Labor Force Attachment Beyond Normal Retirement Age

Berk Yavuzoglu*

July 20, 2015

Abstract

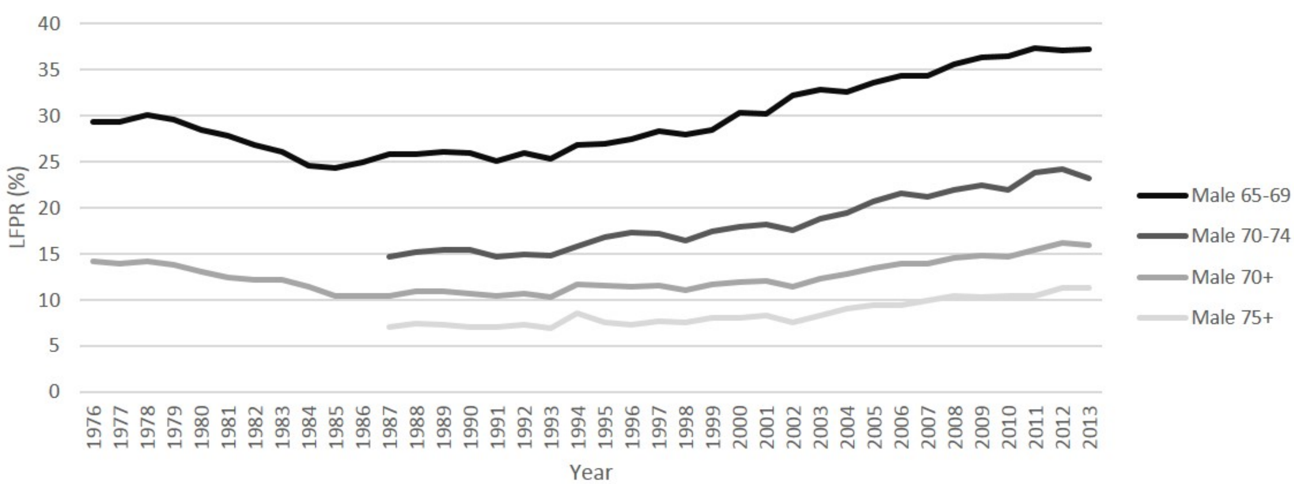
It is essential to understand the labor supply incentives generated by the Social Security (SS) system to Americans beyond normal retirement age, currently 66, since the U.S. population is growing older steadily and the fiscal burden of SS is sizable. This paper analyzes the joint determination of labor supply, consumption (savings) and the decision to apply for SS benefits of elderly single males. I use a dynamic programming formulation and restricted data from the Health and Retirement Study. I focus on the participation decision rather than the retirement decision because a significant portion of the elderly return to work after being non-participants for a while. I account for this through wage, health status and health expenses shocks. Undertaking a counterfactual analysis, I find that the year 2000 SS amendment abolishing the "earnings test" for the age group $66-70$ explains one-fourth of the recent increase in the elderly labor force participation rate (LFPR). Applying the "earnings test" to my post-2000 sample decreases LFPR by 2.7 percentage points and mean hours worked by 115 hours at this age group. I further find via counterfactual analyses that the labor supply decision is sensitive to changes in SS benefit and payroll tax amounts on the extensive margin, but the effects on the intensive margin are not substantial. Decreasing SS benefits by 20 percent increases the participation rate of the elderly aged $66-75$ by 37 percent. Because a change in the payroll tax rate is effectively a change in the wage rate, I estimate labor supply elasticities for the elderly and find that the elasticities are around unit elasticity.

*Department of Economics, University of Wisconsin-Madison, Madison, WI, 53705. E-mail: yavuzoglu@wisc.edu.
I am grateful to John Kennan, James Walker, Rasmus Lentz, Christopher Taber, Insan Tunali, Karl Scholz, Salvador Navarro, Eric French, Serafin Grundl and Francisco Franchetti for their helpful comments. I also thank the National Bureau of Economic Research for providing me pre-doctoral fellowship through this paper. I obtained access to the Restricted Health and Retirement Survey dataset through James Walker's NICHD grant.

1 Motivation

The LFPR beyond normal retirement age[1] was 26.2 percent for the age group $66-69$, 20.5 percent for the age group $70-74$, and 7.0 percent for 75+ for single males in 2006 in the U.S.[2] These levels have exhibited an upward trend since 1995 as shown in Figure 1.[3] This upward trend in the elderly participation behavior helps finance some of the fiscal burden of SS. Moreover, the U.S. population is growing older steadily, which reflects both aging of the baby boom generation and increased longevity. With the increasing stock of elderly population and sizable fiscal burden of SS, it is essential to understand behavioral responses of these people to the changes in the SS system to come up with any policy analysis.

Figure 1: Trends in Elderly Labor Force Participation Rates: Single Males



Source: Bureau of Labor Statistics

Mandatory retirement was a widespread practice in the U.S. labor market prior to the year 1978 and 1986 amendments in the Age Discrimination in Employment Act.[4] Since all the elderly can decide whether to work at any age after these amendments, the recent literature treats retirement as an individual decision. Yet, it is not obvious what the term retirement stands for. It can either

[1]It was 65 in 2002 and increased by 2 months each year until 2009. It is currently 66 and will be increased to 67 by 2 month increments in between years 2021 and 2026.

[2]These statistics are enormous compared to the European countries. See Table C.1 in the Appendix. Moreover, life expectancies at age 65 are higher in most of the European countries. See Table C.2 in the Appendix.

[3]During that time, real value of the mean asset levels have been increasing as well except a temporary decrease in 2009. See Figure D.1 in the Appendix.

[4]Lazear (1979) shows that mandatory retirement can be designed as a life-cycle Pareto optimal contract solving the "agency problem" where workers are paid less than their value of marginal productivity when young and more when old.

mean collecting retirement benefits or simply quitting the labor force. Notice that retirement is not necessarily a permanent state in the latter case since an elderly person might return to work after being a non-participant for a while. Hence, I focus on the participation decision of individuals beyond normal retirement age.

In this paper I analyze the labor supply, consumption and Social Security benefits application decision of elderly single males jointly, using a dynamic programming formulation. The aim of the paper is understanding the labor supply decisions of single males beyond normal retirement age which is not well studied in the literature. I focus only on singles to avoid complexities arising from modeling the joint decision making by couples along with shared budget constraint and leisure complementarity.[5] As a counter factual analysis, I provide an estimate of what the effect of the "earnings test"[6] would be on my post-2000 sample if it was not abolished by the year 2000 SS amendment. This quantifies the effect of the year 2000 SS amendment on the recent increase in the elderly participation rates provided in Figure 1. I further decrease SS benefit amounts by 20 percent, and estimate labor supply elasticities for the elderly to understand the effect of payroll taxes on the labor supply decision since a change in the payroll tax rate is effectively a change in the wage rate.[7]

The specification of the dynamic programming model in this paper extends French (2005). Unlike French (2005), I include three different health status categories,[8] health expenses, medicare, education levels and allow limited borrowing. French (2005) shows that the "earnings test" is the main reason for the non-participation decision of elderly people and solves the early retirement puzzle by incorporating pension benefits into his model. Rust and Phelan (1997) find that health care expenses and Medicare as well as SS rules are the important determinants of the retirement decision for financially constrained people. Recent work by Blau and Goodstein (2010), using an econometric model which is a linear approximation to the decision rule for employment, estimates

[5] 22.8 percent of males aged $58-94$, the age group of interest in this paper, are single which corresponds to 9.6 percent of the population. 12.1 percent of them are never married. I omit cohabiting elderly males in my study. Only 5.0 percent of single males in my sample get married within 6 years. Note that my model does not account for marriage probability. Even though the elderly single females problem resembles very much the elderly single males problem, I focus only on single males currently to make sure everything works well and runs smoothly for a group considering the huge computational time required for estimating structural life-cycle models. Solving the model for single females will be relatively quick and is an extension to this paper as of now.

[6] See Section 6.1 for a discussion about the "earnings test."

[7] The change in the wage rate is determined by the economic incidence of tax. See Section 6.3 for a discussion.

[8] French (2005) has difficulty in matching labor force participation of unhealthy individuals due to the binary discretization of health status.

that 25 to 50 percent of the recent increase in elderly LFPR is attributable to the SS rules, 16 to 18 percent to increase in education and another 15 to 18 percent to increase in LFPR of married women.[9]

Blau and Gilleskie (2008) investigate the effect of health insurance on retirement behavior. They find that changes in the access to the retiree health insurance plans provided by employers or Medicare have substantial effects on participation behavior for people with poor health, but only a modest effect for people with good health. French and Jones (2011) have a similar context to Blau and Gilleskie (2008), and they find that Medicare and employer provided health insurance, value of which is closely tied to the health care uncertainty, are important determinants of the retirement decision. Casanova (2010) approaches the retirement problem as a joint couple decision allowing for leisure complementarity and shared budget constraint in a dynamic programming framework.[10] She shows that individual models of retirement decision cannot capture the incentives of couples. All the papers mentioned above focus on the retirement decision and utilize structural models, except Blau and Goodstein (2010). Departing from the recent literature, Maestas (2010) models participation behavior and focuses on returning to work after being a non-participant (she calls it unretirement) using a reduced form model. She finds that in between 1992 and 2002, 26 percent of the elderly unretired and 82 percent of this was anticipated.

Since the elderly population is steadily increasing and the fiscal burden of SS is sizable, understanding behavioral responses of the elderly people to the changes in the SS system is essential to come up with any policy analysis. My paper aims to accomplish this by specifying a flexible model capturing most of the documented determinants of the elderly non-participation decision in the literature.

[9]Figure D.2 in the Appendix shows that even LFPRs of singles with high school or college diploma have an increasing pattern since 1995. Since we control for marital status and education, there should be another reason behind the recent increase in the elderly LFPR which Blau and Goodstein (2010) fail to explain. The reason could be the increase in the overall health status of the elderly.

[10]Casanova (2010) focuses on married people and models participation as a dichotomous decision including full-time work, part-time work and non-participation rather than a continuous hours worked decision. She further assumes that individuals start receiving Social Security benefits in the first period they choose not to participate in the labor force. Casanova (2010) does not account for changes in health status in her model.

2 Data and Preliminary Examination

Data

I use Health and Retirement Survey (HRS) data, which is a nationally representative panel data of adults in the U.S. aged 50+, conducted biannually and first fielded in 1992. It contains information on labor force participation, health, financial variables, family characteristics and a host of other topics. The results in this paper are obtained using a subsample of the HRS data comprising non-disabled single males aged $58-95$ from 2002 to 2008. The working sample consists of $1,691$ individuals with a total of $3,991$ observations. Appendix A explains the steps used to obtain the working sample from the raw data. I assume that attrition is missing completely at random (or ignorable).

Preliminary Examination

This section provides a multinomial logit analysis of the labor force participation decision of single men beyond normal retirement age. The aim is to provide basic information about the data before executing a structural labor supply analysis of single elderly males. Since the normal retirement age has gradually increased from 65 in 2002 to 66 in 2008 with 2 month increments, and the HRS provides age data with 1 year increments, I consider 66 years as the cutoff age in this analysis. LFPR of single males aged 66 to 69 is 30.4 percent, aged 70 to 74 is 23.0 percent whereas the same statistic for single males aged 75+ is 8.2 percent in my sample. Since the unemployment rate is very low for single males at older ages, only 0.9 percent in my sample, I do not distinguish unemployment and out of the labor force states like Rust and Phelan (1997).

