached to the total income to be integrated out.

The second case is associated with the retiree coverage insurance, which provides health insurance independent of individual's labor supply until age 65. In the third case of the insurance without retiree coverage, individual continues being insured as long as he keeps working. In the fourth case, health insurance remains unavailable if there was no insurance in last period. Meanwhile, when individual has an insurance tied to his labor supply, the insurance would cease in next period if the individual exited from the labor force in the current period.

4.7 Value Function

Taking into all the factors described above, individuals make their LFP and consumption decisions at each age to maximize their present discounted utility, conditional on the union of state variables Ω_t.

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

Survival rate p_t is affected by age and the joint status of physical and cognitive health h_t.

$$p_t = Pr(s_{t+1} = 1 | s_t = 1, h_t) \tag{9}$$

Utility from bequest depends on the asset left to next period. Following Van der Klaauw and Wolpin (2008), this paper assumes the simple form below:

$$B(\Omega_{t+1}) = \iota A_{t+1} \tag{10}$$

Finally, the state variables Ω_t included in our model are : age, education, AIME, physical health, cognitive health, asset, Social Security status in last period, health insurance type, occupation and labor force participation in last period, experience, the random components to income and to the non-pecuniary utility.

5 Solution and Estimation Method

5.1 Model Solution

I solve the model by the backward induction. Model's policy functions, which consist of the discrete LFP choice and the continuous consumption decision, has no analytical form and is obtained numerically. The solution process follows the steps below.

1. Given each LFP status d_t, calculate the choice-specific value $\text{CSV}^d(C_t, X_t, \zeta_t, \varepsilon_t^d)$, which is a function of consumption C_t conditional on observed state variables X_t, unobserved state variables ζ_t and ε_t^d. There are two types of unobserve state variables in our model: the shock to total income ζ_t and the choice-specific shock to non-pecuniary utility ε_t^d.

2. Search for the optimal consumption which maximizes the choice-specific value function at each possible value of the observed and unobserved state variables. Notice that the consumption optimization given each LFP choice is independent of the shock to non-pecuniary utility ε_t, because this shock is assumed to be additive. In this step, I obtain the choice-specific optimal consumption $C_t^{d*}(X_t, \zeta_t)$ and the corresponding optimal choice-specific value $\text{CSV}^{d*}(C_t^{d*}, X_t, \zeta_t)$ (net of the preference shocks ε_t^d). These two items are functions of the observed state variables X_t and the unobserved shock to total income ζ_t.

3. By comparing the optimal choice-specific values $\text{CSV}^{d*}(C_t^{d*}, X_t, \zeta_t, \varepsilon_t^d)$ over the LFP choices, individuals choose their optimal LFP choices. The model solutions are eventually characterized by the LFP choice and the optimal consumption conditional on each LFP choice. They are deterministic functions of the observed state variables X_t and unobserved state variables ε_t^d and ζ_t. However, conditional only on the observed state variables, the LFP decision and the consumption decision are stochastic.

In the second step, I search for the optimal consumption conditional on the LFP choice. Because the choice-specific value function $\text{CSV}^d(C_t, X_t, \zeta_t)$ net of the shock ε_t^d may not be continuous in consumption due to the consumption floor and borrowing constraint, it is inappropriate to use the derivative-based optimization method to search for the optimal consumption. Instead, I discretize the consumption into finite grid points and search over these points. I follow the method used by French and Jones (2011) to fasten the search process. In particular, I only search over all the grid points in the final stage (at age 90) during the backward induction. For the earlier stages, given each set of observed state variables X_t, I start the search from the value of consumption in period t+1 optimized at the same states as X_t (except age). That is, the search in period t starts at the value of $C_{t+1}^{d*}(X_{t+1}, \zeta_{t+1})$, such that (X_{t+1}, ζ_{t+1}) are the same as (X_t, ζ_t). Based on this point, I then search over a neighborhood instead of the whole consumption space. Specifically, for each starting point *Cbest* I define the neighborhood [*Cbest-Cnear, Cbest+Cnear*]. I firstly compare the utility at *Cbest*, *Cbest-Cnear* and *Cbest+Cnear* . If *Cbest* provides the highest utility, which suggests at least a local maximum is within this range, then I search over this range [*Cbest-Cnear, Cbest+Cnear*]. If the function is generally monotonic increasing or decreasing in this range (i.e. $U(Cbest - Cnear) \leq U(Cbest) < U(Cbest + Cnear)$ or the other way around), I set *Cbest+Cnear* (*Cbest-Cnear* in the case of monotonic decreasing) as the new starting point and repeat the same step. I discretize consumption into 100 grid points and set the neighborhood as ± 5 grid points. I compared the results with the full search results, and the bias is small. [19]

