Social Security Reform, Occupational Retirement
and the Heterogeneous Roles of Physical and
Cognitive Health*

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Abstract

This paper develops and estimates a structural dynamic programming model of retirement and savings with focus on the interplay between different dimensions of health and occupations, as well as its policy implications for Social Security reforms. Motivated by our reduced form evidence, the model incorporates not only physical health but also cognitive health. It allows for the heterogeneous retirement effects across occupations of both dimensions of health via leisure, wages, medical expenditure and mortality. Model is estimated by indirect inference using Health Retirement Survey data. The findings suggest that the effects of physical and cognitive health on labor force participation at older ages vary across occupations. Moreover, in terms of both dimensions of health as a whole, health turns out to affect the labor supply at older ages more in the sedentary occupations. This paper also quantifies the importance of the four channels through which health can affect retirement for both physical and cognitive dimensions. Finally, this paper simulates the heterogeneous response in retirement across occupations under proposed Social Security reforms.

Key Words: Cognitive Health; Occupation; Retirement; Social Security

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1 Introduction

The Social Security fund in the US is going to suffer a large deficit under the circumstance that not only more and more people are getting older but also that older people have much longer life expectancy. Related to this, the Social Security Amendments of 1983 has increased the full retirement age (FRA) from 65 to 67. However, active discussions about increasing the FRA further are still ongoing. For example, the Social Security Policy Options 2015 by Congressional Budget Office examines the options to increase FRA to age 68, to age 70, and to increase it by one month per birth year. In April 2017, Martin Feldstein, the chairman of the Council of Economic Advisers under President Reagan, suggested in the Wall Street Journal that increasing the FRA to age 70, as Reagan did in 1983, can offset revenue loss from Trump’s tax cut. An important question is, how will older people’s health affect the likelihood of delaying their retirement? And how will it differ by occupations? Answer to this question is closely related to the effectiveness of the proposed Social Security reforms. The interplay between various dimensions of health and distinct abilities required, together with a large heterogeneity in demographic variables across occupations, may imply nontrivial heterogenous effects of these policy reforms, and incur unequal welfare changes. This paper establishes and estimates a structural dynamic model of retirement and saving, incorporating not only physical but also cognitive dimension of health. It seeks to understand the heterogeneous roles of different dimensions of health across occupations and its implication on Social Security reforms.

As the skill-biased technological change happens, jobs are becoming less physically demanding whereas they require more cognitive abilities. However, research about the importance of cognitive health on older workers’ labor supply is scant. Moreover, the heterogeneous roles of physical and cognitive health across occupations may imply very distinct policy response. For example, construction workers may be unable to carry heavy materials when they are old because of the physical health deterioration. Teachers with poor memory may suffer from hardship in teaching if they find it difficult to recall knowledge. These individuals, with poor health in distinct dimensions, both are less likely to delay their retirement when the Social Security reform happens. Meanwhile, increasing the FRA implies a reduction in the Social Security retirement benefits, and people with difficulty delaying their retirement due to their poor health are going to suffer a larger welfare loss. For example, conditional on retiring at age 62, individuals with FRA at 65 can receive 80% of the full benefits, and this proportion declines to 70% for those with FRA at 67. If FRA was raised to 70, this number will be further reduced to 55% according to current formula. This issue has been already noticed by policy makers. As Social Security Amendment of 1983 describes: “Requires the
Secretary of HHS (Department of Health and Human Services) to conduct a comprehensive study and analysis of the implications of the changes in retirement age for those individuals affected by the provision for increasing full retirement age who, because they are engaging in physically demanding employment or because they are unable to extend their working careers for health reasons, may not find their work lifetimes are increased as a result of general improvements in longevity”. However, based on the traditional measure of health which largely weighs on the physical dimension, most researchers and policy makers have focused on the physically demanding occupations. The impacts of Social Security reforms on the welfare of workers from the sedentary occupations may thus be underestimated.

To address the above concerns, this paper constructs a structural dynamic programming model of labor supply and saving decisions of male household heads in the United States. The model includes 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. In particular, the model captures the interaction between occupations and different dimensions of health. To do this, the model allows the disutility of working depends not only on physical and cognitive health status but also on their interaction with occupations. It also allows the wage penalty of poor physical and cognitive health to be occupation-dependent. On top of these, both types of health can shift medical expenditure and survival probabilities. I estimate the model by indirect inference with HRS data from 1996 to 2012. Based on the estimates, this paper firstly quantifies the importance of physical and cognitive health on labor force participation across occupations. It finds that, under current Social Security rules, if individuals were assumed to maintain good physical health, the labor force participation rate between age 65 and 69 increases by 18.76% for manual and service workers, compared to 14.93% for sales and clerical workers and 13.15% for managerial and professional workers. On the contrary, if persistent good cognitive health were assumed, the labor force participation rates increase respectively by 13.37% and 9.51% for sales+clerical occupations and for managerial+professional occupations, whereas there is negligible change for manual+service occupations. Importantly, if both physical and cognitive health were fixed as good, the increase in labor force participation rate is found larger for sedentary occupations than manual+service occupation. This result, which is in contrast to the usual opinion that poor health mainly affects the retirement of workers in physically demanding jobs, reveals the need to pay more attention to the health issue in cognitively demanding occupations.

Besides the aggregate effects, I also evaluate the relative importance of different underlying channels that physical and cognitive health can affect older individuals’ retirement. Following previous
studies such as Capatina (2015), the model allows both physical and cognitive health to affect individual’s utility through leisure, wage, medical expenditure and mortality. In terms of the combination of both dimensions of health, our results suggest that the channels of leisure and mortality are the most important ones. For manual and service occupations, labor force participation rates increase 3.5% and 2.99% respectively if these two channels are shut down, compared to the 8.81% increase if all channels are switched off. The relative importance of different channels are similar for the other occupations. However, if we examine these channels for a specific dimension of health, very large heterogeneity across occupations raises. For example, physical health has the largest effect on retirement through the leisure channel for manual and service occupations, whereas its effects through mortality channels across occupations are much more homogeneous.

Finally this paper quantifies the changes in labor force participation for workers across occupations under different proposed Social Security reforms. When full retirement age is increased from age 65 to 70, workers in manual and service occupation are found to be most responsive in labor force participation. Although workers in these occupations on average have worse physical health, the small effect of cognitive health and the strong income and substitution effects of financial factors are the main reasons for this large elasticity of labor supply.

An increasing number of studies about retirement have relied on structural models not only to capture the dynamics in financial and health variables, but also to implement counterfactual experiments by simulating individuals’ behaviors under 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 (French (2005)), 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 take into account demographic variables such as health and life expectancy. Due to the modelling complexity, the computational budget limits the number of state variables. Therefore the measure of health used in these studies is usually a single broad self-reported variable. Bound, Stinebrickner, and Waidmann (2010) have the particular focus on the role of health in retirement. They firstly deal with the measurement bias in this self-reported health measure within a structural dynamic programming model framework. Capatina (2015) also focuses on the retirement and saving effects of health for older individuals. Particularly, she accounts for the importance of four underlying channels: leisure, wage, medical expense and life expectancy. However these two papers are still based on a single comprehensive measure of health. To the best of my knowledge, my paper is the first one
models not only physical but also cognitive dimensions of health, and examines their different roles in retirement and savings across occupations. In this paper, I model the endogenous saving decisions as French (2005), Van der Klaauw and Wolpin (2008) and French and Jones (2011). I also take care of the justification bias of self-report health following Bound, Schoenbaum, Stinebrickner, and Waidmann (1999).1 As a further step from Capatina (2015), this paper accounts for the importance of underlying channels for both physical and cognitive dimensions of health respectively.

Also, previous studies have mainly focused on the aggregate response in labor supply and savings to the Social Security reforms.2 This paper explores the heterogeneous response in individuals’ labor supply and savings across occupations, as well as the potential inequality in welfare changes induced by those reforms. The reason why occupation instead of other social status is focused is because the different dimensions of health should have retirement effects directly interact with occupations due to their distinct ability requirements. As suggested by the guiding evidences in next section, the labor supply of individuals from manual and service occupations are more affected by their physical health, whereas cognitive health has larger effect for professional and managerial occupations. Since there is a large gap in social economic status across occupations, the potential uneven welfare changes also deserve policy makers’ concern about inequality. Importantly, by considering not only physical health but also cognitive health, this paper reveals that the retirement effects of health for workers from sedentary occupations are underestimated. This finding may encourage policy makers to reevaluate the Social Security program after reforms, such as its progressivity and the welfare implications.

Finally, this paper is also 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, under the Social Security reforms that increase the retirement ages, older individuals with poor health may have limited ability to postpone their retirement, these studies ask how much is the health capacity to work for older workers. For example, Cutler, Meara, and Richards-Shubik (2013) and Coile, Milligan, and Wise (2016) estimate the relationship between health and labor force participation using individuals aged 57-61, those younger than the early retirement age. Based on this relationship, they simulate the labor force participation for individuals aged 62-64 with their actual health measures. Then the additional capacity to work for individuals aged 62-64 with their actual health measures. Then the additional capacity to work for individuals

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1I use the predicted “health stock” as a direct measure for physical health. Bound, Stinebrickner, and Waidmann (2010) assume the self-reported health is a sum of this “health stock” and a random shock endogenous to labor supply. By allowing this extra endogenous random component, computational complexity increases drastically.