Tables 1 and 2 provide summary statistics for select variables by labor force status for age groups $66-74$ and 75+, respectively. I define part-time work as working less than $1,600$ hours in a year.[11] As seen from these Tables 1 and 2, people in the labor force are younger, more educated and healthier on average. Full-time workers are less likely to have Medicare and more likely to have private health insurances. There is a question in HRS inquiring about the primary health insurance

[11] This assumption causes me to assign elderly people who are working full-time (more than 30 hours a week) part of a year then quitting the labor force as part-time workers, which is the case for only 4.6 percent of the workers in my sample. Since this is a small statistic and the unit of time is one year in my structural model, I stick to this definition.

Table 1: Sample Means (Standard Deviations) of Select Variables by Labor Force Participation Status for Single Males Aged 66-74

Variable	Full sample	Full-Time Workers	Part-Time Workers	Out of Labor Force
Age	69.985	69.064	69.876	70.159
High School Dropout (reference)	0.295	0.248	0.180	0.325
High School Graduate	0.508	0.516	0.444	0.519
University Graduate	0.197	0.236	0.376	0.157
"Fair" Health	0.333	0.217	0.247	0.368
Good Health (reference)	0.324	0.306	0.337	0.325
"Very Good" Health	0.343	0.478	0.416	0.307
Black	0.209	0.287	0.208	0.197
Medicare	0.955	0.892	0.961	0.964
Has Private Insurance	0.478	0.580	0.534	0.451
Health Expenses - last 2 years	1,139.329 (3,402.939)	1,087.637 (1,891.527)	1,101.152 (2,805.693)	1,155.108 (3,690.692)
Assets (in $1,000)	325.279 (657.957)	377.208 (815.799)	480.299 (989.001)	287.452 (535.485)
Number of Children	2.599 (2.225)	2.732 (2.479)	2.404 (1.738)	2.614 (2.262)
Receive Social Security Benefits	0.950	0.924	0.983	0.948
Receive Pension	0.489	0.420	0.421	0.513
Receive SSI	0.045	0.000	0.011	0.058
Sample size	1,280	157	168	945

plan for a subset of the respondents. In my sample, 14.3 percent of respondents in the age group $66-74$ who responded to this question identified their primary insurance as different than Medicare. A further inspection by labor force status reveals that 47.4 percent of full-time workers, 9.7 percent of part-time workers and 8.9 percent of non-participants have a primary health insurance different than Medicare in that age group. Notice that blacks are more likely to participate in the labor force and part-time participants have higher asset levels. Moreover, only a small fraction of the non-participants receive Supplemental Security Income (SSI) which implies that either their unearned income or financial resources are above program limits.

To estimate a multinomial logit model of labor force status, consider the latent utility model:

$$y_{ij}^{*} = \theta_{ij}^{'} z_i + \eta_{ij} \; for \; j = 1, 2, 3. \tag{1}$$

where i denotes individuals, y_{ij}^{*}'s denote the unobserved utilities obtained from the choice of labor

Table 2: Sample Means (Standard Deviations) of Select Variables by Labor Force Participation Status for Single Males Aged 75+

Variable	Full sample	Full-Time Workers	Part-Time Workers	Out of Labor Force
Age	82.814	79.320	79.981	83.080
High School Dropout (reference)	0.407	0.340	0.302	0.415
High School Graduate	0.440	0.420	0.406	0.442
University Graduate	0.154	0.240	0.292	0.143
"Fair" Health	0.405	0.200	0.226	0.421
Good Health (reference)	0.318	0.460	0.406	0.309
"Very Good" Health	0.278	0.340	0.368	0.270
Black	0.145	0.120	0.113	0.148
Medicare	0.973	0.980	0.972	0.973
Has Private Health Insurance	0.552	0.700	0.538	0.548
Health Expenses - last 2 years	2,042.713	1,328.160	1,145.613	2,116.125
	(8,024.231)	(2,611.560)	(1,773.819)	(8,341.904)
Assets (in $1,000)	353.765	765.263	798.521	315.763
	(856.189)	(1,359.691)	(1,919.149)	(715.047)
Number of Children	3.024	2.940	3.104	3.021
	(2.287)	(2.385)	(2.212)	(2.290)
Receive Social Security Benefits	0.970	0.980	0.981	0.969
Receive Pension	0.577	0.300	0.349	0.598
Receive SSI	0.031	0.020	0.000	0.033
Sample size	1,938	50	106	1,782

force participation status j, z_i is the vector of explanatory variables given in Tables 1 and 2 excluding endogenous variables, θ_{ij}'s are the corresponding vectors of unknown coefficients and η_{ij}'s are the random disturbances.

Let $r = \max\,(y_1^*,\, y_2^*,\, y_3^*,)$. Then, the labor status is given by

$$lfp = \left\{ \begin{array}{c} 1 = \text{full-time, if } r = y_1^*, \\ 2 = \text{part-time, if } r = y_2^*, \\ 3 = \text{out of labor force, if } r = y_3^*. \end{array} \right\} \tag{2}$$

I assume that η_j's satisfy the Independence of Irrelevant Alternatives (IIA) hypothesis, so they have type I extreme value distribution. McFadden (1974) proves that this specification corresponds to the Multinomial Logit model.

Table 3: Multinomial Logit Estimates of Labor Force Status on Some Possible Determinants for Single Males Aged 66-74

Variable	Full-Time		Part-Time	
	Coef.	Std. Err.	Coef.	Std. Err.
Age	-0.159^{***}	0.035	-0.033	0.034
High School Graduate	0.192	0.219	0.435^{*}	0.236
University Graduate	0.550^{**}	0.265	1.514^{***}	0.268
"Fair" Health	-0.394^{*}	0.242	-0.342	0.216
Very Good Health	0.439^{**}	0.206	0.090	0.203
Black	0.674^{***}	0.205	0.308	0.216
Health Expenses (in \$1000)	0.003	0.019	-0.011	0.025
Has Children	-0.066	0.204	0.368^{*}	0.204
Constant	8.865^{***}	2.419	-0.219	2.417
No. of observations	1,280			
Log-likelihood w/o covariates	-967.3			
Log-likelihood with covariates	-916.2			

Robust standard errors are in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Good health is the reference group for health status. High school dropouts is the reference group for education.

The choice probabilities are given by

$$\pi_j = \Pr(lfp = j \mid z) = \frac{\exp(\theta_j' z)}{\sum_{k=1}^{3} \exp(\theta_k' z)}, \; j = 1, \; 2, \; 3. \tag{3}$$

Since $\sum_{j=1}^{3} \pi_j = 1$, I choose people who are out of the labor force as the reference group and set $\theta_3 = 0$. Then, I obtain consistent estimates for θ_j's by maximizing the following likelihood function

$$L = \prod_{lfp=1} \pi_1 \prod_{lfp=2} \pi_2 \prod_{lfp=3} \pi_3. \tag{4}$$

The results of this estimation can be found in Table 3 for the age group $66 - 74$.[12] Notice that the log odds of staying in the labor force decrease with age and increase with education level and health stock. The results also suggest that being black increases full-time participation probability while having children increases part-time participation probability for which I do not have a good explanation.

[12] Multinomial logit estimates for the age group 75+ can be found in Table C.3 in the Appendix.

3 Model

I use a dynamic programming formulation. I have a three dimensional vector of control variables: consumption, hours worked in a year and a dummy variable indicating whether the individual applied for SS benefits. Consumption (c_t) and hours worked (h_t) are continuous variables obtained via splines after using discretizations.[13] b_t denotes the dummy variable indicating whether the individual applied for SS benefit or not.

The observed heterogeneity comes from a five dimensional vector of state variables: assets, wages, health status, education and Principal Insurance Amount (PIA), the term which gives the basis for SS benefit amounts. I use 11 asset states denoted by A_t, 6 wage states denoted by w_t and 5 PIA states.[14] There are 4 health status categories: "very good," good, "fair" and dead[15] denoted by hs_t taking values 1, 2, 3 and 4, respectively. I have 3 education (ed) groups: no high school diploma ($ed < 12$ years of education), high school graduates ($12 \leq ed < 16$ years of education) and university graduates ($ed \geq 16$ years of education).[16] I use a projection method to accommodate continuous state space of assets, wages and PIA. I control for Medicare (m_t) in my model, and include SS benefits (ss_t) and Medicare premium (mp) in the budget constraint.

The subjects make decisions every year in my model. Denote the control variables by d, state variables by x and preference parameters by θ. The flow utility function, for each health status category $i \epsilon \{very\ good\ health,\ good\ health\ and\ fair\ health\}$, is given by:

$$U(x_t, d_t, \theta) = \frac{1}{1-v}\left(c_t^{\theta_{Ci}}\hat{L}^{\theta_{Li}}\right)^{1-v} \tag{5}$$

where

$$\hat{L} = L - (h_t + \theta_{P,f} + \theta_{P,good}I(good\ health) + \theta_{P,fair}I(fair\ health) + \theta_{PA}(age_t - 57)^{\gamma})I(h_t > 0), \tag{6}$$

[13]The initial discretization used for consumption is 3,000, 13,000, 23,000, 33,000, 53,000, 73,000, 93,000, 113,000, 143,000, 173,000 and 203,000. The initial discretization used for hours worked is 0, 750, 1500, 2250, 3000 and 3750.

[14]The initial asset states are given by −15,000, 0, 15,000, 40,000, 80,000, 120,000, 200,000, 300,000, 500,000, 800,000 and 1,300,000. The initial wage states are given by 2, 8, 14, 20, 32 and 44. The initial PIA states are 0, 25^{th}percentile, 50^{th}percentile, 75^{th}percentile and the maximum observed amount.

[15]HRS has 5 self-reported health status categories: excellent, very good, good, fair and poor. I combine the self-reported excellent and very good health status categories and call the new category as "very good," and combine fair and poor health status categories and call the new category as "fair."

[16]My sample is not big enough to conduct separate analyses by education groups.

The coefficient of relative risk aversion is given by v. For each health status category i, θ_{Ci} and θ_{Li} measure the consumption and leisure weights, respectively. $I(.)$ is the indicator function. θ_{Pf} is the fixed cost of work, and $\theta_{P,good}$ and $\theta_{P,fair}$ are the additional participation costs depending on health status level, with $\theta_{P,very\ good}$ normalized to zero. $\theta_{PA}(age_t - 57)^{\gamma}$ measures the participation cost explained by age.

Following De Nardi (2004), people who die value asset bequests according to the function

$$b(A_t) = \theta_B \frac{(A_t + K)^{\theta_{C2}(1-v)}}{1-v} \tag{7}$$

where K measures the curvature of the function. With $K > 0$, the disutility of leaving non-positive bequests in the amount of less than K dollars becomes infinite. The curvature implicitly sets a borrowing constraint since the elderly face mortality uncertainty each period.

The constraints are the wage determination equation, the health status determination equation, the health expenses determination equation and the asset accumulation equation.