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

5.2 Estimation

Upon solving the model, the parameters are estimated by a two step approach. Parameters in health expenditure equations, health transition equations and survival functions are estimated in the first step. Preference parameters and parameters in the wage equations are estimated jointly in the second step by Indirect Inference. Indirect Inference, which is a simulation-based estimation approach, has the advantage if likelihood function is difficult to compute. It searches for the structural parameters which simulate data as close as to the observed data based on a set of chosen criteria. The set of criteria are the parameters of a bunch of auxiliary models which are easy to estimate. In a nutshell, this method searches for the structural parameters which minimizes the distance between the auxiliary parameters estimated with actual data and the ones estimated with the simulated data. 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 estimation criterion of Indirect Inference. When auxiliary models are correctly specified as the data generating process, estimates based on these three metrics are asymptotically equivalent, otherwise LR will be less efficient than Wald and LM with the optimal weighting matrixes. Instead, the advantage of LR is it does not require the estimation of weighting matrix. Compared to Wald and LR, LM has the advantage that parameters of auxiliary models do not need to be estimated on the simulated data to establish the estimation criterion. This is easy to apply especially if it takes time to estimate the parameters of auxiliary model.[20] On the other hand, Wald is preferable if the likelihood or score functions of auxiliary models are not trivial to construct [21]. In this paper, I am

[19] The appendix provides further details for this grid search method when the choice-specific function is not concave.

[20] The estimation of parameters of auxiliary models can also be complex. For instance, when the auxiliary model is logit or probit, numerical optimization is required.

[21] In general, the auxiliary models should not be too complicated, which is the essential motivation for Indirect Inference.

going to deploy the metric analogous to LM to construct the estimation criterion.

Guided by the reduced form evidence in Section 3 and the structural policy functions, I choose the following three sets of auxiliary models:

- Approximate LFP equations: linear probability model of LFP binary indicator on physical health, cognitive health, asset, insurance type, last Social Security status dummy, age and age squared, separately estimated by each occupation.

- Approximate wage equations : linear regression of wage on physical health, cognitive health, experience, experience squared, separately estimated by each occupation and conditional on observed wages.

- Approximate asset change equation: linear regression of changes in asset between t+2 and t on physical health, cognitive health, insurance type, last Social Security status and age dummies.

5.2.1 Identification

This subsection intends to provide a basic intuition for the identification of the structural parameters.

Structural parameters estimated by Indirect Inference can be grouped into three categories. The first category consists of parameters in the non-pecuniary utility component: the occupation-dependent disutility of working λ_{1j}; the extra disutility of working due to poor physical health λ_{2j} and poor cognitive health λ_{3j}. The second category includes parameters in the wage equations: the skill rental prices in each occupations r^j; the constant terms in human capital equation κ_{1j}; the experience premium κ_{2j} and κ_{3j}; the education premium κ_{4j}; the penalty of poor physical health κ_{5j} and of cognitive health κ_{6j}. The last category includes parameters related to the consumption utility: the coefficient of bequest ι, the coefficient of risk aversion ν and the variance of preference shock σ^p.

The variation in wages with respect to the variation in wage determinants help identify the parameters in wage equations. Once the effects of physical and cognitive health on LFP through the channels of wage, medical expense and life expectancy are captured, the remaining variation in LFP against the variation in physical and cognitive health pins down the disutility of working due to the poor physical and cognitive health λ_{2j} and λ_{3j}. Further more, the heterogeneous gradients of LFP over health across occupations identify the occupation-dependent disutility of working due to poor health. At last, once the effects of all factors on LFP are controlled for, the baseline probability of LFP in each occupation identifies the occupation-dependent disutility of working λ_{1j}. In terms of the parameters of pecuniary utility, the age profiles of both LFP and assets help identify these parameters.

6 Data

The model is estimated on the data from the third to eleventh wave of Health and Retirement Study.[22] 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 .[23] Our 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.[24] 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

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

[23] 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 .