2One notable exception is Gustman and Steinmeier (1986a), which study the heterogeneous response in retirement over health and occupations. This paper focuses on a single measure of health and occupations are classified as whether physically demanding or not.
aged 62-64 is quantified as the difference between the actual and simulated labor force participation rates. These papers provide a simple approach to measure the health capacity to work, which has been applied to many other countries. In my paper, instead of directly quantifying individuals’ capacity to work, the counterfactual experiments shed light on how individuals’ ability to work is constrained by their physical and cognitive health, and how does it differ across occupations. The structural model is also explicit about the channels through which health constrains older people’s labor supply. For example, when simulating the labor force participation for individuals aged 62-64 based on the relationship estimated with individuals aged 57-61, the approach used by Cutler, Meara, and Richards-Shubik (2013) and Coile, Milligan, and Wise (2016) assumes that individuals at older ages had the same expectation for their future health as at younger ages with the same health. The structural model is helpful to capture this dynamic of health.  

The next section presents some facts about occupation and health, including the changes of ability requirements of US jobs, the measure of cognitive health used in this paper and the guiding evidence of the heterogeneous retirement effects of physical and cognitive health across occupations. Section 3 is devoted to the structural model and section 4 to the solution and estimation methods. Section 5 describes the data. Section 6 presents the estimates. Counterfactual experiments are implemented in Section 7. Section 8 concludes.

2 Physical and Cognitive Health

2.1 Changes of Ability Requirements of US Jobs

During the past decades, as the skill-biased technological change happens, job characteristics have been going through a remarkable change: more and more jobs require the cognitive abilities, whereas on average they are becoming less physically demanding. O*NET data set provides detailed information about more than 900 occupations in the US, including scores of specific abilities required by each occupation. Based on this data set and the employment data from CPS, I calculate the trends from 1968 to 2015 of required abilities under physical and cognitive categories defined by O*NET, averaged over all occupations in the U.S. and weighted by their employment shares.

As pointed out above, my model can also be used to quantify the capacity to work with more flexibility. I am not sure whether it would be attractive to do it in the counterfactual exercises.

From 964 8-digit occupations in O*NET dataset, I construct a sample based on 6-digit occupations to match with the employment data from CPS. This sample includes 773 6-digit occupations. To obtain the ability scores for those 6-digit occupation with several 8-digit sub-occupations, I simply compute the mean. To calculate the averaged abilities over these 773 occupations, each 6-digit occupation is weighted by its employment in each given year obtained from CPS. Notice that the ability scores for each occupation in O*NET are not penal data, although O*NET has updated the information for selected occupations several times. Therefore, because there is no information about the changes in required abilities within each 6-digit occupation, the variation in calculated trends comes from solely
Since 1968, all 9 abilities defined by O*NET as physical ones have been declining in demand. On the contrary, out of the 21 abilities under cognitive category, requirements for 18 abilities have increased.

Figure 1: Trends of Average Physical Abilities Required by US Jobs since 1968
Figure 2: 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 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 is uneasy to rationalize that respondent will report unhealthy just because of the difficulty in, for example,
recalling details.

In this paper, occupations are defined as three categories, mainly based on whether jobs are physically or cognitively demanding. The first category includes manual and service occupations. The second category covers clerical and sales occupations. Professional and managerial occupations consist the last category.

For the occupation categories used in this paper, I also calculate their required abilities under physical and cognitive categories defined by O*NET. The results in Table 1 and 2 show a large heterogeneity in the required abilities across occupations. However, it is clear that the physical abilities are more required by manual and service occupations than by sales and clerical occupations, as well as by professional and managerial occupations. Particularly, the scores of required physical abilities for managerial and professional occupations are all less than 50% of the ones for manual and services occupations. On the contrary, most of the cognitive abilities are more needed by those sedentary occupations, particularly professional and managerial occupations, than by the manual and service occupations.

Table 1: Physical Abilities Required by Occupations in This Paper

<table>
<thead>
<tr>
<th></th>
<th>Occ. 1</th>
<th>Occ. 2</th>
<th>Occ. 3</th>
<th>Occ.3 / Occ.1</th>
</tr>
</thead>
<tbody>
<tr>
<td>dynamic flexibility</td>
<td>7.05</td>
<td>0.88</td>
<td>0.65</td>
<td>9.3%</td>
</tr>
<tr>
<td>dynamic strength</td>
<td>33.65</td>
<td>10.54</td>
<td>9.39</td>
<td>27.9%</td>
</tr>
<tr>
<td>explosive strength</td>
<td>10.49</td>
<td>2.21</td>
<td>4.53</td>
<td>43.1%</td>
</tr>
<tr>
<td>extent flexibility</td>
<td>42.42</td>
<td>13.77</td>
<td>11.07</td>
<td>26.1%</td>
</tr>
<tr>
<td>gross body coordination</td>
<td>35.95</td>
<td>12.40</td>
<td>11.69</td>
<td>32.5%</td>
</tr>
<tr>
<td>gross body equilibrium</td>
<td>27.52</td>
<td>9.27</td>
<td>9.25</td>
<td>33.6%</td>
</tr>
<tr>
<td>stamina</td>
<td>40.79</td>
<td>14.43</td>
<td>13.56</td>
<td>33.2%</td>
</tr>
<tr>
<td>static strength</td>
<td>44.69</td>
<td>17.23</td>
<td>13.54</td>
<td>30.3%</td>
</tr>
<tr>
<td>trunk strength</td>
<td>48.98</td>
<td>22.95</td>
<td>21.57</td>
<td>44.0%</td>
</tr>
</tbody>
</table>

This table presents the average required abilities for the occupation categories defined in this paper, weighted by the employments in 2014. Last column presents the ratio of required abilities for occupation category 3 to occupation category 1 in percentage. Occ. 1 includes manual and service occupations; Occ. 2 covers sales and clerical occupations; Occ. 3 includes managerial and professional occupations.

David and Dorn (2013) also classify occupations by their required abilities, but with focus on the routine activities of occupations, i.e. whether jobs are substitutable by machine. Currently, I abstract from modelling the occupation change because it will significantly enlarge the state space. Therefore the occupations are exogenous. XX% individuals (XX% observations) have ever changed their occupations and are excluded from our final sample. By this assumption, 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. If this was the case, this paper may underestimate the effects of health on individuals’ labor supply.
Table 2: Cognitive Abilities Required by Occupations in This Paper

<table>
<thead>
<tr>
<th></th>
<th>Occ. 1</th>
<th>Occ. 2</th>
<th>Occ. 3</th>
<th>Occ. 3 / Occ. 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oral Expression</td>
<td>58.28</td>
<td>71.19</td>
<td>76.01</td>
<td>130.4%</td>
</tr>
<tr>
<td>Oral Comprehension</td>
<td>60.75</td>
<td>71.90</td>
<td>75.49</td>
<td>124.3%</td>
</tr>
<tr>
<td>Number Facility</td>
<td>29.76</td>
<td>41.45</td>
<td>44.46</td>
<td>149.4%</td>
</tr>
<tr>
<td>Mathematical Reasoning</td>
<td>28.81</td>
<td>41.66</td>
<td>47.18</td>
<td>163.8%</td>
</tr>
<tr>
<td>Information Ordering</td>
<td>53.15</td>
<td>55.63</td>
<td>63.62</td>
<td>119.7%</td>
</tr>
<tr>
<td>Inductive Reasoning</td>
<td>49.61</td>
<td>52.51</td>
<td>66.53</td>
<td>134.1%</td>
</tr>
<tr>
<td>Fluency of Ideas</td>
<td>34.76</td>
<td>40.34</td>
<td>55.79</td>
<td>160.5%</td>
</tr>
<tr>
<td>Flexibility of Closure</td>
<td>40.77</td>
<td>38.46</td>
<td>48.59</td>
<td>119.2%</td>
</tr>
<tr>
<td>Deductive Reasoning</td>
<td>52.94</td>
<td>54.67</td>
<td>69.11</td>
<td>130.5%</td>
</tr>
<tr>
<td>Category Flexibility</td>
<td>45.73</td>
<td>50.35</td>
<td>56.76</td>
<td>124.1%</td>
</tr>
<tr>
<td>Memorization</td>
<td>30.24</td>
<td>35.49</td>
<td>40.82</td>
<td>135.0%</td>
</tr>
<tr>
<td>Written Expression</td>
<td>41.96</td>
<td>58.29</td>
<td>68.25</td>
<td>162.7%</td>
</tr>
<tr>
<td>Written Comprehension</td>
<td>48.43</td>
<td>62.69</td>
<td>72.76</td>
<td>150.2%</td>
</tr>
<tr>
<td>Visualization</td>
<td>41.79</td>
<td>30.28</td>
<td>41.53</td>
<td>99.4%</td>
</tr>
<tr>
<td>Time Sharing</td>
<td>40.08</td>
<td>39.54</td>
<td>43.29</td>
<td>108.0%</td>
</tr>
<tr>
<td>Speed of Closure</td>
<td>32.34</td>
<td>32.08</td>
<td>40.08</td>
<td>123.9%</td>
</tr>
<tr>
<td>Spatial Orientation</td>
<td>21.94</td>
<td>3.36</td>
<td>5.14</td>
<td>23.4%</td>
</tr>
<tr>
<td>Selective Attention</td>
<td>48.75</td>
<td>49.00</td>
<td>52.41</td>
<td>107.5%</td>
</tr>
<tr>
<td>Problem Sensitivity</td>
<td>58.88</td>
<td>57.59</td>
<td>70.51</td>
<td>119.8%</td>
</tr>
<tr>
<td>Perceptual Speed</td>
<td>41.66</td>
<td>39.47</td>
<td>44.24</td>
<td>102.2%</td>
</tr>
<tr>
<td>Originality</td>
<td>33.29</td>
<td>38.79</td>
<td>53.50</td>
<td>160.7%</td>
</tr>
</tbody>
</table>

This table presents the average required abilities for the occupation categories defined in this paper, weighted by the employments in 2014. Last column presents the ratio of required abilities for occupation category 3 to occupation category 1 in percentage. Occ. 1 includes manual and service occupations; Occ. 2 covers sales and clerical occupations; Occ. 3 includes managerial and professional occupations.