I do not observe wages for more than half of the employed workers. I impute them using the solution methodology for double selection problems provided by Tunali and Yavuzoglu (2012), which relaxes the trivariate normality assumption among the error terms of the two selection equations and the regression equation by following the Edgeworth expansion approach of Lee (1982). The details can be found in Appendix B.

Log wages in the current period depend on age, education and PIA:[17]

$$ln(w_t) = \varsigma_0 + \varsigma_1 age_t + \varsigma_2 \frac{{age_t}^2}{100} + \delta_{high} I(12 \leq ed_t < 16) + \delta_{uni} I(ed_t \geq 16) + \delta_{PIA} \frac{PIA}{100} + AR_t, \tag{8}$$

where

$$AR_t = \rho_{AR} AR_{t-1} + \eta_t, \quad \eta_t \propto N(0, \sigma_\eta^2). \tag{9}$$

According to the human capital theory, workers should be paid their marginal product which decreases over the time due to the decrease in health stock and human capital investment. The resulting wage process is approximated through equations 8 and 9. PIA is included as a proxy for work experience since it is calculated averaging the 35 highest earnings years, and zeros are thrown

[17]Having no high school diploma is the reference category for high school and university graduates.

into the calculation in case an elderly person has a working history of less than 35 years.[18]

Health status next period (including being dead) depends on the current health status, age and education:[19]

$$\mu_{j,i,age_t,ed} = \Pr(hs_{t+1} = j | hs_t = i, age_t, ed). \tag{10}$$

Out of pocket health expenses depend on age, health status, medicare and asset levels:[20]

$$\begin{aligned} ln(he_t) &= \varphi_0 + \varphi_1 age_t + \frac{\varphi_2}{100} {age_t}^2 + \delta_{fair} I(fair\ health) + \delta_{good} I(good\ health) \\ &+ \delta_{medicare} m_t + \delta_{assets} \left(\frac{A_t}{100,000} \right) + \xi_t, \end{aligned} \tag{11}$$

where

$$\xi_t \propto N(0, \sigma_\xi^2). \tag{12}$$

The age dependency of out of pocket health expenses arises from the increasing hazard rates of serious illnesses with age. I assume everyone is entitled to Medicare at age 65, which causes a reduction in out-of-pocket health expenses. This, in turn, provides an incentive for the elderly to leave the labor force. I include asset levels in equation 11 because of the positive correlation between wealth and the quality of care demanded. Moreover, poor people might be covered by Medicaid when confronted with high out-of-pocket health expenses.[21]

The asset accumulation equation is given by:

$$A_{t+1} = (1 + r)A_t + Y_1(w_t h_t, \tau_1) + b_t ss_t - he_t - c_t - mp - Y_2(G_t, \tau_2), \tag{13}$$

where r is the interest rate, $Y_1(w_t h_t, \tau_1)$ is the level of post-FICA tax wage earnings, τ_2 is the tax structure regarding state and federal taxes and $Y_2(G_t, \tau_2)$ is the level of tax amount paid out of gross taxable earnings, G_t. It is generated via:

[18] See Section 4.3 for a discussion about the relationship between Average Indexed Monthly Earnings (AIME) and PIA.

[19] See Section 4.1 for the functional form.

[20] "Very good" health status is the reference category for good and "fair" health statuses.

[21] The magnitude of the standard deviation of the out of pocket health expenses corresponds to the 97.6^{th} percentile of the distribution in my sample. Most elderly would not face extreme out-of-pocket expenses amounts or uncertainty (standard deviation) unless they choose to have exceptional care. For that reason, I use out-of-pocket health expenses values up to the 96^{th} percentile of the distribution to calculate the data moments required for estimation.

$$G_t = w_t h_t + Y_3 \left(b_{t-1} ss_{t-1}, \tau_3 \right) \tag{14}$$

where $Y_3 \left(b_{t-1} ss_{t-1}, \tau_3 \right)$ is the taxable portion of the SS benefits.

I assume that wage decrease, health deterioration, and increasing fixed cost of work associated with health deterioration and aging are the main determinants of the non-participation decision of the elderly. However, non-participation is not a permanent decision so that an elderly might return to work after being a non-participant for a while. The data reveals that 4.6 percent of the non-participants aged $66 - 67$ return to work within 2 years and 7.1 percent within 4 years.[22] I account for this through wage, health status and health expenses shocks.

$$\begin{aligned} V_t(x_t) \quad = \quad & \max_{d_t} [u_t(x_t, d_t, \theta) + \beta (\sum_{j=1}^{3} \Pr(hs_{t+1} = j | hs_t, ed, t) \times \\ & \int \int V(x_{t+1}) dF(w_t | w_{t-1}, ed, PIA, t) dG(he_t | hs_t, A_t, t) \\ & + \Pr(hs_{t+1} = 4 | hs_t, ed, t) \times \\ & \int \int b(A_{t+1}) dF(w_t | w_{t-1}, ed, PIA, t) dG(he_t | hs_t, A_t, t))]. \end{aligned} \tag{15}$$

Equation 15 provides the Bellman equation where $F(.|.)$ and $G(.|.)$ denote the conditional distributions of next period wages and current period out-of-pocket health expenses respectively, and β denotes the intertemporal discount factor. Each period, people transit into one of "very good," good or "fair" health statuses, or they die. If they live, they get a continuation value dependent on their health statuses, and if they die, they receive bequest value. Both the continuation and bequest values of the next period depend on wage and out-of-pocket health expense shocks this period, which I integrate over to obtain expected values. I assume that terminal age is 95 to simplify the problem computationally. This assumption does not mean that everyone dies at 95, but people die with probability 1 at age 95 which is an innocuous assumption since the mortality rate is very high beyond age 95. I solve the problem recursively until age 58. The optimal decision rule will be given by $\delta = (\delta_{58}, \delta_{59}, ..., \delta_{95})$ where $d_t = \delta_t(x_t)$ specifies optimal decision as a function of the state

[22] 2.2 percent of all the non-participants beyond normal retirement age return to work within 2 years and 3.0 percent within 4 years.

variables x_t.

The model will be estimated in two steps. In the first step, I estimate some parameters and calibrate others given by $\{\beta$, r, L, mp, $\Pr(hs_{t+1}|hs_t, age_t, m_t, ed)$, PIA, τ_1, τ_2 and $\tau_3\}$. I assume rational expectations. Given the first stage estimation, I estimate the following parameters using simulated method of moments $\phi = \{\theta_{Ci}$'s, θ_{Li}'s, θ_{Pf}, $\theta_{P,fair}$, $\theta_{P,good}$, θ_{PA}, γ, v in the flow utility function, ϱ, ς_0, ς_1, ς_2, δ_{high}, δ_{uni}, δ_{PIA}, ρ_{AR}, σ_η^2 in the wage determination equation, φ_0, φ_1, φ_2, $\delta_{medicare}$, δ_{fair}, δ_{good} in the out-of-pocket health expenses determination equation, and θ_B and K in the bequest function$\}$.

4 First Stage Estimation

Typical consumption-saving models, such as mine, do not allow joint identification of intertemporal discount factor, β, and relative risk aversion, v, as discussed by Guvenen and Smith (2014).[23] Consequently, I set β equal to 0.96. I further set the yearly interest rate, r, equal to 0.04, the time endowment, L, equal to $6,000$, and yearly Medicare premium, mp, equal to $\$1,062$ for people subscribed to Medicare.[24]

4.1 Health Transition Matrix

It is not viable to estimate equation 10 non-parametrically since it involves a health transition matrix for each possible education and age combination.[25] Consequently, I estimate a parametric model of transition rates via maximum likelihood utilizing the methodology of Robinson (2002):

$$p(j|i) = \Pr(hs_{t+1} = j|hs_t = i, age_t, ed) = exp(a_{ij,ed} + b_{ij,ed}(age_t - 57) + c_{ij,ed}\frac{(age_t - 57)^2}{100}) \quad \text{for } i \neq 4 \text{ and } i \neq j. \tag{16}$$

There is no restriction on $a_{ij,ed}$ values. The age adjustment parameters, $b_{ij,ed}$ and $c_{ij,ed}$, are

[23] In Appendix $D.6$, Guvenen and Smith (2014) estimate their model for various values of v. They observe very strong negative correlation between the chosen value of v and the estimate of β, while the remaining structural parameter estimates stay virtually unchanged. Joint identification of β and v in similar models is only possible with an additional channel, like defined contribution plan participation decision in Lucchino and de Ven (2013).

[24] This corresponds to the 2006 Medicare Part B premium.

[25] This corresponds to $3 \times 37 = 111$ different health transition matrices, and $111 \times 9 = 999$ parameters.

Table 4: Maximum Likelihood Estimates of the Health Status Determination Equation for Male High School Graduates

	$\hat{a}_{ij,ed=high-school}$			
$i \diagdown j$	"very good"	good	"fair"	dead
"very good"	–	−1.970 (0.052)	−3.814 (0.147)	−5.661 (0.225)
good	−1.588 (0.108)	–	−2.113 (0.064)	−4.996 (0.195)
"fair"	−2.996 (0.207)	−1.539 (0.124)	–	−4.066 (0.204)

	$\hat{b}_{ij,ed=high-school}$	$\hat{c}_{ij,ed=high-school}$
$i < j$ (recovery)	−0.033 (0.015)	0.064 (0.048)
$j = 4$ (death)	0.078 (0.016)	0.024 (0.036)
$i > j$ (deterioration)	0.001 (0.001)	0.071 (0.013)

restricted to 3 values: one for recovery ($i < j$), one for mortality ($j = 4$) and one for health deterioration ($i > j$). The parameters estimates for high school graduates can be found in Table 4.[26] Notice that the higher the estimate is (in absolute value) the lower the probability.

To assess the performance of the estimation, I compare the implied 2 year transition rates from the model with the data at the first quartile, median and third quartile of the age distribution, provided in Table 5. The model fit looks reasonable.

Table 5: Observed and Fitted Biannual Health Status Transition Matrices for Male High School Graduates

Observed Frequencies					Fitted Frequencies			
Around the First Age Quartile (63 – 65)					A the First Age Quartile (= 64)			
$i \diagdown j$	"very good"	good	"fair"	dead	"very good"	good	"fair"	dead
"very good"	70.4%	23.4%	4.4%	1.7%	70.6%	22.6%	5.5%	1.4%
good	24.2%	54.4%	19.3%	2.1%	25.7%	52.9%	18.7%	2.6%
"fair"	9.4%	25.9%	57.4%	7.4%	9.3%	25.8%	59.1%	5.7%
Around the Median Age (68 – 70)					At the Median Age (= 69)			
"very good"	66.1%	24.6%	7.9%	1.4%	68.0%	24.2%	6.1%	2.1%
good	22.1%	55.7%	18.5%	3.6%	23.1%	52.9%	20.3%	3.9%
"fair"	7.8%	20.0%	65.1%	7.2%	8.1%	23.5%	59.9%	8.6%
Around the Third Age Quartile (75 – 77)					At the Third Age Quartile (= 76)			
"very good"	61.9%	26.6%	6.8%	4.7%	62.0%	27.3%	7.5%	4.0%
good	21.8%	51.2%	21.4%	5.6%	20.3%	49.8%	23.2%	7.3%
"fair"	6.1%	24.8%	54.7%	14.4%	7.1%	21.0%	57.2%	15.4%

[26] I provide the estimates for high school dropouts and university graduates in Tables C.4-C.7 in the Appendix. The implied biannual transition rates from the model are utilized to get the maximum likelihood estimates.