[24] 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.

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 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.[25] 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.

[25] 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. Our 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.

7 Results

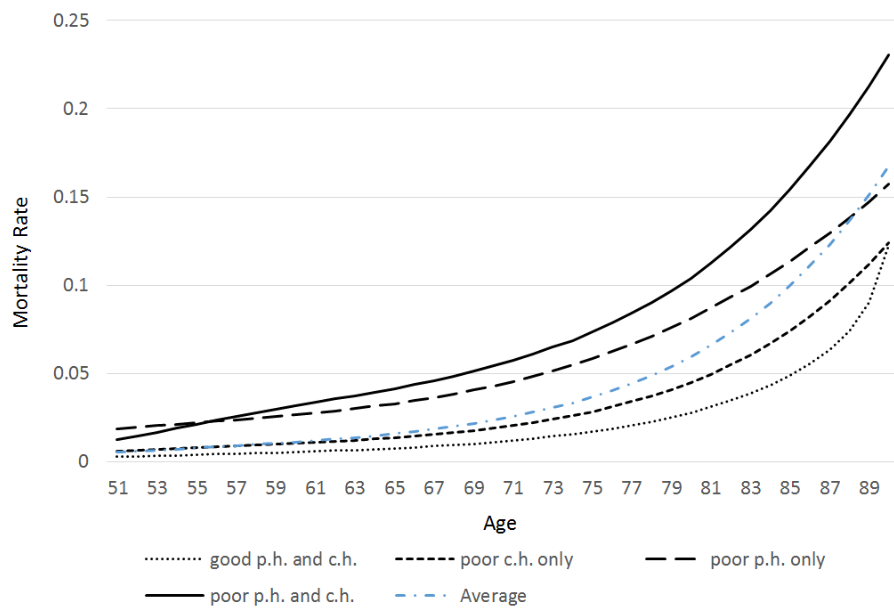
7.1 Mortality Rates

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 8: Estimates of Mortality Rates by Joint Health Status



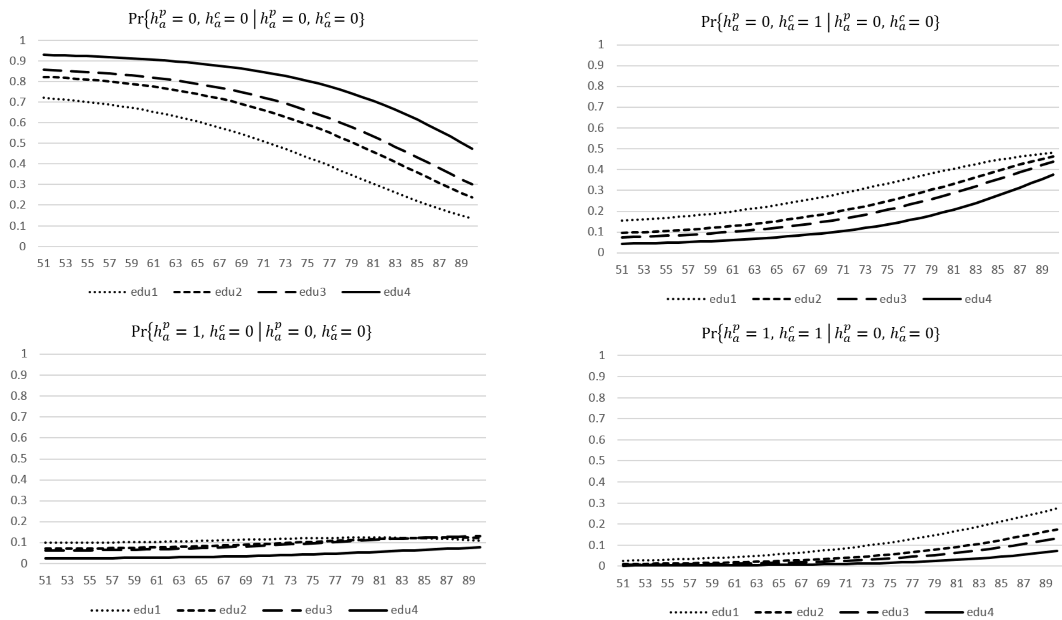
7.2 Health Transition

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.[26]

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.