2.2 Measure of Cognitive Health

While physical health relates to body’s capacity to perform activities that require strength and endurance, the 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 about individual’s happiness, confidence, resilience etc. Depending on the transition over lifecycle, cognition has been commonly classified into crystallized cognition and fluid cognition (e.g. McArdle, Ferrer-Caja, Hamagami, and Woodcock (2002)). While crystallized cognition remains stable over life cycle, fluid cognition has a clear declining pattern as people age. Instead of constructing a comprehensive measure for cognition, I choose to focus on an crucial dimension of fluid cognition: memory. The advantage is that there are variables from HRS directly measure individual’s memory. For each respondent, interviewer reads a randomized list of words

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7For the reduced from exercises and auxiliary models used for structural estimation, the mental health is controlled. However, the structural model does not characterize the effect of mental health specifically. Instead, it is assumed captured by the error components. Mental health has no intuitive effects on retirement interacted with occupations. Also, mental health is supposed to be highly endogenous to individual’s working status. For these reasons I abstract it from my current model and leave it for future studies.
and asks him/her to recall these words. This exercise is carried out twice, one right after reading the list and another one after several subsequent questions. Two variables about how many words recalled by each individual are thus provided. I construct a single variable by summing them up, which has been used in some phycological literature.

The following table shows ample variation in the level of memory across demographic characteristics for the primary sample used in this paper, which is obtained from the HRS data set. Figure 3 shows the age profiles of memory between age 51 to 75 by education and occupation. With respect to education, the number of words recalled at age 51-53 by people who didn’t finish high school averages 9.31, while people with high school degree averages 10.82, with some college averages 11.35 and with college and above averages 12.18. In terms of occupation, at age 51, individuals in manual plus service category and in clerical plus sales category recall 10.18 and 10.34 words on average respectively. Individuals in professional and managerial occupations recall 11.89 words, which is much higher. According to literature in psychology, while some researchers argue cognitive decline starts 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 drastically after the early retirement age 62, which is the period retirement occurs and policy reform targets.

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8Our primary sample consists of male household heads aged 51-61 in their first observed waves in the 3rd to 11th waves of HRS data. Detailed sample definition is in the Data section.
9I 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.
10For 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

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

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. LTHS: less than high school; HS: high school; SC: some college; CA: college and above. Occ1: manual and service occupations; Occ2: clerical and sales occupations; Occ3: professional and managerial occupations.

2.3 Occupation-dependent Effects of Physical and Cognitive Health

Given that jobs are increasingly cognitively demanding and cognition does decline during the period that retirement occurs, we would like to ask how is cognitive decline related to older workers’ retirement in the data. We are particularly interested in whether and how do physical health and cognitive health affect retirement across occupations differently? As a guiding exercise, I estimate
a hazard function of the complement of labor force exit on physical and cognitive health by each occupation separately\textsuperscript{11}. The sample is based on the primary sample used in this paper, and is further restricted on being in labor force in last wave. Occupation is defined as the one in last wave when individual was in the labor force. The dependent variable is a binary indicator which equals to 1 if the individual remains in labor force.\textsuperscript{12}

Figure 4: Heterogeneous Effect of Health across Occupations

<table>
<thead>
<tr>
<th></th>
<th>occ1</th>
<th>occ2</th>
<th>occ3</th>
</tr>
</thead>
<tbody>
<tr>
<td>physical health</td>
<td>0.0803***</td>
<td>0.0627***</td>
<td>0.0497***</td>
</tr>
<tr>
<td></td>
<td>(0.0105)</td>
<td>(0.0194)</td>
<td>(0.0125)</td>
</tr>
<tr>
<td>cognitive health</td>
<td>0.00139</td>
<td>0.00174</td>
<td>0.00327*</td>
</tr>
<tr>
<td></td>
<td>(0.00167)</td>
<td>(0.00309)</td>
<td>(0.00178)</td>
</tr>
<tr>
<td>observations</td>
<td>5,525</td>
<td>1,700</td>
<td>4,282</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.305</td>
<td>0.294</td>
<td>0.256</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>occ1</th>
<th>occ2</th>
<th>occ3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard errors in parentheses. Results are estimated with the primary sample.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>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. Occ1: manual and service occupations; occ2: clerical and sales occupations; occ3: managerial and professional occupations.</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The results in the table of Figure 4 show that the coefficients of cognition are statistically significant only for managerial and professional occupations. In terms of the magnitudes, cognition is also associated with the labor force participation mostly in these occupations but least in manual and service occupations. On the contrary, physical health has the largest magnitude in manual and service occupations but least in the sedentary occupations.

Moreover, I also found that the effect of cognitive health is increasing with age only for managerial and professional occupations. Specifically, I re-estimate the labor force participation regressions by restricting the sample to observations older than each given age\textsuperscript{13}. The left graph in Figure 5 presents the results for cognitive health. A notable feature in this figure is that, when the sample is restricted to older ages, the effect of cognitive health on labor force participation soars for professional and managerial occupations, particularly after the FRA 65. At age 51, recalling one less word is

\textsuperscript{11}For research about labor force transition based on hazard function, see Disney, Emmerson, and Wakefield (2006) as an example.

\textsuperscript{12}In my previous paper based on reduced form regressions, instead of the hazard function, I explored other estimation models such as fixed-effect regressions. I tried specifications with different definitions of occupation, such as defining the occupations by the jobs with longest tenure. The main results do not change. The important reason why here I define occupation as the one in last wave is, as will be shown shortly, I can conveniently instrument the contemporaneous health with the lagged health to address the concern of reverse causality. If the sample is a panel which includes many observations after retirement, using lagged health as instrument is invalid because most of it will still be endogenous to labor force exit.

\textsuperscript{13}Because of the limitation of sample size, the effects by each age $\Pr(P_t = 1|H^p_t, H^c_t, X_t, \text{age} = a)$ are very noisy. Alternatively, the estimates of $\Pr(P_t = 1|H^p_t, H^c_t, X_t, \text{age} >= a)$ are estimated.
associated with 0.327% decrease in the probability of labor force participation. This percentage becomes 0.5% at age 62 and increases to 1.20% at age 68. There is also an increase for clerical and sales occupations, but this trend reverses since age 65. The effect for manual and service occupations is almost flat, before plunging after age 65. On the contrary, the right graph shows no particular increasing or decreasing pattern for the effects of physical health over these occupations.

Figure 5: Heterogeneous Effect of Health across Occupations

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.

To compare the magnitude of the effect of cognitive health and of physical health, I calculate the standardized coefficients of physical and cognitive health, and I plot these effects for individuals older than each given age. The left graph of Figure 6 shows, for manual and service occupation, the labor supply effect of physical health is always larger than the one of cognitive health. For example, the effect of cognitive health is 12.6% of the one of physical health for individuals older than age 56. For individuals with ages greater than 62, this percentage is 10.8%. For professional and managerial occupations, the effect of cognitive health relative to physical health is larger when the sample is restricted to older individuals.

Figure 6: Heterogeneous Effects of Physical and Cognitive Health for Manual and Service Occupation (left) and Professional and Managerial Occupation (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.

This finding may result from the fact that memory becomes more disruptive when it depreciates
to certain degree. It could also be related to the Alzheimer whose onset is usually over 65 years old. Given that the policy proposals considered by this paper focus on increasing retirement age from 67 to 68 even 70, the increasing effect of memory over age becomes more important to be taken into account.

An important concern about the above exercise is the reverse causality, as many recent studies have suggested that retirement has an 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 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 exit from the labor force. Compared with the table in figure 4, the results in the column 2-4 in Figure 6 show that the coefficient of cognition for manual and service occupations becomes smaller, whereas the one for clerical and sales occupations increases significantly. Although the coefficient of cognition for professional and managerial 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.

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. The results are reported in (5)-(7) column in figure 6. The individual fixed-effects are controlled. The results show that effects of cognitive health are much larger for clerical plus sales occupations and professional plus managerial occupations than manual and service occupations.

To summarize, jobs are becoming less physically demanding and require more cognition during past decades. Cognition experiences notable decline during the period when retirement occurs. From the reduced form exercise, we have heuristical evidence suggests that physical health and cognitive health have heterogeneous effects on retirement across occupations. Physical health is associated with retirements in all occupations, but mostly in low-skilled ones. On the contrary, cognitive health affects retirement only in the high-skilled occupations. The heterogeneous effects of different dimensions of health across occupations may suggest distinct responsiveness in labor supply when full retirement is further lifted. Workers across occupations, who also differ greatly in socioeconomic status, may thus incur unequal welfare loss. More importantly, the impact of poor cognitive health, especially for high-skilled workers, is nontrivial. Ignoring it may overestimate high-skilled workers’ capacity to work and underestimate their welfare loss when FRA is increased.