4.2 Taxes

FICA is a federal payroll tax imposed on workers. It has two components: Social Security tax and Medicare tax. During the period 1990-2010, the Social Security tax rate was 6.2 percent of an employee's wages up to a threshold of earnings known as the Social Security Wage Base,[27] and the Medicare tax rate was 1.45 percent of an employee's wages without any cap. I use these values to set τ_1.

The second portion of the tax structure, τ_2, includes federal and state income tax rates. I take the federal income tax rates from the 2006 annual tax rate schedules accounting for standard deductions by age and personal exemptions which phase out after an income threshold. As state income taxes, I use the 2006 Rhode Island tax rate schedule following French and Jones (2011).[28]

The current regulation for federal income taxation of SS benefits is determined by The Deficit Reduction Act of 1993. For a single elderly individual, up to 50 percent of his SS benefits are subject to taxation if his combined income (the sum of adjusted gross income plus nontaxable interest plus one-half of SS benefits) is between $25,000 and $34,000. If his combined income is more than $34,000, up to 85 percent of his SS benefits are taxable. I generate the precise taxable income using IRS Publication Number 915 to set τ_3. In doing this I omit nontaxable interest since I do not have a measure of it.

4.3 Social Security Benefit Levels

Social Security benefit levels are calculated using Average Indexed Monthly Earnings (AIME), which is the average of 35 highest indexed earnings years.[29] Then, a formula is applied on AIME to compute Primary Insurance Amount (PIA) which gives the basis for SS benefit level.

I obtain the AIME levels for 72.1 percent of respondents exploiting their work history from the restricted data set using 2006 as the index year. I observe the SS benefit amount for another 20.8 percent of respondents in my sample even though I cannot see their full work history. I generate

[27] In the time period under study, Social Security Wage Base increased from $84,900 to $102,000. For simplicity, I fix the Social Security Wage Base at the year 2006 value, $94,200, in my analysis.

[28] The taxation of self-employed workers, 30 percent of workers in my sample, is very similar to that of employees. This is why I do not control for taxation of self-employed seperately.

[29] For AIME calculation, earnings levels in any year cannot exceed the maximum taxable earnings level of that year determined by the Social Security Administration. The index used for AIME is called the "national average wage index."

AIME values for this subsample through an inverse function of the benefit levels.[30] I impute the AIME values for the rest of the sample. PIA is given by 90 percent of the first \$656 of AIME plus 32 percent of AIME over \$656 and through \$3,955, plus 15 percent of AIME over \$3,955.

I assume that AIME values are constant, so working another year does not have any effect on that value. For people having at least 35 years of work history, the incremental increase in AIME level is either zero (if the earnings in the extra year does not exceed the 35^{th} highest earning year) or close to zero. Moreover, at least 10 years of working history are required to be entitled to SS benefits. Only 9.4 percent of workers in my sample have 5 to 34 years or working history.

5 Results

5.1 Solution Methodology

I employ the simulated method of moments strategy where I match the following moments:

- By age, participation rate for the age group $60-85$ and mean hours worked for participants for the age group $60-75$ to identify $\theta_{C,i}$ and $\theta_{L,i}$ for each health status i, $\theta_{P,A}$, γ, and v.
- For each health status, average of participation rates between ages $66-74$ to identify $\theta_{P,f}$, $\theta_{P,good}$ and $\theta_{P,fair}$.
- By age, mean wage for the age group $60-75$ to identify ς_0, ς_1 and ς_2.
- For each education level, average of mean wages between ages $61-70$ to identify δ_{high} and δ_{uni}.
- For three PIA intervals, average of mean wages between ages $62-67$ to identify δ_{PIA}.
- Covariance of wages between ages 65 and 67 for participants to identify ρ_{AR}.
- Average of standard deviation of wages between ages $62-67$ to identify σ^2_η.
- By health status, mean out-of-pocket health expenses for age groups ages $68-69$ and $78-79$ to identify γ_0, γ_1, γ_2, δ_{good} and δ_{fair}.

[30] In doing so, I increase SS benefit amount of early retirees by 25 percent which is equivalent to assuming that they retired 36 months earlier than their full retirement age. I index the benefit amounts according to the 2006 level. I also consider Medicare premiums deducted from SS benefit check while calculating AIME levels.

- Mean out-of-pocket health expenses for age groups $61-63$ and $68-70$ to identify $\delta_{medicare}$.
- Mean out-of-pocket health expenses for age group $67-75$ by assets levels $0-40,000$, $40,000-200,000$ and $200,000-1,000,000$ to identify δ_{assets}.
- Average of standard deviation of out-of-pocket health expenses between ages $62-67$ to identify σ^2_{ξ}.

I assume that at the terminal age agents are non-participants and consume all of their assets. In solving the model, I calculate the expectations of value and bequest functions using the Gauss-Hermite quadratures of order 5 to account for the wage and health expense shocks. The next step is to randomly draw $1,000$ observations from the data using the Mersenne Twister random number generator and simulate their behavior with interpolation/extrapolation. Subsequently, the distance between the simulated and the data moments are computed. In doing this, I use the the inverse of the variance covariance matrix of the data moments as the weight matrix to obtain efficient estimates.[31] This process is repeated with different parameter vector choices using the Nelder-Mead algorithm. The solution is given by the parameters minimizing the distance between the simulated and the true data moments.

5.2 Parameter Estimates

The estimates are provided in Table 6. While the leisure share parameter estimates are positively correlated with health status, the consumption share parameter estimates do not differ by health status. Given the same age and PIA levels, compared to people having no high school diploma, high school graduates earn 8 percent more on average while college graduates earn 34 percent more. The part of wages unexplained by the observables shows 71 percent persistency over a year.

Given the same age and asset levels, the elderly with good health pay 6 percent less out-of-pocket health expenses than ones with “very good” health whereas the elderly with “fair” health pay 14 percent more on average. Having Medicare decreases out-of-pocket health expenses dramatically. Given the same age level and health status, $\$100,000$ increase in asset levels are associated with a 5 percent increase in out-of health expenses on average.

[31] The variance covariance matrix of data moments is estimated via bootstrap using $1,000$ replications.

Table 6: The Estimates of the Structural Parameters

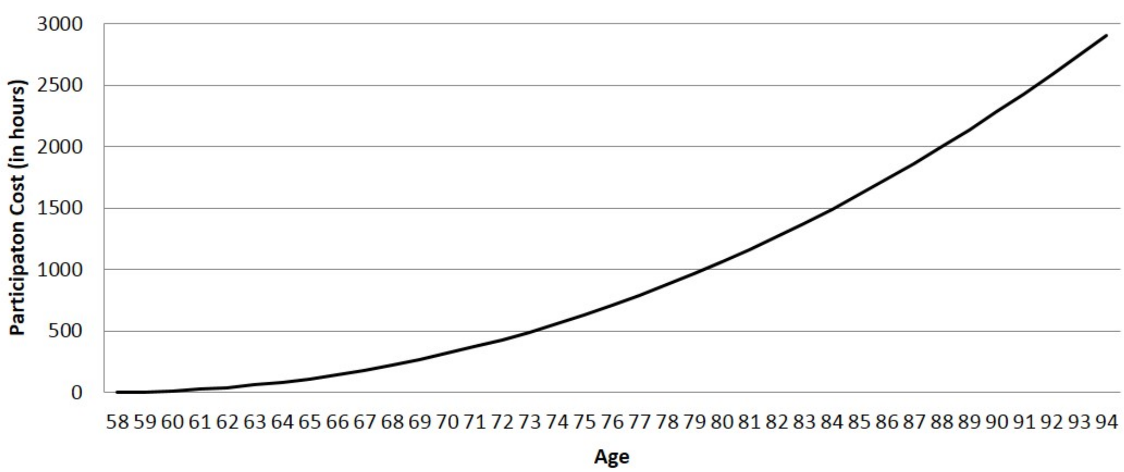
Parameter	Explanation	Coef.	Std. Error	Parameter	Explanation	Coef.	Std. Error
	Flow Utility Parameters				*Wage Equation Parameters*		
$\theta_{C,verygood}$	Cons. weight, "very good" health	0.421	0.010	ς_0	Constant	1.169	0.020
$\theta_{C,good}$	Cons. weight, good health	0.429	0.008	ς_1	Age	0.065	0.001
$\theta_{C,fair}$	Cons. weight, "fair" health	0.427	0.012	ς_2	Age squared/100	-0.076	0.001
$\theta_{L,verygood}$	Leisure weight, "very good" health	0.614	0.013	$\delta_{high\ school}$	High school wage premium	0.079	0.014
$\theta_{L,good}$	Leisure weight, good health	0.528	0.015	$\delta_{university}$	University wage premium	0.337	0.029
$\theta_{L,fair}$	Leisure weight, "fair" health	0.502	0.019	δ_{PIA}	PIA/100 (proxy for experience)	0.010	0.000
θ_{Pf}	Fixed cost of work (hours worked)	1,146.9	35.6	ρ_{AR}	AR term	0.708	0.046
$\theta_{P,good}$	Add. part. cost - good health	606.8	5.3	σ^2_η	Variance of the error	0.061	0.004
$\theta_{P,fair}$	Add. part. cost -"fair" health	1,934.2	30.6		*Health Expenses Equation Parameters*		
θ_{PA}	Participation cost due age - Shifter	1.391	0.17	γ_0	Constant	4.095	0.055
γ	Participation cost due age - Convexity	2.117	0.021	γ_1	Age	0.015	0.0001
v	Relative risk aversion	4.099	0.136	γ_2	Age squared/100	0.0007	0.0002
				δ_{good}	Premium for good health	-0.058	0.006
				δ_{fair}	Premium for "fair" health	0.138	0.023
	Bequest Function Parameters			$\delta_{medicare}$	Premium for Medicare	-0.561	0.002
θ_B	Bequest shifter	0.00007	0.000001	δ_{assets}	Premium for assets ($100,000)	0.045	0.007
K	Curvature	11,990	72	σ^2_ξ	Variance of the error	1.891	0.016

Notes: Bootstrapped standard errors (using 100 replications) are reported.

No high school diploma is the reference category for wage premium parameters.
"Very good" health is the reference category for health expenses premium coefficients.

The curvature estimate implies that the elderly can have unsecured debt up to $11,990,[32] which can be thought as maxing out credit cards rather than borrowing against SS benefits. Figure 2 provides the participation cost due to age.

Figure 2: Participation Cost Explained by Age



[32]The elderly can have more debts as long as they have corresponding assets for these debts, like mortgage. The bequest function implies having an asset level less than $-\$11,990$ produces infinite disutility. The data suggest that some elderly people do borrow small amounts of money. While 3.6 percent of the elderly have negative assets levels in the data, only 1.0 percent have asset levels less than $-\$11,990$.