[26]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 9: Transition Probabilities of Health conditional on $\{h_t^p = 0, h_t^c = 0\}$



7.3 Preference Parameters and Wage Equation

Preference parameters and parameters of wage equations 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 and spousal income equation, are held fixed in the second step estimation. The estimates of preference and wage parameters are presented in Table 7:

Table 7: Estimates of Preference and Wage Parameters

	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)
Wage			
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)
Pecuniary utility			
Bequest motive ι	0.044		
	(0.00016)		
Coeff. of risk aversion ν	1.835		
	(0.0067)		

Parameters are estimated by Indirect Inference. 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 our 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.

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, which is probably due to the assumed multiplicative form for pecuniary and non-pecuniary utility. This paper, similar to the rest studies, takes an additive form.

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. [27] $-\lambda_2$ 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 occupation-dependent effects of physical and cognitive health are less clear 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.

8 Counterfactual Experiment

8.1 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, our 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.[28] 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

[27] 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.

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

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 8 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 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, we 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 8: 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 8 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.

8.2 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 9: 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 9. 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 9 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.[29] 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

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

their retirement, our 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 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.

9 Conclusion

Since 1960s, skill-biased technical change has been increasing 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 10: 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 [30]. 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 10 and 11 list the mapping between the three categories defined in this paper and HRS 2-digit masked occupations.

Table 10: 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 our sample. This classification is applied to HRS wave 1 to 7.

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

Table 11: 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 our 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, we 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 [31].

C.0.2 State Variables

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

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

begins 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, we 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, we 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, we 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, we cannot distinguish whether it is his first time or not if he stops working without the assistance of extra varaibles. Therefore we 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 [32].

Appendix D Private Pension

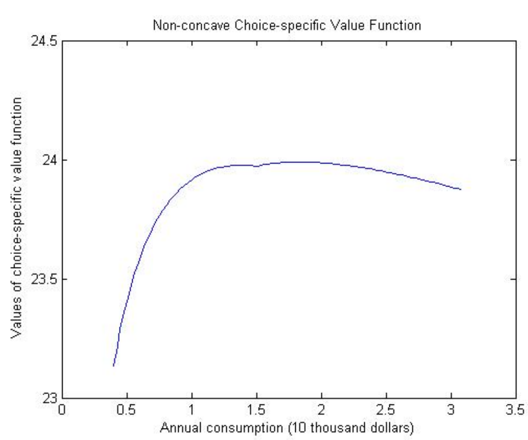
Private pension is an important supplement to Social Security, particularly for people with high income. Coile and Gruber (2007) reveals that private pension has equivalent importance in incentivizing older people to retire. There are two main plans of the private pensions: the defined-benefit pension 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

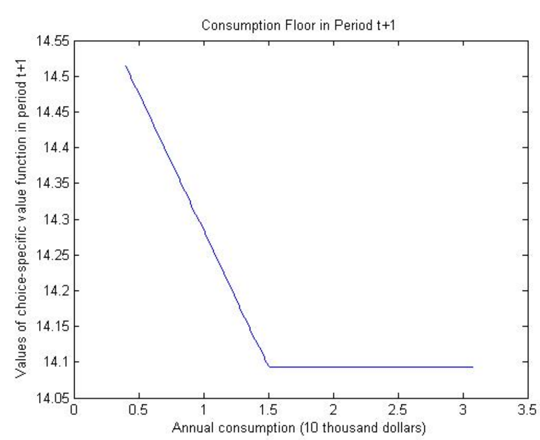
[32] French and Jones (2011) models the Social Security application. Thus whether it is the first time of benefits taking can be determined directly from the choice variable. Van der Klaauw and Wolpin (2008) does not have Social Security application as a choice variable. Nevertheless they add the age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

every individual respectively.[33]. Alternatively, Van der Klaauw and Wolpin (2008) abstracts from modelling the DC plan because it requires adding an extra decision variable similar to saving [34] 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 $U(Cbest + Cnear) > U(Cbest) < U(Cbest + Cnear)$, we 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.





[33]Examples include Blau and Gilleskie (2008) and Bound, Stinebrickner, and Waidmann (2010)
[34]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 [35][36]. 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.