3 Model

3.1 Choice Set

Individuals come from three occupations: Occupation $j = 1$ includes manual and service occupations, occupation $j = 2$ includes sales and clerical occupations and occupation $j = 3$ covers managerial and professional occupations. In the current version of the model, individuals are not allowed to change occupations and their occupations are given by the ones in their first observed waves. At each age, individuals choose either participating in the labor force or being out. We assume that being out of labor force is an absorbing state. That is, individuals cannot return to the labor force once they choose leaving. For notational simplicity, I use dummy variable $d_{jt}$ to indicate the individual’s labor supply status at age $a$. $j = 1, 2, 3$ denote individual’s participation in each occupation. Individual is out of the labor force if $d_{jt} = 1$.

14We 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.
Besides the labor supply decision, the individual also chooses how much to consume in each period. The consumption is a continuous variable. Maximum consumption is subject to the borrowing constraint. There is also a consumption floor for each individual, which captures the government transfer, such as Supplemental Insurance Income (SSI), for very poor people. Individuals in the model make their labor supply decisions up to age $A^* = 75$ and their consumption decisions until age $A^{**} = 90$.

For computational feasibility, we do not model specifically individual’s Social Security application as French (2005). Instead, we have several alternative assumptions about the timing of Social Security receipt. Blau and Gilleskie (2008) and Bound, Stinebrickner, and Waidmann (2010) assume that individuals start to collect Social Security benefits in their first year of leaving the labor force after eligible age (age 62). One of the limitation of this assumption is that individuals are not subject to the Social Security earning test by construction, if they continue working after the early retirement age, since they do not collect the Social Security by assumption. This deprives the model of an incentive to retire immediately after age 62. Under this assumption, individuals are only affected by Social Security earning test if they reentered the labor force. Van der Klaauw and Wolpin (2008)’s assumption I do not understand quite well yet. The current version model is following the assumption of Blau and Gilleskie (2008) and Bound, Stinebrickner, and Waidmann (2010).

### 3.2 Utility Function

The utility function consists of a pecuniary and a non-pecuniary component. Pecuniary utility is in CRRA utility form with coefficient of risk aversion $1 - \nu$ and an marginal utility of consumption shifter $\phi_0$. Non-pecuniary is linear and depends on individuals’ labor force participation status, occupation, physical and cognitive health. Importantly, as captured by parameters $\lambda_{2j}$ and $\lambda_{3j}$, we assume that the effects of physical and cognitive health on non-pecuniary utility interact with individual’s occupation. This is to reflect the intuition that workers with poor physical and/or cognitive health can suffer differently across occupations.

$$U(\Omega_t, c_t, d_t) = \frac{1}{\nu} C_t^\nu \cdot \phi_0 + L_t$$  \hspace{1cm} (1)
where

\[ L_t = \sum_{j=1}^{4} \lambda_{1j} d_{jt}^j + \sum_{j=1}^{4} \left( \lambda_{2j} h_{jt}^h + \lambda_{3j} h_{jt}^c \right) \cdot d_{jt}^j + \varepsilon_{jt} \]  

(2)

\[ C_t \] is the consumption and \( L_t \) is the non-pecuniary utility from leisure. \( h_t \) are the health of different types: physical health(\( h_{jt}^p \)) and cognition (\( h_{jt}^c \)).

The utility is also subject to the preference shocks \( \varepsilon_{jt} \), which has an i.i.d. extreme type one distribution \(^{15}\). The structural interpretation of these shocks is that they are state variables unobserved to researcher but observed to the individuals themselves. The preference shocks are assumed to be choice-specific. The joint distribution of these shocks affects individual’s labor supply choice. Notice that the preference shock is additive to consumption, so consumption decision is independent of this shock once conditional on the labor supply decision. Therefore, conditional on the observed state variables, these choice-specific shocks \( \varepsilon \)'s only induce the randomness in the discrete labor supply choices. The consumption conditional on observed state variables is also going to be stochastic. However, it does not result from these preference shocks \( \varepsilon \)'s, but instead from the random shocks to income, which will be specified in following context.

### 3.3 Budget Constraint

Individuals’ assets accumulate as the following formula:

\[ (1 + r)A_t + Y_t = C_t + A_{t+1} + ME_t \]  

(3)

It is subject to the borrowing constraint \( A_{t+1} = (1 + r)A_t + Y_t - ME_t - C_t \geq A_{min} \), where \( A_{min} \) is the minimum asset required. Meanwhile, we 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 individual can choose consumption between the range \( [C_{min}, C_{Max}] \), where \( C_{max} = (1 + r)A_t + Y_t - ME_t - A_{min} \). In the extreme case that the individual’s asset and income is too low and/or the out-of-pocket medical expense is too high, it happens that \( C_{max} \leq C_{min} \). If we assume that individual attains the consumption floor \( C_t = C_{min} \). Then the asset in period t+1 is going to be lower than \( A_{min} \) and the borrowing constraint will not hold. Therefore we assume that the government provides a basic

\(^{15}\)In the future we have to release the assumption that shocks are independent over choices.
transfer which equals to \( \max \{0, C_{min} - ((1 + r) A_t + Y_t - ME_t - Amin) \} \). \(^{16}\)

### 3.4 Income

The income consists of individuals’ labor earnings, social security benefit and private pension, and his spousal income:

\[
Y_t = \sum_{j=1}^{3} d_j^j W_j^j + d_4^j (ss_t + P_t) + W_s^s
\]

(4)

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

\[
W_j^j = r^j \cdot \exp \left( \kappa_1^j X_t + \kappa_2^j X_t^2 + \kappa_3^j E + \kappa_4^j h_t^p + \kappa_5^j h_t^p \right)
\]

(5)

Following French (2005) and French and Jones (2011), spousal income is predicted by a set of demographies (age, education) \(^{17}\). Social Security retirement benefits \( ss_t \) are calculated by formulas strictly following Social Security Administration. Private pension is difficult to model because the plans vary individually. Bound, Stinebrickner, and Waidmann (2010) solves the model by each individual, whereas Van der Klaauw and Wolpin (2008) restricts the sample to individuals without private pension. French (2005) and French and Jones (2011) essentially approximate the private pension by existed state variables. Similarly, current model version also approximates the private pension because of the computation and sample size constraints.

### 3.5 Social Security

We calculate the Social Security income closely following the rules of Social Security Administration. According to these rules, the Social Security retirement benefits is calculated in following steps: Firstly individual’s higher 35 years earnings are considered to calculate the AIME (Average Indexed Monthly Earnings). The earnings before age 60 are adjusted by the national average wage index to reflect the real wage increase. In the second step, PIA (Primary Insurance Amounts) is calculated

\(^{16}\)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. I don’t really understand why.

\(^{17}\)French (2005) assumes spouse income is a function of individual income and age.
as the sum of a three separate percentages of the portions of AIME. It functions equivalently as a progressive taxation. At last, to calculate the Social Security benefits, the PIA is multiplied by a adjustment factor, which depends on the age that individual starts drawing the benefits. Individuals who started to collect their retirement benefits at age 65 will receive the same benefits amounts as the PIA. AIME is a state variable in our model. We calculate the PIA and finally the Social Security Income based on it.

Individuals aged 62 to 69 who are taking Social Security benefits but still working are subject to the Social Security earnings test. 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 taxed by the Social Security earnings test. Thus, the earnings test requires benefit recalculation when individuals eventually retire. However many studies are abstracted from this recalculation. If we abstract from this recalculation, the model is deprived of a mechanism for the spike of retirement at age 65. On the contrary, an incentive to retire at age 62 is created by construction.

As mentioned before, we do not model the Social Security application independently. By assumption, individual starts to draw Social Security benefits once they turn to not working from working after age 62. One consequence of this assumption is that individuals who continue working after age 62 without interruption are assumed to take no Social Security benefits. Therefore these individuals are not subject to the earnings test by construction.

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

Firstly 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 computational constraint, 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.

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18 After 2000, the earnings test for individuals with age 65 and older are abolished
19 see French and Jones (2011)
20 As far as we know, the only exception which keeps the earned credit as a state variable is Van der Klaauw and
3.5.1 Transition Rule

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

\[ AIME_{t+1} = AIME_a + \max\{0, W_t - \min(\hat{W}_{t-1})\}/35 \]

We denote the current earnings as \( W_t \) and the earnings history until age \( t-1 \) as \( \hat{W}_{t-1} \). 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 has not worked enough 35 years, \( \min(\hat{W}_{t-1}) \) 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 and it is intractable. There are two approaches to simplify it given current studies. In French and Jones (2011) they use a portion of AIME as a proxy for the \( \min(\hat{W}_{t-1}) \). Specifically, they assume the product of current AIME and an age-dependent percentage coefficients \( \alpha_t \) (i.e. \( \alpha_t AIME_t \)) as the proxy and they estimate the percentage coefficients by simulation the earnings history. In French (2005), he simply assumes the current AIME as the proxy for minimum earnings, namely, the percentage coefficients \( \alpha_t \) being 1. While the simulation-based estimates of \( \alpha_t \) can be developed, the current version of this paper follows the simpler assumption with \( \alpha_t = 1 \). In terms of the second approach, I am not sure whether is a simplification assumption or it is how SSA regulates. According to Van der Klaauw and Wolpin (2008), the AIME is computed based on all years earnings since age 21, exclusive of the lowest 5 years \(^{21}\). Van der Klaauw and Wolpin (2008) then assumes the lowest five years earnings occurred before the starting age (age 50) of their model. With these assumptions, the transition rule of AIME in this study is:

\[ AIME_{t+1} = (AIME_a \cdot (a - 21 - 5) + W_t)/(t + 1 - 21 - 5) \]

3.5.2 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 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

\(^{21}\)I found many sources describe the calculation of AIME as this, which is not fully consistent with the usage of highest 35 years earnings. I am not sure it is an old regulation or it is just a simplification.
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 variables. 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.