5.3 Model Fit

Figures 3, 4 and 5 provides the model fit of participation rate, mean hours worked and mean wages for participants, respectively. Simulated profiles are the paths of average behavior here and elsewhere in the paper. Table 7 provides the model fit of the average of mean wages between ages 61 and 70 by education group. Table 8 shows the model fit of the average of mean wages between ages 62 and 67 by three PIA intervals. Table 9 provides the model fit of the average of participation rates between ages 66 and 74 by health status. Table 10 provides the model fit of the average of mean health expenses between ages $68-69$ and $78-79$ by health status. Table 11 shows model fit of the average health expenses between ages $67-75$ by asset levels. Finally, Table 12 provides the model fit of the remaining moments. The model fits the data well with reasonable estimates.

Figure 3: Model Fit - Participation Rate by Age

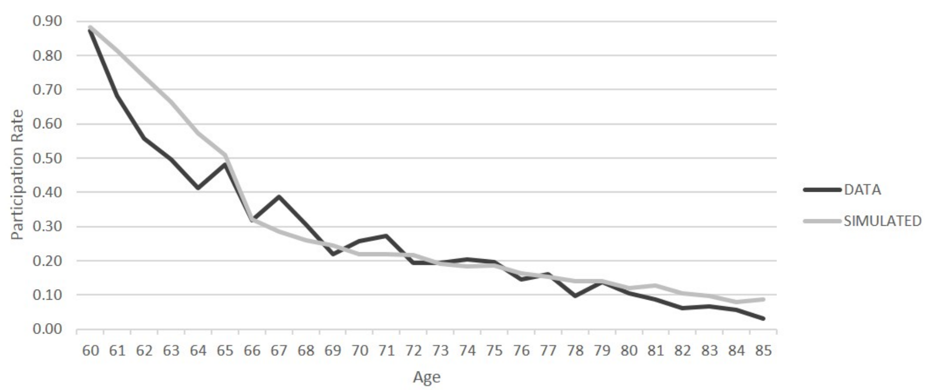


Figure 4: Model Fit - Mean Hours Worked for Participants by Age

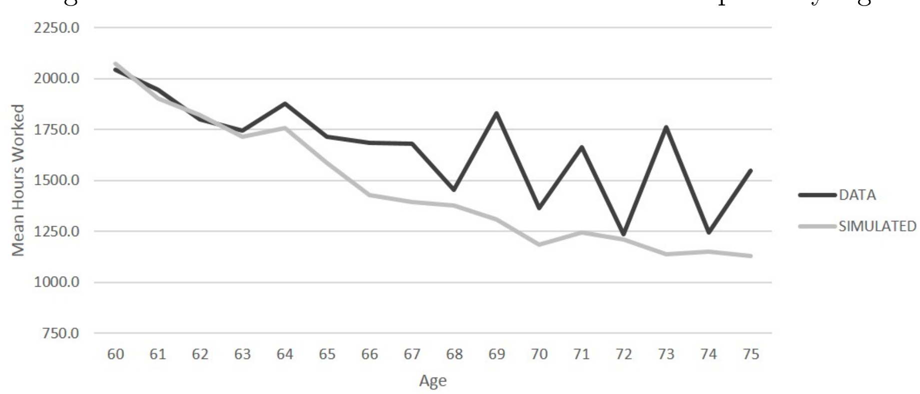


Figure 5: Model Fit - Mean Wages for Participants by Age

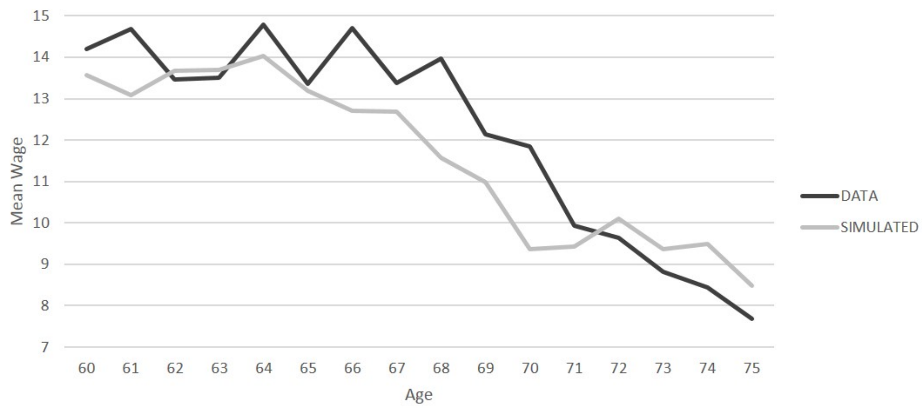


Table 7: Model Fit - Average of Mean Wages of Each Age Between 61 − 70 by Education

Education Status	Data	Simulation
No High School Diploma	10.74	11.08
High School Graduates	12.86	12.31
University Graduates	16.60	15.84

Table 8: Model Fit - Average of Mean Wages Between Ages 62 − 67 by PIA

PIA Level	Data	Simulation
PIA $< 1,000$	12.79	11.46
$1,000 <$PIA $< 1,500$	13.33	13.64
PIA $> 1,500$	15.18	14.08

Table 9: Model Fit - Average of Participation Rates Between Ages 66 − 74 by Health Status

Health Status	Data	Simulation
"Very Good"	0.337	0.296
"Good"	0.262	0.242
"Fair"	0.193	0.151

Table 10: Average of Mean Health Expenses Between Ages 68 − 69 and 78 − 79 by Health Status

	Ages 68 − 69		Ages 78 − 79	
Health Status	Data	Simulation	Data	Simulation
"Very Good"	628	579	653	712
"Good"	739	771	714	646
"Fair"	735	764	798	765

Table 11: Average Health Expenses Between Ages $67-75$ by Assets

Assets	Data	Simulation
$0-40,000$	495	617
$40,000-200,000$	747	579
$200,000-1,000,000$	841	706

Table 12: Model Fit - Rest

	Data	Simulation
Covariance of Wages Between Ages 65 and 67 (For Participants in Both Periods)	12.72	14.72
Average of Standard Deviation of Wages Between Ages 62 and 67	5.18	4.94
Average of Health Expenses Between Ages $61-63$	784	801
Average of Health Expenses Between Ages $68-70$	708	700
Average of Standard Deviation of Health Expenses Between Ages 62 and 67	1,233	1,212

6 Counterfactuals

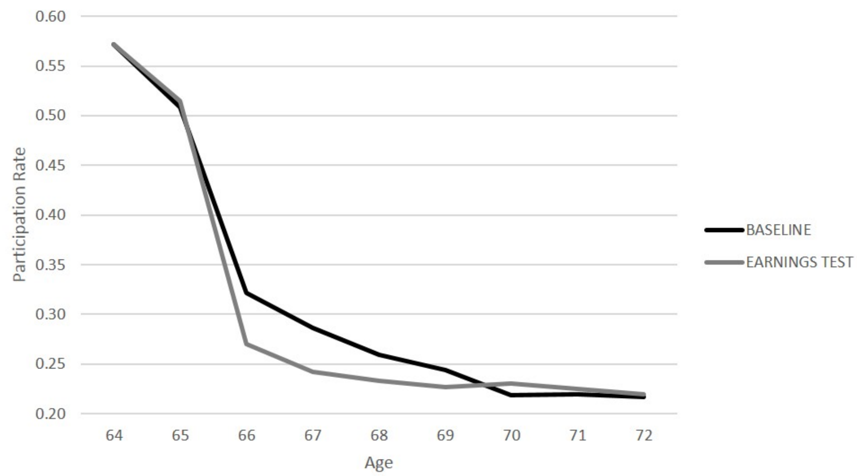
6.1 The Effect of Year 2000 Social Security Amendments

"Earnings test" is a program deferring part (or all) of SS benefits of people whose earnings exceed a threshold level to later years by indexing the withheld amount with the delayed retirement credit. Until year 2000, it applied to the elderly until the age 70, and it currently applies only on the elderly who start collecting their SS benefits before normal retirement age. The annual delayed retirement credit was 3.0 percent in 1989 and was raised by 0.5 percentage point every two years since then until 2008. That corresponded to 5.5 percent delayed retirement credit right before the year 2000 SS amendment, which was actuarially unfair. It is 8 percent now and can be considered actuarially fair.[33] "Earnings test" withholds \$1 in benefits for every \$2 of earnings in excess of the lower exempt amount, and \$1 in benefits for every \$3 of earnings in excess of the higher exempt amount. The lower and higher exempt amount are determined by the Social Security Administration.

The time period studied in the paper is $2002-2008$, right after the abolishment of the "earnings test". It is possible to see the behavioral effects of the year 2000 SS amendment by applying the pre-2000 rules on my sample. I set the delayed retirement credit to 4.5 percent and use the year

[33] Assume that the yearly retirement benefits of a SS beneficiary is equal to \$10,000. The CDC report in 2009 indicates that the life expectancy at age 65 was around 19 years. Since the SS makes the yearly cost-of-living adjustment on the retirement benefits, I assume that the real value of the benefits stays the same. If this beneficiary delays getting retirement for a year, he gets \$10,800 for 18 years on average, and if he does not delay the retirement, he gets \$10,000 for 19 years on average. Note that $10,800 * 18 \backsimeq 10,000 * 19$.

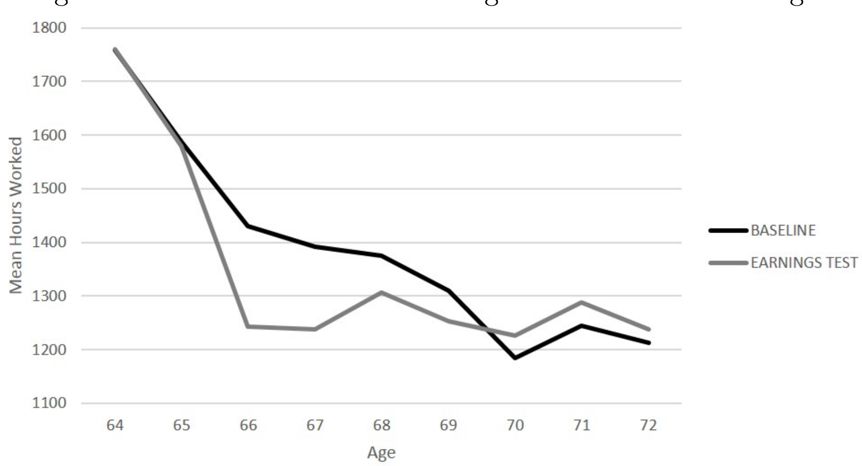
Figure 6: The Effect of "Earnings Test"-Extensive Margin



2006 values of lower and higher exempt amounts rather than the year 2000 values.

Figure 6 shows that LFPR of the elderly aged $66-69$ decreases by 3.5 percentage points with the introduction of "earnings test" which explains one-fourth of the recent increase in the elderly participation rates. The effect on the intensive margin is is provided in Figure 7 which shows that the mean annual hours worked decreases by 117 hours in the same age group. The mean earnings of participants at age 66 with the introduction of "earnings test", $\$15,000$, gets close to the lower exempt amount of "earnings test", $\$12,480$. This suggests that the elderly limited their hours supplied to avoid the implicit taxation imposed by the "earnings test."