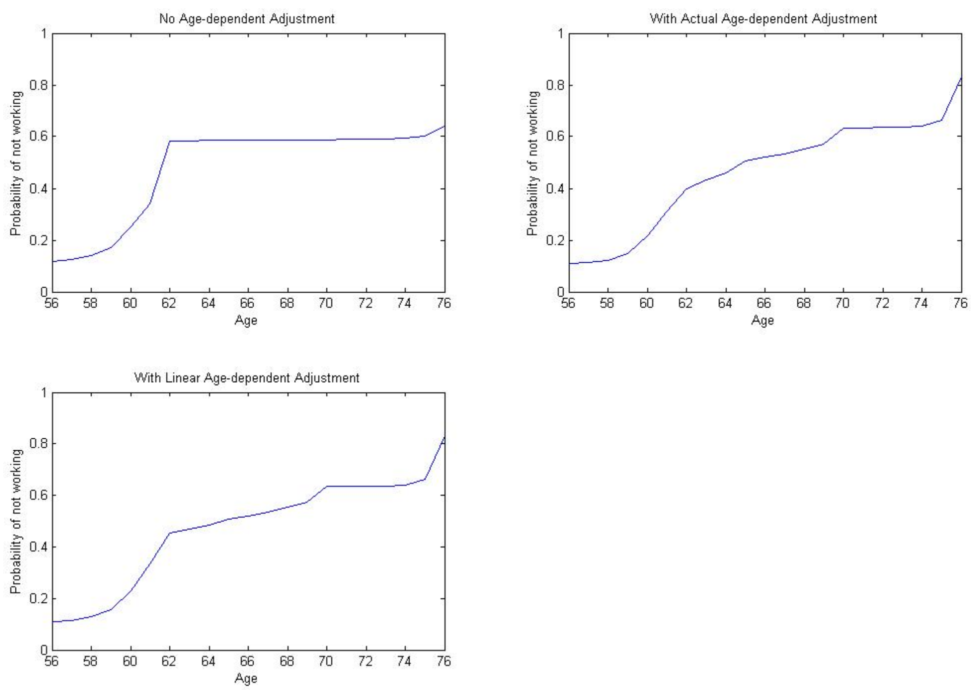
   Another issue is the variance of medical expenses. In the current model the medical expenses is deterministic and it affects individuals' decisions just through the budget constraint. As Rust and Phelan (1997) and French and Jones (2011) pointed out, the uncertainty of the medical expenses together with 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

[35] However if we 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.

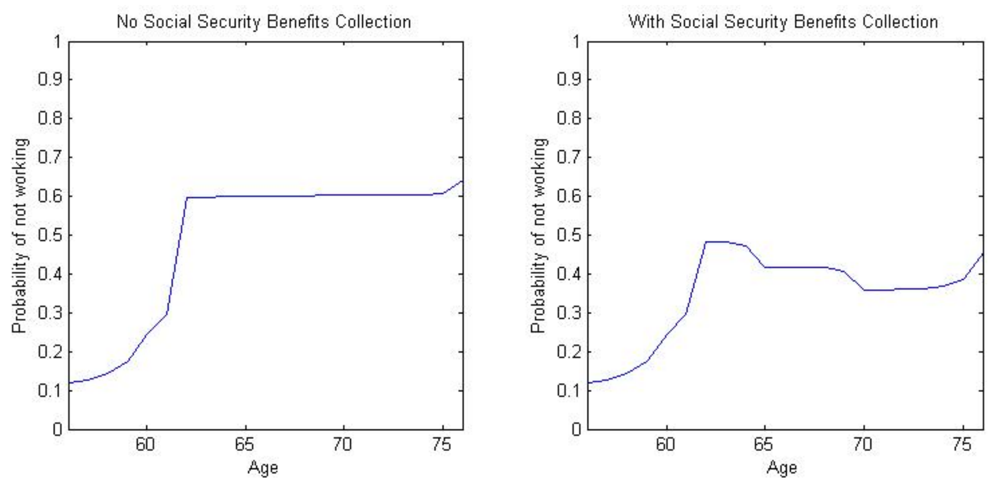
[36] If we want to recalculate the Social Security benefits because the money collected by earning test is refunded in the future, then this gives incentive to not working after age 65 instead of age 62. This is because, thought the earning test is applied since age 62, the recalculation of the benefits 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. We plot how does the probabilities of not working vary over ages under 3 specifications. Under the first specification, we assume no age-dependent adjustment, so individual always receives 100% PIA as the monthly benefits. In the second specification we 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[37]. The earnings test is only applied to individuals younger than 65 since 2000. In our model, individuals cannot receive the public pension and keep working in their first year of Social Security benefits collection, because we 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, we 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. We 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 our 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.