3.6 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. With respect to these two types of pensions, Van der Klaauw and Wolpin (2008) abstracts from modelling the DC plan because it requires adding an extra decision variable similar to saving. French and Jones (2011) further abstract from modelling the private pension based on the detailed employer-specific plans. Instead, they construct a complex while

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22French 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.

23The contribution to DC pension is similar to save through pension wealth.
reduced-form model for the private pension, without specifically distinguishing the DB and DC plans.

The private pension plans are employer-specific and very heterogeneous. Completely modelling this essentially requires solving the model with respect to every individual respectively. Examples include Blau and Gilleskie (2008) and Bound, Stinebrickner, and Waidmann (2010). The alternative

3.7 Medical Expense and Health Insurance

The out-of-pocket medical care expense:

\[ ME_t = g(h_{1t}^p, H_t, \epsilon_t) \] (6)

Right-skewed health expenditure shocks has long tail. Health insurance lowers mean expenditure but also narrows the variance. Risk-averse individuals value health insurance very much.

The health transition rules:\n
\[ h_{kt+1}^k = \theta_1^k + \theta_2^k h_{kt}^k + \theta_3^k 1(w_t = 0) + \theta_4^k 1(w_t = 1) + \theta_5^k a + u_{kt}^k, \quad k = p, c, m \] (7)

The insurance offered by the employer \( H^*_{kt} \) has three types, which determines the insurance coverage of individual \( H_t \):

1. \( H^*_{kt} = 0 \): not offered health insurance by the employer;
2. \( H^*_{kt} = 1 \): offered health insurance without retiree coverage;
3. \( H^*_{kt} = 2 \): offered health insurance with retiree coverage.

The health insurance coverage at age \( a \):

\[ H_t = \begin{cases} 
1 & \text{if } (1) \ a > 65; \ (2) \ H^*_c = 2 \text{ and } a > c; \ (3) \ H^*_t = 1 \text{ and } w_t^0 = 0; \\
0 & \text{else}
\end{cases} \] (8)

We assume that the individuals expect the insurance type in next period by following rules:

(1) If \( H^*_{kt} = 2 \) then \( H^*_{kt+1} = 2 \) (2) If \( H^*_{kt} = 1 \) and \((w_{t+1}^2 = 1 \text{ or } w_{t+1}^1 = 1)\), then \( H^*_{kt+1} = 1 \) (3)

\[ ^{24} \text{I am not sure whether I want to model the effect of retirement on health in the GE model.} \]
If $H^*_t = 0$ or $(H^*_t = 1$ and $w^0_{t+1} = 1)$ then $H^*_{t+1} = 0$. The first case is the one that individual benefits the retiree coverage insurance. We assume in the second case that the individual continues the tied health insurance as long as he continuous working. In the third cases, health insurance remains unavailable if there was no insurance in last period. Meanwhile, when the individual has a tied insurance in current period, the insurance ceases if the individual chooses not working in next period.

3.8 Value Function

The model starts with the standard dynamic programming value function of homogeneous individuals at age $a$. At each age, Individuals choose their labor supply and consumption to maximize their discounted lifetime utility. We assume that all individuals retire after age $A^* = 75$ and the maximum life expectancy is $A^{**} = 90$.

$$V_t(\Omega_a) = \max_{c_t,d_t} \left\{ U(\Omega_a,c_t,d_t) + \beta \int \left( p^g_{t,j}V(\Omega_{t+1}) + (1 - p^g_{t,j})B(\Omega_{t+1}) \right) dF(\Omega_{t+1} | \Omega_a, c_t, d_t) \right\} \quad (9)$$

Survival rate $p_t$ is determined by age, physical health $h^p_t$ and gender $g$. It is also occupation-specific to reflect the mortality gradient over socio-economic status.

$$p^g_{t,j} = Pr(s_{t+1} = 1 | s_t = 1, \text{physical health}, gender=g, occupation=j) \quad (10)$$

Utility from bequest depends on the asset left to $A_{t+1}$. We assume the marginal utility of bequest is also occupation-dependent since rich and poor people tend to have different bequest motives.

$$B(\Omega_{t+1}) = \nu^j A_{t+1} \quad (11)$$

---

25 For simplicity, we ignore the potential insurance type changes induced by the occupation switches, neither the full-time/ part-time work change.

26 By these assumptions, individuals will not obtain insurance if they reenter the labor force. This assumption is also maintained by French and Jones (2011). Notice that this assumption only affects individuals younger than 65, because those above 65 benefit the Medicare whatsoever. If necessary to change this assumption, we may assume a constant probability of achieving insurance in period $t+1$, which is similar to Bound, Stinebrickner, and Waidmann (2010).

27 Same ages assumed as Van der Klaauw and Wolpin (2008).

28 If not model saving, then no bequest.
4 Solution and Estimation Method

4.1 Model Solution

We solve the model by backward induction. Model’s solution, which consists of the discrete labor supply choice and continuous consumption decision, is achieved numerically. The model solution follows the following steps.

1. Given each labor supply status $l$, write down the choice specific value as a function of consumption, also conditional on all the observed and unobserved state variables. That is, $\text{CSV}_l(C_t, X_t, \zeta_t, \varepsilon^l_t)$. Remember there are two types of unobserved state variables: the wage shock $\zeta_t$ and choice-specific preference shock $\varepsilon^l_t$.

2. Calculate the optimal consumption that maximize the choice specific value function. We solve for the optimal consumption $C^*_t(X_t, \zeta_t)$ and the corresponding value $\text{CSV}^*_l(C^*_t, X_t, \zeta_t, \varepsilon_t)$. Notice that consumption is not conditional on the preference shock $\varepsilon_T$ because the shock is assumed to be additive. Also notice that the consumption is a continuous variable in the theoretical model while we are going to discretize it in the search of optimal consumption. $\text{CSV}^*_l(C^*_t, X_t, \zeta_t, \varepsilon_t)$ eventually boils down to a function of $X_t$, $\zeta_t$ and $\varepsilon_t$, namely $\text{CSV}^*_l(X_t, \zeta_t, \varepsilon_t)$.

3. Given $\text{CSV}^*_l(X_t, \zeta_t, \varepsilon_t)$, we search for the optimal labor supply choice. Conditional on $X_t$ and $\zeta_t$, we calculate the expected maximum value function ($\text{emax}$) by integrating out the $\varepsilon_s$ given their joint distribution. Finally, the model solution is the probability or each labor supply choice and its corresponding consumption, conditional on the observed state variables $X_t$ and unobserved state variables $\zeta_t$.

In the step 2 we search for the optimal consumption for each labor supply choice while in the third step the discrete labor supply choices are compared based on the choice-specific value functions with optimal consumptions. Because the choice-specific value function $\text{CSV}_l(C_t, X_t, \zeta_t, \varepsilon^l_t)$ is not necessarily continuous in consumption because of the expected maximum value function (Emax), to search for the optimal consumption, it is inappropriate to use the derivative-based optimization method. Instead, we discretize the consumption into finite grid points and search over these points. We follow the method by French and Jones (2011) to lessen the computational burden. That is, we only search all the points in the final stage. For the earlier stages, given each set of observed state variables $X_t$, we start our search from the consumption point that is optimized in age $t+1$ with the
same observed state variables $X_{t+1}$ as $X_t$ (except age). Then we search just a neighborhood instead of the whole consumption space. Specifically, for each starting point $C_{best}$ we define $[C_{best}-C_{near}, C_{best}+C_{near}]$ and compare the utility at these three points. If $C_{best}$ provides the highest utility, which suggests at least a local maximum is within this range, then we search over this range $[C_{best}-C_{near}, C_{best}+C_{near}]$. If the value function is generally monotonic increasing or decreasing in this range ($U(C_{best} - C_{near}) \leq U(C_{best}) < U(C_{best} + C_{near})$ or the other way around), we set the $C_{best}+C_{near}$ ($C_{best}-C_{near}$ in the case of decreasing utility) as new starting point and repeat the same step. In the current version of model we discretize consumption into 100 grid points and set the neighborhood as $\pm 5$ points. We compare the results with the full search solutions and the bias is minimal.

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 $C_{near}$ 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 $U(C_{best} + C_{near}) > U(C_{best}) < U(C_{best} + C_{near})$, we reset $C_{best}$ to $C_{best}-C_{near}$ or $C_{best}+C_{near}$ depending on which provides the higher utility. This leads to slightly higher bias in the optimal consumption if $C_{near}$ is small, but the bias is trivially small (I will show how large is the bias w.r.t. the various values of $C_{near}$ in future.).
4.1.1 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.

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. 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-time) 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. I am not sure whether you want to consider changing the income shocks to the medical expenses shocks.

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

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29 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.