Figure 7: The Effect of The "Earnings Test" - Intensive Margin



6.2 Changing Social Security Benefit Amounts

In this analysis, I decrease SS benefit amounts by 20 percent. This is mainly an income effect for the elderly with a small substitution effect arising from a possible change in the decision to start collecting retirement benefits. The participation decision is sensitive to SS benefits as seen in Figure 8. 20 percent decrease in SS benefits is associated with a 36 percent increase in LFPR of the age group $66-75$.[34] However, there is not a significant response in the intensive margin as presented in Figure 9.

Figure 8: Participation Rates under 20% Decreased SS Benefit Levels

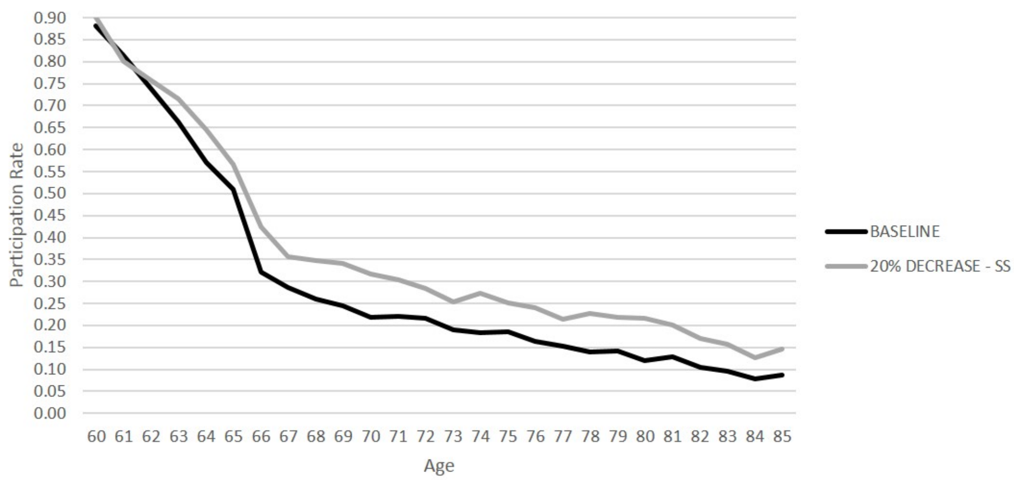
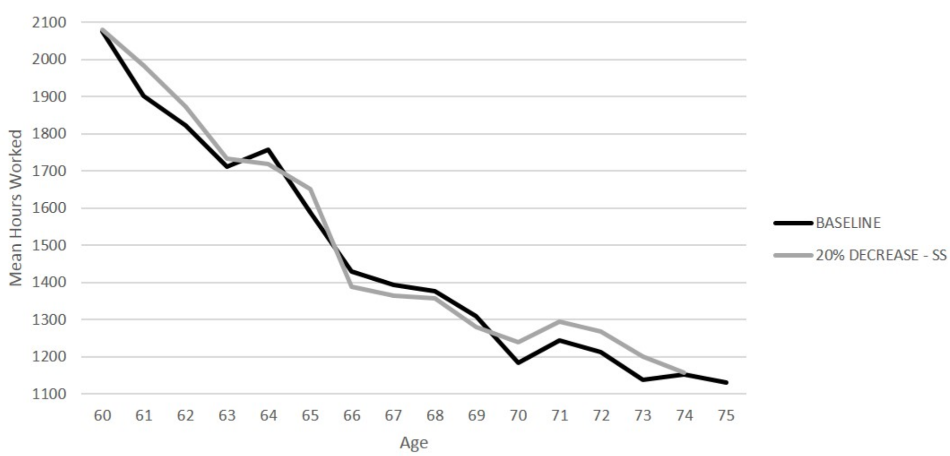


Figure 9: Mean Hours Worked under 20% Decreased SS Benefit Levels

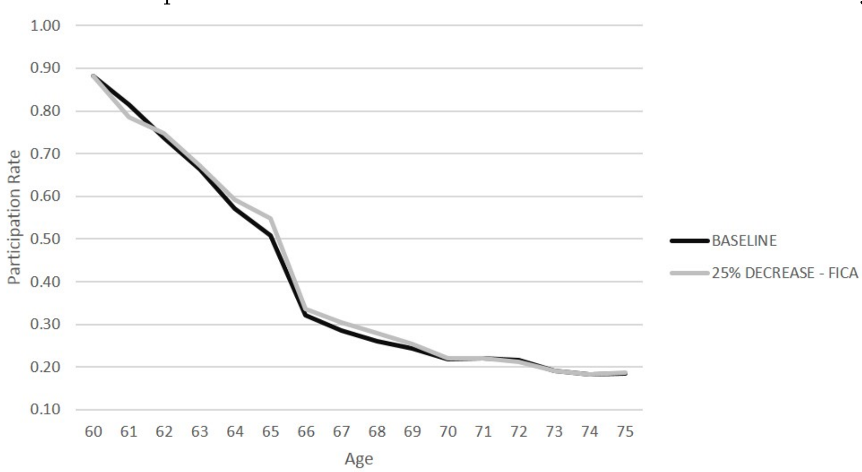


[34]For those who find 20 percent decrease in SS benefits politically unacceptable, 10 and 5 percent decrease cause participation rates to increase by 16 and 9 percent, respectively. The resulting simulated profiles for these two cases are in between the baseline and 20 percent decrease profiles.

6.3 Labor Supply Elasticities and Changes in Payroll Taxes

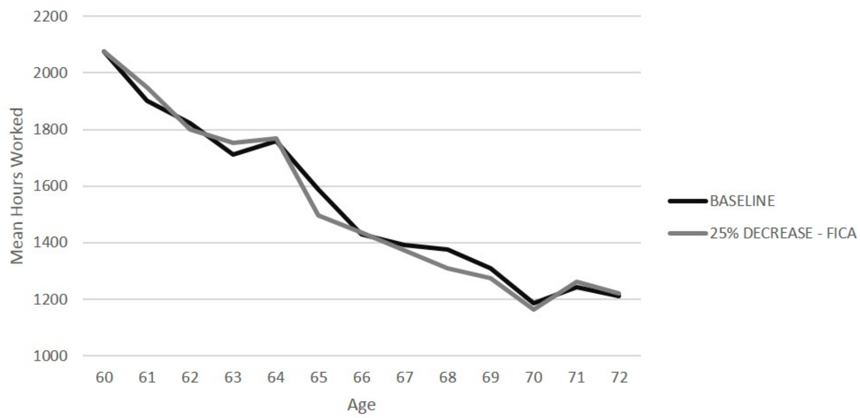
In my last counterfactual analysis, I examine the effect of a change in payroll taxes on the elderly labor supply decisions. Notice that a change in the payroll tax rate is effectively a change in the wage rate. The corresponding change in the wage rate is determined by the economic incidence of tax. Joint Committee on Taxation (2001) postulates that the incidence of the federal payroll taxes falls entirely on employees. Li (2015) finds that workers bear the full burden of the federal payroll tax in the U.S. using a difference-in-difference approach. Exploiting the year 1981 amendment in payroll taxation in Chile, Gruber (1997) obtains the same result. However, as I show below the labor supply elasticities are around unit elasticity for elderly people. This finding renders the argument that the tax incidence falls entirely on employees suspect. In what follows, I conduct my analysis assuming that the incidence is passed entirely to the workers to get an upper bound on the effect of FICA tax interventions. This assumption also allows me to calculate labor supply elasticities.

Figure 10: Participation Rates under Decreased FICA Amounts for Everyone



I first decrease FICA tax amounts by 25 for everyone starting at the age 58, the initial age in my dynamic programming set-up. This can be thought as a 3.825 percent increase in wages as well. This kind of analysis have both income and substitution effects on the elderly. Figure 10 shows that such a policy change affects the extensive margin mainly beyond normal retirement age. The corresponding increase in the LFPR for people aged $66-70$ is 4.8 percent (upper bound on the effect of reducing FICA taxes by 25 percent), which corresponds to a labor supply elasticity of 1.25. Figure 11 provides the labor supply responses on the intensive margin. The effects are not

Figure 11: Mean Hours Worked under Decreased FICA Amounts for Everyone



substantial. The elderly increase their annual hours supplied by 19 hours on average between ages $61-64$, but decrease it by an average of 38 hours between ages $65-70$.

If FICA taxes are reduced only for people aged 70+, the response in the extensive margin is observed mainly between ages $70-76$. The corresponding increase in LFPR is 2.3 percent at this age group (upper bound on the effect of reducing FICA taxes by 25 percent for people aged 70+), which corresponds to a labor supply elasticity of 0.6. The effect on the intensive margin is not substantial again.

Figure 12: Participation Rates under Decreased FICA Amounts for People Aged 70+

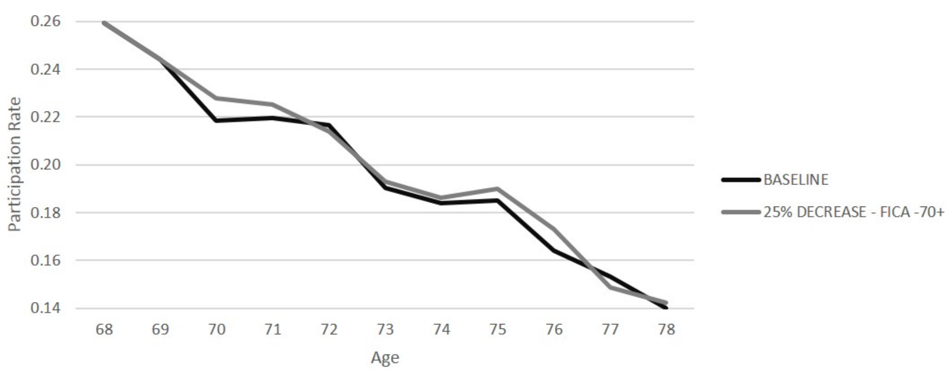
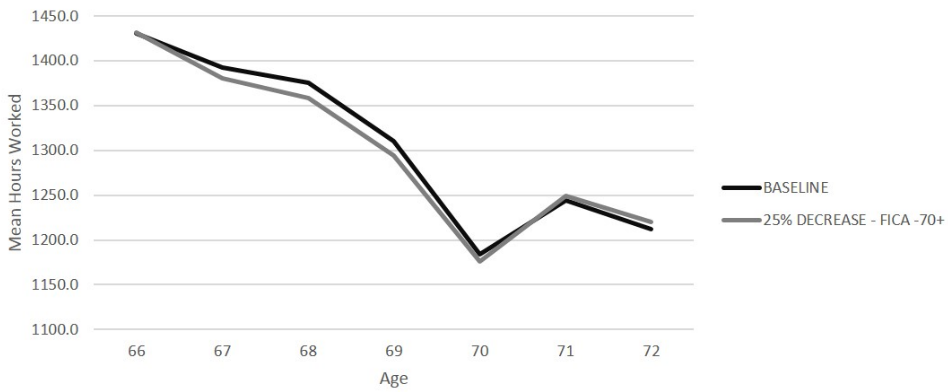


Figure 13: Mean Hours Worked under Decreased FICA Amounts for People Aged 70+



7 Conclusion

This paper analyzes the joint determination of labor supply, consumption and the decision to apply for SS benefits of elderly single males using a dynamic programming formulation and restricted data from the Health and Retirement Study. I first conduct a preliminary multinomial logit analysis, then formulate a dynamic programming model enhancing the understanding of the elderly labor force decision. In doing so, I focus on the labor supply decision rather than the retirement decision since a significant portion of the elderly return to work after being non-participants for a while. It is essential to understand the incentives provided by the SS system on the elderly labor supply decision since the U.S. population is steadily aging and the fiscal burden of SS is sizable.