[37]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 we 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 our 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 [38].

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 [39]. 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 our 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

[38] 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.

[39] In our 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. We 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, we 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 we have no information regarding to individual's job status in period t-1. This is because while we do have information about the job in period t-2, we don't know when did that job finish. However, given that these observations account for a very small fraction of our sample, we assume that the job in period t-2 had extended to period t-1. Namely, in this minor case we assume the job status in period t-1 remained the same as in period t-2 [40]. 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 [41], we 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, we 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

[40] 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, we 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.

[41] 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 our 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

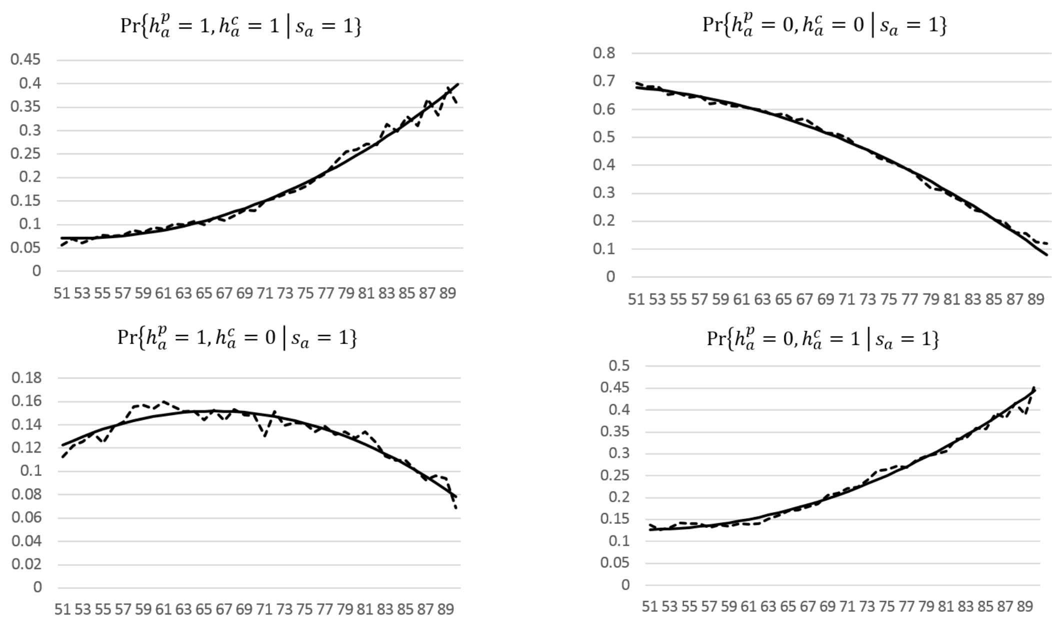
Existing literature usually assumes that mortality depends on health and age. Restricting the sample for the structural estimation to observations alive in last period, mortality rates can be estimated by regressing mortality indicator on health and age polynomials. The limitation of this approach is 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.