30 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\textsuperscript{31}. 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 probabilities of being out of the labor force over age, conditional on having/ not having Social Security benefits collected in last year.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{plots.png}
\caption{Probabilities of being out of the labor force over age, conditional on having/ not having Social Security benefits collected in last year.}
\end{figure}

4.2 Estimation

Upon solving the model, the parameters are estimated by indirect inference. This method, which is a simulation-based estimation approach, has the advantage when the likelihood function of the economic model is difficult to compute. It searches for the structural parameters which generate the simulated data that are closest to the observed data by some criteria. These criteria are based on a bunch of auxiliary models which are simple to compute and serve as a window for the description of actual data. In a nutshell, this method searches for the structural parameters which minimizes the distance between the auxiliary parameters estimated from actual data and from simulated data. The auxiliary models do not require being correctly specified for the consistent estimates of the economic model. The estimates by indirect inference are asymptotically equivalent to maximum likelihood estimates when the auxiliary models are correct specified.

Analogous to hypothesis test of Wald, LR and LM, there are three metrics to construct the estimation criterion. When the auxiliary model is correctly specified, estimates by these three metrics

\textsuperscript{31}In 1992, the low exempt amount is 9,120$ and the high exempt amount is 14,500$. 

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criteria are all asymptotically equivalent to maximum likelihood estimates, otherwise LR will be less efficient than Wald and LM when the weighting matrices are chosen optimally. Instead, the advantage of LR is that it does not require the estimation of weighting matrix. Compared to Wald and LR, LM has the advantage that parameters in auxiliary models do not need to be estimated with simulated data to form the estimation criterion, and this tends to be computationally friendly. On the other hand, Wald is preferable if the likelihood or score functions of auxiliary models are not trivial to construct. In this paper, I am going to deploy the metric similar to LM to form the estimation criterion. However, instead of using the score functions based on maximum likelihood, to form the criterion, I am going to utilizing the first order conditions derived from least squares methods that will be used for some estimations of the auxiliary models.

4.2.1 Identification

This section intends to offer a basic intuition for the identification of the structural parameters. However, due to the complexity of the structural model, we cannot offer the strict proof for the identification of each parameter.

The parameters in health expenditure equation are going to be estimated in the first step estimation. Variation in the health expenditure across health status and individual’s insurance status identify the corresponding parameters in this equation.

Besides the parameters to be estimated in the first step, the rest parameters which are going to be estimated jointly by indirect inference can be grouped into three kinds basically. The first group of parameters are those appear in the non-pecuniary utility component, which include the fixed costs of occupation change ($\eta_{12}, \eta_{13}, \eta_{21}, \eta_{23}, \eta_{31}, \eta_{32}$), the occupation-dependent constant of working disutility ($\lambda_1, \lambda_2, \lambda_3$), the occupation-dependent disutility of poor physical health ($\xi_{11}, \xi_{12}, \xi_{13}$) and cognitive health ($\xi_{21}, \xi_{22}, \xi_{23}$), the occupation-dependent fixed costs of reworking ($\tilde{\eta}_1, \tilde{\eta}_2, \tilde{\eta}_3$). Parameters in the wage equations are of the second group. They are all assumed occupation-specific. Specifically, they are the constant terms of human capital equation ($hc_1, hc_2, hc_3$); the coefficients in quadratic experience ($\kappa_{11}, \kappa_{12}, \kappa_{13}$ and $\kappa_{21}, \kappa_{22}, \kappa_{23}$); the slopes of education ($\kappa_{31}, \kappa_{32}, \kappa_{33}$), the slopes of physical health and cognitive health ($\kappa_{41}, \kappa_{42}, \kappa_{43}$ and $\kappa_{51}, \kappa_{52}, \kappa_{53}$). The last group of parameters are the ones related to the consumption utility, namely, the coefficient of bequest ($\iota$), the coefficient of risk aversion ($1 - \nu$), the variance of preference shock ($\sigma^p$), the constant marginal

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32LM forms the estimation criterion by the score functions. The estimation of parameters in auxiliary models can be nontrivial, for example, when the auxiliary model is logit or probit and maximum likelihood estimation is required.

33In general, the auxiliary models should be simple, because this is the essential motivation for indirect inference.

34This term also combines with the occupation skill price level, because they are not separately identified.
utility of consumption \((mc)\) and the weight of non-pecuniary utility \((\tau)\).

For the concern of selection bias, the parameters in wage equations are going to be estimated in the second step jointly with the estimation of structural labor supply function. The occupation-dependent parameters will be identified

After the effects of physical and cognitive health on labor supply through earnings are captured by the earnings equation, the variation of labor supply choice over the variation of physical and cognitive health identifies the disutility of poor physical and cognitive health through leisure. The heterogeneous gradients across occupations identify the occupation-dependent disutility of poor physical and cognitive health. After the effects of all other factors are controlled for, the probability of working in each occupation identifies the occupation-dependent utility/disutility of working. The rates of inter-occupation changes identify the fixed costs of occupation changes. The rates of observations returned to work from not working identify the fixed cost of reworking.

5 Data

The data come from the third to eleventh wave of Health and Retirement Survey (HRS).\(^{35}\) They 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. The wave 1 and 2 are not used because the measure of memory is not consistent with subsequent waves.\(^{36}\) The 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. Also, observations with missing value in any state variable are dropped. Finally, this sample includes 21370 observations and 5698 individuals. \(^{37}\) Based on the state variables from this sample, labor force participation, wage and wealth change are simulated. Notice that further sample restrictions are applied when the auxiliary models are estimated. For approximate labor force participation equations, since they are estimated by occupations separately, and occupations are defined as the ones in last period when individuals were in the labor force, accordingly the sample is restricted to

\(^{35}\)The data product cleaned by Rand Corporation is used.

\(^{36}\)For the word recall test, the first two waves use a list with 20 words whereas the other waves use a list with 10 words. I refrain from re-scaling the measures in first two waves because I found the mean words recalled for the first waves are quite distinct from the means multiplied by two in other waves.

\(^{37}\)IMPORTANT AND OPEN TO DISCUSSION: For the current version of this paper, observations with occupation changed between period t-1 and t and observations that transit from out of labor force back into the labor force are dropped, because the current structural model does not allow occupation change and assumes retirement is an absorbing state. Without imposing these two restrictions, there are 21759 observations and 5729 individuals. Notice that these two restrictions are imposed for observations instead of individuals. If individuals (with all observations) who have ever changed occupations or have transited back into the labor force are excluded, the sample remains 4892 individuals and 17545 observations.
observations that were in the labor force in last period. For approximate wage equations, the sample is restricted to working observations of which wages are observed.

The primary sample is for generating the simulated sample, which is used to estimate preference and wage parameters in the second stage by indirect inference. For the first stage estimation, which includes the estimation of health transition equation, mortality equation and medical expenditure equation, following French (2005), an expanded sample is utilized. Because my HRS data covers a span of 16 years, from 1996 to 2012, the oldest individuals in the primary sample were aged 61 in 1996 and by 2012 they were 77 years old. However, the structural model requires the health transition equation, mortality equation and medical expenditure equation until age 90. Therefore the first stage estimation is based on the full sample of males from third the eleventh wave of HRS. The underlying assumption is that these equations are consistent for individuals in primary sample and in full sample.

5.1 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. 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 infor-
motion 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.

5.2 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.

5.2.1 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
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. 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 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. 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, 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).

5.2.2 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 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.

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40There 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.

41This is defined by working in last period but not working in current period.
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.

6 Results

6.1 Mortality

The survival probability is commonly assumed conditional on health and age. Ideally, conditional on being alive at age t, we would like to have alive and deceased observations within one year since this age. Then with survival indicator and health variables at age t, we can estimate the function for survival probability at each age. Particularly we take care of any age-dependent effects of health because the survival probabilities are estimated with observations at each age respectively. Alternatively, if sample size does not allow us to estimate the survival probabilities by each age, we can pool observations of all ages together, and then estimate survival probabilities with polynomials of age as covariate. This estimation can be based on logit/ probit or hazard function. The advantage of this approach is that the estimated survival probabilities are generally consistent with the sample used for structural estimation. The limitation is a high requirement of data quality and sample size. If the sample is representative, the estimates are nevertheless not guaranteed to match the life tables from external sources such as Social Security Administration, because of the imprecision due to small sample size. Literature based on this approach includes Rust and Phelan (1997), Van der Klaauw and Wolpin (2008). Rust and Phelan (1997) extrapolates mortality beyond sample age while Van der Klaauw and Wolpin (2008) uses subjective probability of living as supplementary data.

Alternatively, much research directly or indirectly cites the mortality data from external source such as Social Security Administration. Gustman and Steinmeier (2005), Haan and Prowse (2014) Haan and Prowse (2014) supplement their data with high-quality external mortality information instead of estimating the mortality function. Because external mortality usually does not condition on health, this research basically assumes that the health variables in their models do not shift individuals mortality. To allow mortality to be shifted by health variables in the model, French (2005) links the mortality conditional on health to external unconditional mortality by Bayesian rule. Bound, Stinebrickner, and Waidmann (2010) estimated a proportional hazard function based on the estimation sample, but made use of only the estimated health shifter, by multiplying it with mortality obtained from Social Security Administration.
The limitation of the approach by Bound, Stinebrickner, and Waidmann (2010) is that health essentially shifts the baseline mortality by a fixed proportion over age. The baseline mortality, obtained from external sources, is the national average at each age. This mortality at age 51, for example, associates with people with good health in general. Having bad health therefore should shift individual’s survival probability from this average largely. On the contrary, the baseline mortality rate at age 81 corresponds with people mostly with poor health. Because it already captures the effect of average poor health, individual mortality of someone with poor health should not departure from this baseline mortality greatly.