The specification of my model is flexible in terms of capturing most of the documented determinants of the elderly non-participation decision in the literature. I apply "earnings test," which was abolished by the year 2000 SS amendment, on my sample via a counter-factual analysis to quantify the effect of the year 2000 SS amendment on the recent increase in the elderly participation rates. I find that the abolishment of the "earnings test" increased the participation rate of the elderly single males aged $66-70$ by 3.5 percentage points on the extensive margin and mean annual hours worked by 117 hours on the intensive margin. The effect on the extensive margin explains one-fourth of the recent increase in the elderly participation rates. Moreover, the decrease in the intensive margin brings the mean earnings level close to the lower exempt amount of "earnings test." This finding suggests that prior to the year 2000 SS amendment, the elderly limited their hours supplied to avoid the implicit taxation imposed by the “earnings test” via an unfair delayed retirement credit.

In my other counterfactual analyses, I consider changes in SS rules. I find that decreasing SS benefits by 20 percent increases the participation rate of the elderly single males aged $66-75$ by 36 percent without a substantial effect on the intensive margin. The effect of changing FICA taxes can be found by assuming that the incidence is passed entirely to the workers, which is postulated by the literature. However, I estimate that the labor supply elasticities are around unit elasticity for elderly people, which sheds doubt on the incidence postulation at the elderly ages. Thus, 4.8 percent increase in the LFPR for elderly aged $66-70$ in response to reducing FICA taxes by 25 percent can only be interpreted as an upper bound. The effect of changing FICA taxes on the intensive margin is not substantial again. These results suggest that the policy recommendations arising within the public debate to change the SS rules might have a marked effect on the participation decision of individuals beyond normal retirement age.

References

Blau, D. M. and D. B. Gilleskie (2008): "The Role of Retiree Health Insurance in the Employment Behavior of Older Men," *International Economic Review*, 49, 475–514.

Blau, D. M. and R. M. Goodstein (2010): "Can Social Security Explain Trends in Labor Force Participation of Older Men in the United States?" *Journal of Human Resources*, 45, 328–363.

Casanova, M. (2010): "Happy Together: A Structural Model of Couples' Joint Retirement Choices," Working paper.

De Nardi, M. (2004): "Wealth Inequality and Intergenerational Links," *The Review of Economic Studies*, 71, 743–768.

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

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

Gruber, J. (1997): "The Incidence of Payroll Taxation: Evidence from Chile," *Journal of Labor Economics*, 15, S72–S101.

Guvenen, F. and A. A. Smith (2014): "Inferring Labor Income Risk and Partial Insurance from Economic Choices," *Econometrica*, 82, 2085–2129.

Joint Committee on Taxation (2001): "Overview of Present Law and Economic Analysis Relating to Marginal Tax Rates and the President's Individual Income Tax Rate Proposals," .

Lazear, E. P. (1979): "Why Is There Mandatory Retirement?" *The Journal of Political Economy*, 87, 1261–1284.

Lee, L. F. (1982): "Some Approaches to the Correction of Selectivity Bias," *Review of Economic Studies*, 49, 355–372.

Li, H. (2015): "Who Pays the Social Security Tax?" Working Paper.

Lucchino, P. and J. V. de Ven (2013): "Empirical Analysis of Household Savings Decisions in Context of Uncertainty: A cross-sectional approach," National Institute of Economic and Social Research Discussion Paper 417.

Maestas, N. (2010): "Back to Work: Expectations and Realizations of Work after Retirement," *Journal of Human Resources*, 45, 718–748.

McFadden, D. L. (1974): "Conditional Logit Analysis of Qualitative Choice Behavior," in *Frontiers in Econometrics*, ed. by P. Zarembka, Academic Press, New York, 105–142.

Robinson, J. (2002): "A Long-Term-Care Status Transition Model," Unpublished Paper.

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

Tunali, I. (1986): "A General Structure for Models of Double-Selection and an Application to a Joint Migration/Earnings Process with Re-migration," *Research in Labor Economics*, 8B, 235–282.

Tunali, I. and B. Yavuzoglu (2012): "Edgeworth Expansion Based Correction of Selectivity Bias in Models of Double Selection," Working Paper.

APPENDIX

A Data

HRS includes some confirmation questions for the health insurance section. While generating the health insurance data, I exploit these confirmation questions. I also use the tracker file released by HRS which accounts for misspecified cases of age and marital status. I define marital status as a dummy variable where the non-married class is composed of separated, divorced, widowed, never married and other categories. Health expenses are obtained by summing up out-of-pocket expenses for hospital, nursing home, outpatient surgery, doctor visit, dental, prescription drugs, in-home health care, and special facility and other health service costs in the last 2 years. I exploit HRS Core Income and Wealth Imputations data for the missing asset values, which is consistent with the HRS and provided by the RAND Corporation. The number of other health insurance includes private insurance, employment insurance and government insurance other than Medicare. In defining labor force participation status, I impute hours worked and weeks worked observations for 1.02 percent of workers who report only one of them. I further assign people who are listed as temporarily laid off with blank usual hours and weeks worked observations as non-participant. Table C.8 provides the steps used to obtain the working sample.

B Imputation of Missing Wages

Missing wages for participants are imputed using the solution methodology provided by Tunali and Yavuzoglu (2012) for double selection problems, which do not impose any condition on the form of the distribution of the random disturbance in the regression (partially observed outcome) equation, but conveniently assume bivariate normality between the random disturbances of the two selection equations. Assume that home-work (or non-participation), part–time employment and full-time employment utilities can be expressed as follows where z is a vector of observed variables, θ_j's are the corresponding vectors of unknown coefficients and υ_j's are the random disturbances.

$$Home - work\, utility : U_0^* = \theta_0^{'} z + \nu_0, \tag{17}$$

$$Part - time\, work\, utility : U_1^* = \theta_1^{'} z + \nu_1, \tag{18}$$

$$Full - time\, work\, utility : U_2^* = \theta_2^{'} z + \nu_2. \tag{19}$$

Assuming that individuals choose the state with highest utility, their decisions can be captured using the utility differences:

$$y_1^* = U_1^* - U_0^* = (\theta_1^{'} - \theta_0^{'})z + (\upsilon_1 - \upsilon_0) = \beta_1^{'} z + \sigma_1 u_1, \tag{20}$$

$$y_2^* = U_2^* - U_1^* = (\theta_2^{'} - \theta_1^{'})z + (\upsilon_2 - \upsilon_1) = \beta_2^{'} z + \sigma_2 u_2. \tag{21}$$

Note that y_1^* can be expressed as the propensity to be part-time employed rather than being a non-participant and y_2^* as the incremental propensity to engage in full-time employment rather than part–time employment. Then, $y_1^* + y_2^*$ gives the propensity to engage in full-time employment over home-work. The three way classification observed in the sample arises as follows:

$$lfp = \left\{ \begin{array}{c} 1 = \text{full-time employment, if } y_2^* > 0 \text{ and } y_1^* + y_2^* > 0, \\ 2 = \text{part-time employment, if } y_1^* > 0 \text{ and } y_2^* < 0, \\ 3 = \text{home-work, if } y_1^* < 0 \text{ and } y_1^* + y_2^* < 0. \end{array} \right\} \tag{22}$$

In this case the support of $(y_1^*,\, y_2^*)$ is broken down into three mutually exclusive regions, which respectively correspond to $lfp = 1,\, 2,$ and 3. The classification in the sample is obtained via a pair from the triplet $\{y_1^*,\, y_2^*,\, y_1^* + y_2^*\}$. Normalizing the variances of y_1^* and $y_1^* + y_2^*$ to 1 has an implication for the variance of y_2^* ($\sigma_2^2 = -2\rho_{12}$ where ρ_{12} is the correlation between u_1 and u_2). This is why I may apply the normalization to one of $\sigma_{11} = \sigma_1^2$ and $\sigma_{22} = \sigma_2^2$, but must leave the other variance free to take on any positive value. In the analysis, I take $\sigma_{11} = 1$ and let σ_{22} be free. In the first step, I rely on maximum likelihood estimation and obtain consistent estimates of β_1, β_2, ρ_{12} and σ_2 subject to $\sigma_1 = 1$. The likelihood function is given by

$$L = \prod_{lfp=1} P_1 \prod_{lfp=2} P_2 \prod_{lfp=3} P_3, \tag{23}$$

where $P_j = Pr(lfp = j)$ for $j = 1,\, 2,\, 3$. The explanatory variables used in this stage are age, age^2/100, health status categories, education categories and being black where being black is omitted from the second selection equation for identification purposes (See Tunali (1986) for a discussion).

The regression equation for this problem is a Mincer-type wage equation given below where X_3 is the set of explanatory variables including age, age^2/100, health status categories, education categories and being black:

$$\log(wage) = \beta_3^{'} X_3 + \sigma_3 u_3. \tag{24}$$

The aim is to estimate β_3 for $lfp = 1,\, 2$. Details of such an estimation can be found in Tunali and Yavuzoglu (2012). Note that robust correction obtained via Edgeworth expansion nests the conventional trivariate normality correction, and therefore both the conventional trivariate normality specification and the presence of the selectivity bias can be tested via this estimation. While the evidence is in favor of the robust selectivity correction for part-time employment, it is in favor of of the conventional trivariate normality specification for full-time employment in this example.

C Tables

Table C.1: LFPRs of Different Age Groups along with Retirement Ages in Different Countries

Country	Early Retirement Age	Normal Retirement Age	LFPR, 50-54	LFPR, 55-59	LFPR, 60-64	LFPR, 65-69	LFPR, 70-74	LFPR, 75+
Austria	62 (57)	65 (60)	81.2%	55.2%	15.8%	7.1%	3.0%	1.3%
Belgium	60	65 (64)	71.3%	44.8%	16.0%	4.5%	n/a	n/a
Denmark	60	65	87.3%	83.2%	42.1%	13.1%	n/a	n/a
Finland	62	65	86.2%	72.9%	38.7%	7.6%	3.9%	n/a
France	none	60	84.1%	58.1%	15.1%	2.8%	1.2%	0.3%
Germany	63	65	85.0%	73.9%	33.3%	6.7%	3.0%	1.0%
Greece	60 (55)	62 (57)	70.3%	53.5%	32.7%	9.8%	n/a	n/a
Ireland	none	65	73.9%	62.7%	44.8%	17.2%	7.8%	3.4%
Italy	57	65 (60)	71.2%	45.1%	19.2%	7.5%	2.9%	0.9%
Netherlands	none	65	79.5%	63.9%	26.9%	8.2%	n/a	n/a
Norway	none	67	84.6%	77.4%	57.3%	20.6%	6.0%	n/a
Spain	60	65	71.3%	57.5%	34.6%	5.3%	1.6%	0.4%
Sweden	61	65	88.0%	83.0%	62.5%	13.2%	6.8%	n/a
UK	none	65 (60)	82.6%	71.2%	44.3%	16.3%	6.0%	1.6%
USA	62	65.5	78.3%	69.9%	48.4%	29.5%	17.8%	6.1%

Notes: Parentheses indicate the eligibility age for women when different. Columns 2-3 are obtained from "Social Security Programs throughout the World: Europe, 2006" by U.S. Social Security Administration. Columns $4-9$ are obtained from 2006 Health and Retirement Survey for the U.S. and 2006 OECD database for the rest of the countries. Note that the 2006 OECD database includes agricultural workers. LFPRs of elderly people in countries with high agricultural production, like Ireland, can be naturally high since the definition of agricultural work is vague and scope of it is very broad. This further reinforces the discrepancy in elderly LFPRs among the U.S. and the developed European countries. Note that LFPR for the age group $66-69$ in the U.S. is 26.2 percent (accounting for the normal retirement age, 65.5 years, in 2006).