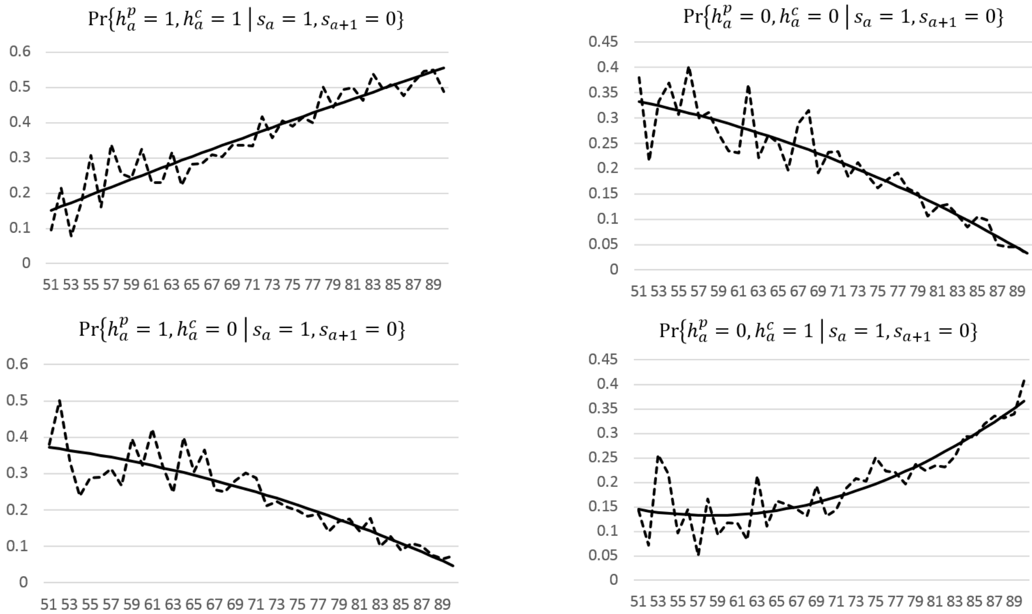
This paper estimates the mortality rates following French (2005). The unconditional survival probability $Pr(s_{t+1} = 0|s_a = 1,)$ is obtained from Social Security Administration actuarial life tables. We use HRS data to estimate the health shifter $Pr(h_t^p, h_t^c|s_{t+1} = 0, s_a = 1)/Pr(h_t^p, h_t^c|s_a = 1)$. 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 we can see the fitness is very good.

Figure 11: Probabilities of Health States Conditional on Being Alive at Each Age



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

Figure 12: Probabilities of Health States Conditional on Deceasing after Each Age



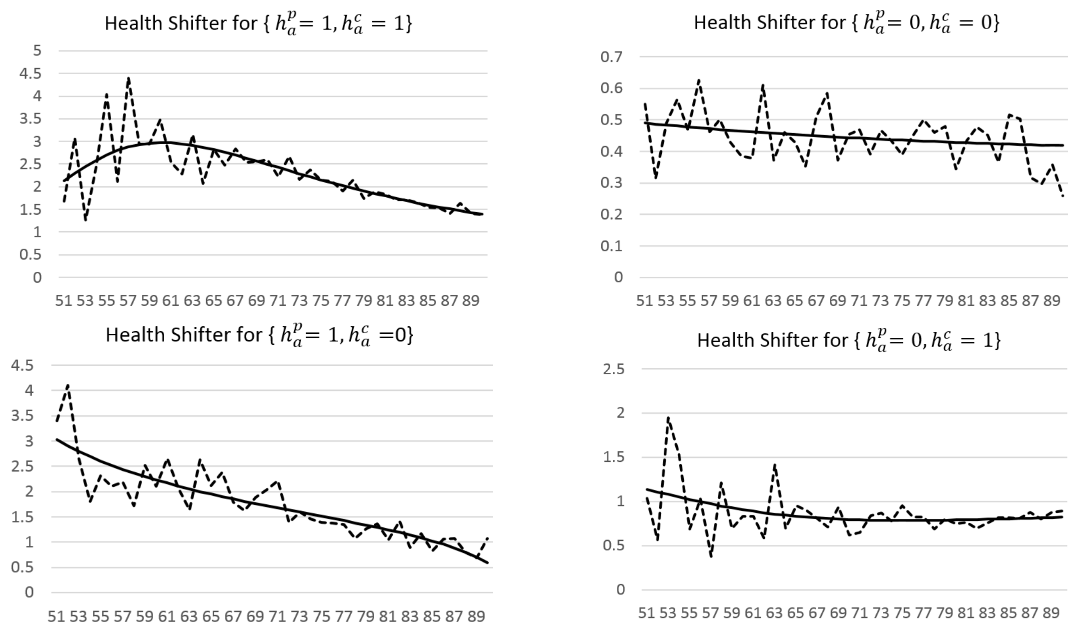
. Dash lines are the raw probabilities and solid lines are smoothed.

Figure 11 and Figure 12 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 [42], 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 13. 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. We 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.