In this paper, similar to French (2005), I use Bayesian rule to calculate the mortality, which is assumed physical and cognitive health-dependent. Given that both physical and cognitive health have been discretized into two states, individual’s survival probability at each age thus depends on four joint health states: \( \{h^p_t = 0, h^c_t = 0\} \), \( \{h^p_t = 1, h^c_t = 0\} \), \( \{h^p_t = 0, h^c_t = 1\} \) and \( \{h^p_t = 1, h^c_t = 1\} \), where \( h_t \) is the indicator which equals to 1 if physical or cognitive health is poor. 42

\[
Pr(s_{t+1} = 0|s_a = 1, h^p_t, h^c_t) = \frac{Pr(h^p_t, h^c_t|s_{t+1} = 0, s_a = 1,)}{Pr(h^p_t, h^c_t|s_a = 1,)} \times Pr(s_{t+1} = 0|s_a = 1,)
\]

As shown by the above formula, the survival probability conditional on health can be decomposed into an unconditional survival probability and an age-specific health shifter. The shifter depends on the numbers in each health states of individuals who are alive at age \( a \) and who die between age \( a \) and \( t+1 \). For example, individuals alive at age 51 have good health in general whereas those died between 51 and 52 have relatively much worse health. This fact will generate a large multiplier of poor heath for survival probability at 51. However, although it is still the case that individuals who died between 81 and 82 had poor health, individuals that are alive at 81 (regardless or they died or not before 82) also have relatively poor health. This fact will not shift the survival probability of individual with bad health greatly.

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 \( Pr(h^p_t, h^c_t|s_{t+1} = 0, s_a = 1, ) / Pr(h^p_t, h^c_t|s_a = 1, ) \). 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 also use quadratic polynomials of age to approximate \( Pr(h^p_t, h^c_t|s_{t+1} = 0, s_a = 1, ) \) and

42Currently I define poor health as that the original measure of physical or cognitive health is under a given percentile of the pooled distribution (across individuals and waves). This given percentile is defined as the proportion of reported “fair” or “poor” for self-reported health.
\( Pr(h^p_t, h^c_t | s_n = 1) \) to obtain smooth functions. From the figures below we can see the fitness is very good.

**Figure 8: Probabilities of Health States Conditional on Being Alive at Each Age**

![Graphs of probabilities](image)

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

**Figure 9: Probabilities of Health States Conditional on Deceasing after Each Age**

![Graphs of probabilities](image)

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

Figure 1 and Figure 2 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 \(^{43}\), 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 3. 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.

**Figure 10: Mortality Shifters for Different Health States**

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

### 6.2 Health Transition

The joint state for physical and cognitive health have four alternatives: \( \{h_t^p = 0, h_t^c = 0\} \), \( \{h_t^p = 1, h_t^c = 0\} \), \( \{h_t^p = 0, h_t^c = 1\} \) and \( \{h_t^p = 1, h_t^c = 1\} \), where value 1 denotes poor health. This joint health state in period \( t+1 \) is assumed to be conditional on the joint health state in period \( t \),

\(^{43}\)Hereinafter, alive individuals are referred to those alive at age \( a \) and deceased individuals are referred to those deceased between age \( a \) and \( t + 1 \).
permanent income (PI) and age. I estimate a multinomial logit of joint health state in period t+1 on these variables. Specifically, the regressions include quadratic age and PI dummies as independent variables, and they are separately estimated by each joint health state in period t.

The estimates of health transition probabilities conditional on each joint health state are shown below. In general, probabilities of getting into a health state worse than the current one increase as individual ages. Similarly, probabilities of recovering from a worse health state decline with age. People with less education are more likely to transit into a worse health state and less likely to recover into a better health state.

One notice should be kept in mind is that these health transition probabilities are estimated conditioning on survival in next period. Therefore, probabilities of being physically unhealthy are going to be larger once we consider the observations of death. This is because of poor physical health is more correlated with death than cognitive health.

Figure 11: Transition Probabilities of Health conditional on \( \{h^p_t = 0, h^c_t = 0\} \)

---

\(^{44}\) I am using education as an alternative until the availability of earnings history.

\(^{45}\) I did not estimate the regressions separately by the interaction of PI and joint health states, because sample size is very small for some groups. PI therefore shifts the constant term, and interacts with age only through the logit functional form. According to the exploratory estimates, difference between these two functional forms is very small.
Figure 12: Transition Probabilities of Health conditional on \( \{h_i^p = 1, h_i^c = 1\} \)

Figure 13: Transition Probabilities of Health conditional on \( \{h_i^p = 0, h_i^c = 1\} \)
6.3 Preference Parameters and Wage Equation

Preference parameters and parameters for wage equations are estimated jointly in the second step by indirect inference. Parameters estimated in the first step, i.e. parameters for health transition equations, mortality equations, medical expenditure equations, spousal income equation and SSDI benefit equation, are held fixed during the second step estimation. The estimates for preference and wage parameters are presented in table 4:
Table 4: Estimates of Preference and Wage Parameters

<table>
<thead>
<tr>
<th></th>
<th>Occ.1</th>
<th>Occ.2</th>
<th>Occ.3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Non-pecuniary utility</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\lambda_1$</td>
<td>-0.099</td>
<td>0.051</td>
<td>-0.013</td>
</tr>
<tr>
<td>$\lambda_2$</td>
<td>-0.608</td>
<td>-0.290</td>
<td>-0.306</td>
</tr>
<tr>
<td>$\lambda_3$</td>
<td>0.201</td>
<td>-0.198</td>
<td>-0.014</td>
</tr>
<tr>
<td><strong>Wage</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\kappa_1$</td>
<td>5.266</td>
<td>5.134</td>
<td>4.824</td>
</tr>
<tr>
<td>$\kappa_2$</td>
<td>-0.366</td>
<td>-0.372</td>
<td>-0.276</td>
</tr>
<tr>
<td>$\kappa_{42}$</td>
<td>0.232</td>
<td>0.276</td>
<td>0.314</td>
</tr>
<tr>
<td>$\kappa_{43}$</td>
<td>0.252</td>
<td>0.233</td>
<td>0.415</td>
</tr>
<tr>
<td>$\kappa_{44}$</td>
<td>0.228</td>
<td>0.372</td>
<td>0.609</td>
</tr>
<tr>
<td>$\kappa_5$</td>
<td>-0.088</td>
<td>0.021</td>
<td>-0.110</td>
</tr>
<tr>
<td>$\kappa_6$</td>
<td>-0.084</td>
<td>-0.239</td>
<td>-0.162</td>
</tr>
<tr>
<td><strong>Pecuniary utility</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\iota$</td>
<td>0.044</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\nu$</td>
<td>-0.835</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Parameters are estimated by indirect inference. Only $\kappa_{1j}$ are reported because $r_j$ and $\kappa_{1j}$ cannot be separately identified. Current version of model the experience is assumed linear in wage equation. Therefore $k_{3j}$ are set as 0. Education takes four discrete values in our model, so $\kappa_4$ correspond with the premium of three discrete higher education levels (less than high school is omitted as baseline). Standard errors are not available yet. They will come out soon in next version of this paper.

The estimate of coefficient of risk aversion $1 - \nu$ is 1.587, which is close to estimates in previous research, 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 around 5. The main reason may be that previous studies with estimated values 1-2 assumed additivity for pecuniary and non-pecuniary components, as this paper does, whereas they are multiplicative in French and Jones’ model.

For the parameters of non-pecuniary utility, we normalize the utility of being out of labor force to be zero. Notice that it is the same regardless of individual’s health status, because I am not sure whether I can identify the ones with good and bad health separately. $\lambda_1$ is the utility of being in the labor force with good health. It is close to 0 in all the three occupations, with lowest value in manual and service occupations. This is consist with the intuition that working in manual and service occupations are less comfortable than occupations in the office, although the difference is very small when health is good. $\lambda_2$ and $\lambda_3$ are the focus of this paper. $\lambda_2$ is negative across all occupations suggest that having poor physical health incurs negative utility for labor force participation in all occupations.

$\lambda_1$ is negative only in manual and service occupations. Its values associate with sales, clerical, managerial and professional occupations are positive. This suggests having good health and working in these occupations are more preferable than staying at home on average (with good and poor health).

\[\text{\textsuperscript{46}}\text{Notice that the sign for } \lambda_1 \text{ is negative only in manual and service occupations. Its values associate with sales, clerical, managerial and professional occupations are positive. This suggests having good health and working in these occupations are more preferable than staying at home on average (with good and poor health).}\]
occupations. However, the magnitude is lowest for manual and service occupation with -0.779 and highest in professional and managerial occupations with -0.410. If work in manual and service occupations, being physically unhealthy leads to almost twofold disutility as working in professional and managerial occupations. On the contrary, being cognitively unhealthy incurs larger disutility if work in professional and managerial occupations (-0.196) than in those physically demanding jobs (0.114), while this disutility is largest in sales and clerical occupations.

The heterogeneous roles of physical and cognitive health across occupations are less clear for earnings. For physical health, being unhealthy corresponds with lower earnings in manual and service occupations than in those sedentary occupations. For cognitive health, all estimates have positive signs, which suggests poor health is associated with, if any, higher wage. Actually, the results of structural estimates in wage equation are quite consistent with the estimation of auxiliary wage equation. For the auxiliary wage equation, after allowing fixed effects, most parameters associated with both dimensions of health become insignificant and with wrong (unexpected) signs. The reason for choosing fixed-effects specification is that the effect of physical health for manual and service occupations and the effect of cognitive health for managerial and professional jobs have largest magnitudes, though they are also statistically insignificant.