Table C.2: Female and Male Life Expectancy at Age 65 in Various Countries

Country	Life Expectancy at Age 65 Male	Life Expectancy at Age 65 Female
Austria	82.3	85.7
Belgium	82.0	85.6
Denmark	81.2	84.2
Finland	82.0	86.3
France	83.2	87.7
Germany	82.2	85.5
Greece	82.5	84.4
Ireland	81.8	85.3
Italy	82.9	86.8
Netherlands	81.9	85.4
Norway	82.7	85.8
Spain	82.9	87.0
Sweden	82.7	85.9
UK	82.5	85.2
USA	82.0	84.7

Notes: The statistics are obtained from Centers for Disease Control and Prevention (CDC) for the U.S. and United Nations Economic Commission for Europe (UNECE) Statistical Database for the rest of the countries for the calendar year 2006.

Table C.3: Multinomial Logit Estimates of Labor Force Status on Some Possible Determinants for Single Males Aged 75+

Variable	Full-Time		Part-Time	
	Coef.	Std. Err.	Coef.	Std. Err.
Age	-0.173^{***}	0.040	-0.141^{***}	0.025
High School Graduate	0.037	0.349	0.161	0.250
University Graduate	0.586	0.390	0.951^{***}	0.277
"Fair" Health	-0.999^{**}	0.394	-0.714^{***}	0.269
Very Good Health	-0.160	0.325	0.009	0.241
Black	-0.146	0.472	-0.119	0.345
Health Expenses (in $1000)	-0.004	0.021	-0.020	0.016
Has Children	-0.119	0.407	0.837^{**}	0.410
Constant	10.792^{***}	3.099	7.921^{***}	1.993
No. of observations	1,938			
Log-likelihood w/o covariates	-640.4			
Log-likelihood with covariates	-584.8			

Robust standard errors are in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Good health is the reference group for health status. High school dropouts is the reference group for education.

Table C.4: Maximum Likelihood Estimates of the Health Status Determination Equation for Male High School Dropouts

	$\hat{a}_{ij,ed=high-school-dropout}$			
$i \setminus j$	"very good"	good	"fair"	dead
"very good"	–	-1.561 (0.150)	-2.793 (0.230)	-5.100 (0.307)
good	-1.878 (0.139)	–	-1.550 (0.142)	-5.035 (0.245)
"fair"	-3.283 (0.233)	-1.986 (0.154)	–	-4.077 (0.194)
	$\hat{b}_{ij,ed=high-school-dropout}$		$\hat{c}_{ij,ed=high-school-dropout}$	
$i < j$ (recovery)	-0.021 (0.014)		0.060 (0.040)	
$j = 4$ (death)	0.080 (0.008)		0.004 (0.004)	
$i > j$ (deterioration)	-0.026 (0.017)		0.128 (0.048)	

Table C.5: Observed and Fitted Biannual Health Status Transition Matrices for Male High School Dropouts

	Observed Frequencies				Fitted Frequencies			
	Around the First Age Quartile $(65-67)$				At the First Age Quartile $(=66)$			
$i \setminus j$	"very good"	good	"fair"	dead	"very good"	good	"fair"	dead
"very good"	59.1%	29.2%	8.2%	3.6%	58.7%	26.7%	11.8%	2.8%
good	18.1%	48.0%	29.0%	4.9%	19.4%	49.1%	28.3%	3.2%
"fair"	7.9%	19.6%	64.3%	8.2%	6.7%	18.2%	68.4%	6.8%
	Around the Median Age $(71-73)$				At the Median Age $(=72)$			
"very good"	61.0%	23.9%	9.1%	6.0%	56.5%	27.3%	12.2%	4.5%
good	18.3%	44.5%	32.5%	4.7%	18.4%	48.0%	28.8%	5.2%
"fair"	3.6%	17.5%	65.9%	12.9%	6.3%	17.3%	65.8%	11.0%
	Around the Third Age Quartile $(77-79)$				At the Third Age Quartile $(=78)$			
"very good"	44.3%	25.0%	21.6%	9.1%	49.2%	29.6%	14.4%	7.9%
good	20.6%	42.0%	29.2%	8.2%	17.5%	42.6%	31.6%	9.4%
"fair"	5.3%	14.4%	57.4%	22.9%	6.1%	16.6%	59.3%	18.9%

Table C.6: Maximum Likelihood Estimates of the Health Status Determination Equation for Male University Graduates

$i \diagdown j$	"very good"	good	"fair"	dead
	$\hat{a}_{ij,ed=uni-grad}$			
"very good"	–	-2.584 (0.102)	-4.986 (0.266)	-5.714 (0.306)
good	-1.631 (0.111)	–	-2.663 (0.129)	-4.917 (0.290)
"fair"	-3.236 (0.393)	-1.623 (0.156)	–	-3.687 (0.295)
	$\hat{b}_{ij,ed=uni-grad}$		$\hat{c}_{ij,ed=uni-grad}$	
$i < j$ (recovery)	-0.012 (0.008)		0.003 (0.008)	
$j = 4$ (death)	0.072 (0.015)		0.005 (0.026)	
$i > j$ (deterioration)	0.038 (0.006)		-0.002 (0.003)	

Table C.7: Observed and Fitted Biannual Health Status Transition Matrices for Male University Graduates

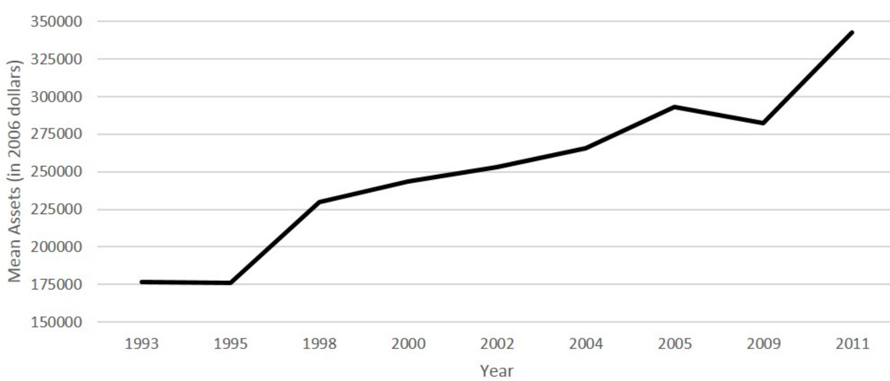
	Observed Frequencies				Fitted Frequencies			
	Around the First Age Quartile $(63-65)$				At the First Age Quartile $(=64)$			
$i \diagdown j$	"very good"	good	"fair"	dead	"very good"	good	"fair"	dead
"very good"	76.6%	19.5%	2.7%	1.3%	80.6%	16.2%	2.4%	1.2%
good	28.4%	57.3%	12.2%	2.2%	29.1%	54.8%	13.6%	2.7%
"fair"	5.3%	28.3%	60.0%	6.3%	9.1%	26.7%	56.5%	7.7%
	Around the Median Age $(68-70)$				At the Median Age $(=69)$			
"very good"	77.3%	19.9%	1.6%	1.2%	76.6%	19.1%	3.1%	1.8%
good	26.4%	57.6%	12.0%	4.0%	27.0%	53.3%	16.2%	3.9%
"fair"	7.2%	18.1%	59.7%	15.0%	8.3%	25.0%	55.8%	11.1%
	Around the Third Age Quartile $(75-77)$				At the Third Age Quartile $(=76)$			
"very good"	76.7%	19.5%	2.8%	1.1%	69.7%	23.5%	4.4%	3.1%
good	24.7%	47.9%	21.8%	5.6%	23.9%	49.8%	20.1%	6.8%
"fair"	3.9%	21.0%	55.3%	19.8%	7.3%	22.4%	52.6%	18.2%

Table C.8: Steps Used to Obtain the Working Sample

Year	2002	2004	2006	2008	Total
Sample	18, 167	20, 129	18, 469	17, 217	73, 982
Disabled	−1, 500	−1, 754	−1, 703	−1, 486	−6, 443
Participation status different than employed, unemployed or out of labor force	−241	−294	−79	−54	−668
Refused to report both hours worked in a week and weeks worked in a year	−46	−60	−35	−37	−178
Unknown health status	−9	−11	−18	−11	−49
Unknown marital status	−4	−6	−3	−3	−16
Unknown Social Security Information	−55	−29	−22	−23	−129
Unknown years of education	−4	−25	−23	−26	−78
Blank assets or outliers having assets of more than $20 million	−8	−18	−39	−16	−81
Outlier participants having hourly wages of less than $2 or more than $100	−5	−7	−4	−5	−21
Younger than 58 years old	−2, 289	−4, 414	−3, 246	−2, 352	−12, 301
Older than 94 years old	−87	−102	−101	−113	−403
Subtotal	13, 919	13, 409	13, 196	13, 091	53, 615
Married					−33, 115
Households with more than one member					−2, 224
Females					−14, 285
Total					3, 991

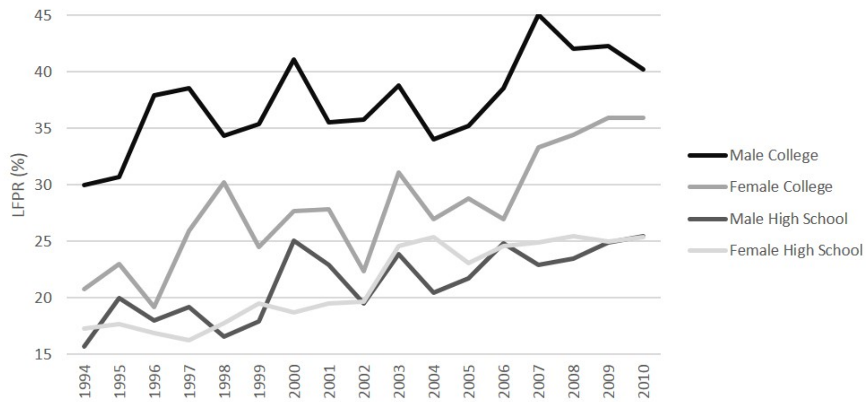
D Figures

Figure D.1: Mean Asset Levels of Single Elderly Males Aged 65+



Source: Obtained using Wealth and Asset Ownership Data from U.S. Census Bureau.

Figure D.2: Trends in Labor Force Participation for Single Elderly Aged 65 − 74 by Gender and Education Level



Source: Obtained using March CPS Data