[42] 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 13: 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 14: Transition Probabilities of Health conditional on $\{h_t^p = 1, h_t^c = 1\}$

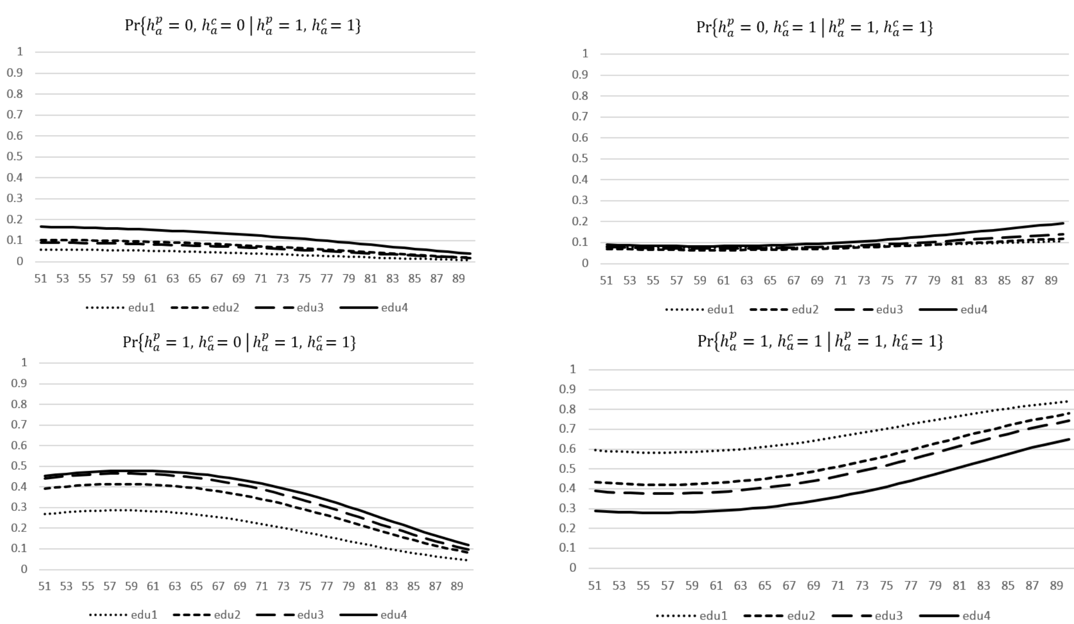


Figure 15: Transition Probabilities of Health conditional on $\{h_t^p = 0, h_t^c = 1\}$

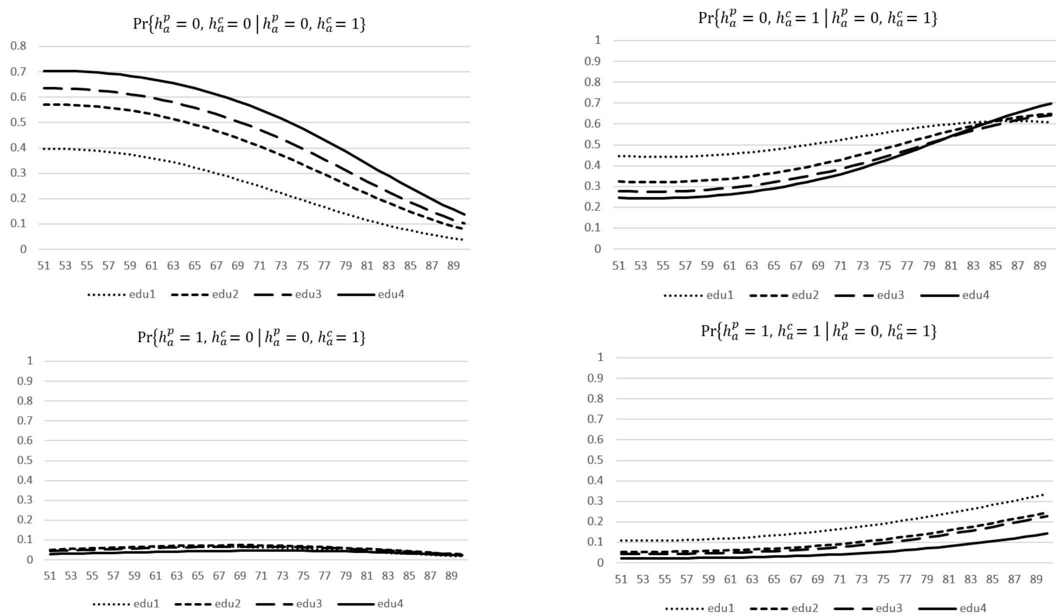


Figure 16: Transition Probabilities of Health conditional on $\{h_t^p = 1, h_t^c = 0\}$