7 Counterfactual Experiment

7.1 Occupational Effects of Physical and Cognitive Health

After obtaining the structural estimates, counterfactual experiments are implemented to answer the research questions that this paper is after. The first research question is how physical and cognitive health affect older workers’ retirement heterogeneously across occupations, and what are those underlying channels. Following previous research, both physical and cognitive health are allowed to affect individual’s labor force participation via four channels in the model: disutility of working, wage, medical expenditure and life expectancy. The first counterfactual exercise shuts down these channels respectively to see how older people’s labor force participation rate changes.

The first row of table 5 is the baseline participation rate between age 65 to 70, simulated based on the estimates in table 4. When all the channels that physical health can affect individual’s utility are shut down, the labor force participation rates across all occupations increase substantially. Moreover, the increase is largest for manual and service occupations by 18.42% and smallest for managerial and professional occupations by 13.15% On the contrary, when the effects of cognitive health on
utility are muted, managerial and professional workers raise their labor force participation by 9.51%,
around 72% of the change when the effect of physical health is turned off, whereas the labor force
participation rate barely increase for manual and service workers, even with a slight decline. Finally,
when all the channels that both physical and cognitive health can affect utility are closed, we
found that clerical and sales workers increase the labor force participation rate largest, followed
by those in managerial and professional jobs. Relatively, the labor supply change from manual and
service occupations becomes the smallest. By extending the scope of health from traditional physical
dimension to also cognitive dimension, we found that workers from sedentary occupations, whose
labor supply usually considered to be less harassed by health issues, are actually affected by this
broader dimension of health gravely.

<table>
<thead>
<tr>
<th>Table 5: Changes in Labor Force Participation Rates between 65 and 69 when Different Effects of Health are Muted</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Physical Health</strong></td>
</tr>
<tr>
<td>Occ.1</td>
</tr>
<tr>
<td><strong>Baseline</strong></td>
</tr>
<tr>
<td><strong>Wage</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>Leisure</strong></td>
</tr>
<tr>
<td><strong>Mediexp</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>Mortality</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>All</strong></td>
</tr>
</tbody>
</table>

Occupation 1: manual and service occupations; Occupation 2: Sales and clerical occupations; Occupation 3: Managerial and professional occupations. Changes from baseline are in square brackets.

### 7.2 Increase in Full Retirement Age

The first counterfactual experiment reveals the heterogeneous roles of physical and cognitive health in labor force participation across occupations. Further more, we are interested in whether and how physical and cognitive health affect older workers’ labor force participation response to the increase in FRA. The first counterfactual policy to be evaluated is to increase the FRA from current 65 to proposed 70. For this policy change, simulations under two specifications are compared. The first (baseline) specification evaluates the labor force participation change simulated based on the actual parameters estimated from the data, whereas the second specification evaluates the change in
LFP induced by increased FRA under an environment that health does not affect individuals’ utility. The second specification intends to explore workers’ labor supply change when health does not play a role. The comparison of LFP changes under these two specifications is going to shed light on how poor health constrains older workers’ ability to respond to increased FRA. Starting from a neat setting, we only focus on the physical health first. As poor physical health tends constrain workers’ work capacity, we expect that when health effects are muted, the rise in labor supply induced by the increase in FRA is going to be larger than the one in the specification that health affects utility. Moreover, we would expect this rise will be largest for manual and service workers, who are supposed to suffer mostly from poor physical health.

Table 6: Changes in Labor Force Participation Rates between 65 and 69 when Full Retirement Age is Increased

<table>
<thead>
<tr>
<th>Occupation 1</th>
<th>Occupation 2</th>
<th>Occupation 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Baseline:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FRA 65</td>
<td>52.15%</td>
<td>63.02%</td>
</tr>
<tr>
<td>FRA 70</td>
<td>74.35%</td>
<td>80.03%</td>
</tr>
<tr>
<td>[22.20%]</td>
<td>[17.01%]</td>
<td>[10.06%]</td>
</tr>
<tr>
<td><strong>Physical health does not affect utility:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FRA 65</td>
<td>70.90%</td>
<td>77.95%</td>
</tr>
<tr>
<td>FRA 70</td>
<td>87.23%</td>
<td>86.28%</td>
</tr>
<tr>
<td>[16.32%]</td>
<td>[8.33%]</td>
<td>[6.10%]</td>
</tr>
</tbody>
</table>

Occupation 1: manual and service occupations; Occupation 2: Sales and clerical occupations; Occupation 3: Managerial and professional occupations. Changes from baseline are in square brackets.

The results are shown in Table 6. When FRA is increased from age 65 to 70, workers increase their labor force participation between age 65 and 70. Social Security retirement benefits are lower under new FRA and both the substitution effect and income effect lead to the delay of retirement. Although the labor supply of workers from physically demanding jobs are more likely to be constrained by their poor health, we found that their labor force participation is actually more responsive to this policy change. This is probably due to the fact that usually they have fewer savings and thus both the substitute and income effect induced by lower retirement benefits are stronger for them. 47

The main puzzling finding is, for all occupations, when poor physical health is assumed to have no effect on utility, the change in labor force participation rate due to the increase of FRA is actually smaller than the one under the specification that health can affect workers’ decisions. For example,

47Gustman and Steinmeier (1986a) also found larger labor supply response for more physically demanding jobs than less physically demanding jobs to the increase of FRA by 1983 Amendment.
when poor health can incur disutility of working, manual and service workers increase their labor force participation rate by 22.7% when FRA is increased to 70, but this change is 16.32% when the effect of physical health is turned off. I am now wondering whether these numbers are actually comparable.

8 Conclusion

Since 1960s the skill-biased technological change happened, jobs in the United States are becoming less physically demanding and require more cognitive abilities. Previous studies about retirement mainly focused on older workers’ physical dimension of health, or used a comprehensive measure which arguably reflects limited information about individual’s cognitive health status. The different roles of physical and cognitive dimensions of health were also not distinguished. While cognitive abilities are becoming more important for contemporary jobs and cognitive abilities decline during the period when retirements occur, the importance of cognitive dimension of health calls for more attention. This paper considers both physical as well as cognitive dimensions of health and studies their heterogeneous roles in affecting workers’ retirements across occupations. We found that while physical health affects retirement across all occupations, the effect is largest for manual and service occupations. On the contrary, poor cognitive health is found little retirement effect for workers from these occupations, whereas contributes to the labor force exit for workers in sales and clerical, professional and managerial occupations notably. When the effects of cognitive health are muted, the labor force participation rate between age 65 to 69 increases 9.51% for managerial and professional workers. Finally, when both physical and cognitive health are considered, we found that sedentary occupations decrease their labor force participation rates even more than the manual and service occupations, which strikingly contrasts the existing belief that workers in sedentary occupations suffer the least from health issues.

This paper then evaluates the importance of different channels that health can affect retirement, for both physical and cognitive dimensions. The channels of leisure and mortality are found most important.

When FRA is increased, we found that the financial incentive is the main driver for delayed retirement. In a counterfactual setting that only physical health matters, individuals in manual and service occupations increase their labor force participation greatly when FRA is increased. Although they are more affected by poor physical health issue, lower retirement benefits provide extra financial incentives to delay their retirement.
References


Appendices

Appendix A  Wage Equation

The structural model assumes that labor income is determined by physical health, cognitive health, education and experience. However, I found out that controlled for asset is important for obtaining reasonable estimates of the coefficients of health. Suppose the number of state variables can not be further increased and I am not going to include asset as a determinant of wage, how should I choose the auxiliary model? I could think about three alternatives:

- The auxiliary wage equation includes only health, education and experience and excludes asset.
- When estimated with actual data, the auxiliary wage equation includes asset. While minimizing the distance between parameters estimated with simulated and actual data, we do not target on the coefficients of asset.
- The auxiliary wage equation includes asset. While minimizing the distance between parameters estimated with simulated and actual data, we also target on the coefficients of asset.

The first alternative is not advisable, because the estimated wage effects of health would be biased and it would lead to erroneous interpretation of the effects of health. For the third alternative, the simulated wage depends only on those state variables directly. Although asset is correlated with these state variables in the real data, and thus is correlated with wage, once these state variables are controlled in the auxiliary wage regression, the coefficient of asset would be 0. Therefore for the third alternative, by changing the structural parameters, we are still minimize the distance between parameters of auxiliary models estimated with actual and simulated data for the coefficients of health, education and experience only, the same as second alternative. Moreover, changing the structural parameters cannot minimize the distance for the coefficient of asset in the auxiliary wage equation and the loss value will be large. For the second alternative, when estimate with the actual data, be careful that the constant term of auxiliary wage equation should be the one for observation with the mean asset instead of with zero asset. Therefore we should demean the asset before including it as an independent variable for the estimation of auxiliary model with actual data.

Regardless of these different alternatives, it is unsatisfying to include some variables in the auxiliary model that are fully missing in the structural model. Allowing for unobserved heterogeneity for the wage equation is necessary.
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 7 and 8 list the mapping between the three categories defined in this paper and HRS 2-digit masked occupations.

Table 7: 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.

Table 8: 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.