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Labor Force Attachment Beyond Normal Retirement Age

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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, using a dynamic programming formulation and restricted data from the Health and Retirement Study. The focus is 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. The model accounts 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 3.5 percentage points and mean hours worked by 117 hours at this age group. I further find via counterfactual analyses that the elderly 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.

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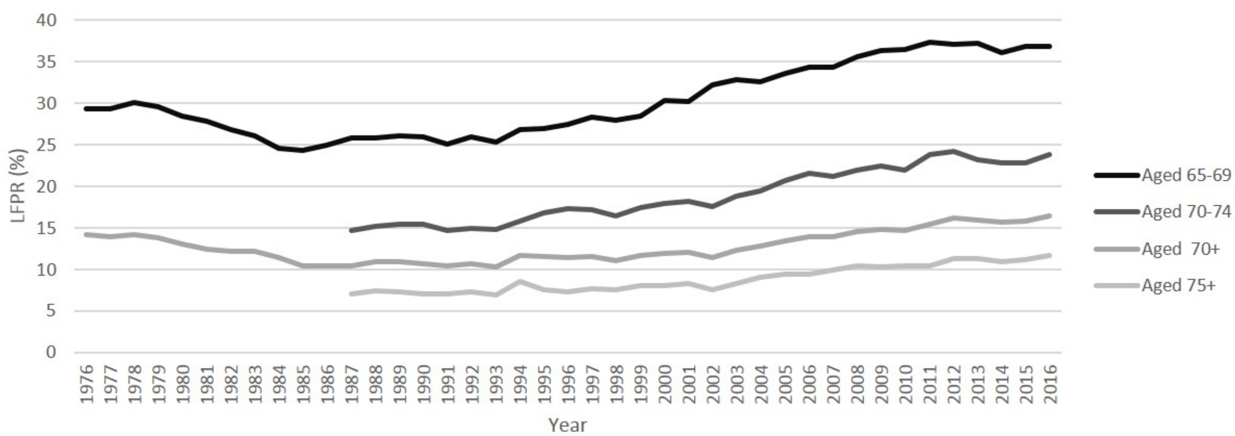
1 Motivation

The labor force participation rate (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 the age group 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 Social Security (SS). On the other hand, 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 the sizable fiscal burden of SS, it is essential to understand behavioral responses of elderly people to the changes in the SS system to come up with any policy analysis.

Figure 1: Trends in Elderly Labor Force Participation Rates by Age: Men



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 then increased by 2 months each year until age 66, current normal retirement age. Normal retirement age will further be increased to 67 with 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 and median asset levels have been increasing as well except a decrease around year 2009 due to the subprime mortgage crisis. See Figures D.1 and D.2 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. In the latter case, retirement is not necessarily a permanent state as an elderly person might return to work after being a non-participant for a while. Accordingly the focus of the paper is rather on the participation decision.

This paper analyzes the labor supply, consumption and Social Security benefits application decisions 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.[5] I focus only on singles to avoid complexities arising from modeling the joint decision making by couples with shared budget constraint and leisure complementarity. I further restrict my sample to males for the purpose of computational tractability by assuming that the participation decisions at the older ages do not alter SS benefit levels. This is a reasonable assumption as the overwhelming majority of elderly males have a full work history, according to SS rules, of 35 years. On the other hand, the majority of elderly females have a work history of less than 35 years mainly due to employment gaps they experience at early ages. Section 4.3 provides further discussion on this issue. 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.

The specification of the dynamic programming model in this paper extends French (2005) by including health expenses, Medicare, education levels and three different health status categories[7] and allowing 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

[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 at this age group. 10.5 percent of them are never married. I do not model the marriage decision for the sake of computational tractability which might be warranted given that only 7.6 percent of elderly single males get married within 6 years in my sample.

[6] Section 6.1 provides a discussion on the "earnings test."

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

is a linear approximation to the decision rule for employment, estimates 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.[8]

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 modest effects 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.[9] 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. Her analysis provides estimates for both the objective measure of labor force participation and the subjective measure of retirement perception of individuals. Confining attention to labor supply behavior, she finds that 23.8 percent of the elderly aged 50 or more unretired in between years 1992 and 2002.

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. This 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.

[8]Figure D.3 in the Appendix illustrates the trends in LFPRs of single elderly Americans by gender and education level. It is evident that LFPRs exhibit an increasing pattern since mid-90s, except for male college graduates. This suggests that there should be additional factors behind the recent increase in the elderly LFPR, one of which should be the improvements in the overall health of the elderly observed in the last three decades.

[9]Casanova (2010) focuses on married people and models labor force participation as a dichotomous decision (full-time work, part-time work and non-participation) rather than a continuous hours worked decision. As her focus in on the joint retirement decision, she does not model "unretirement" behavior and conveniently assumes that elderly start receiving SS benefits in the first period they choose not to participate in the labor force. Her model overlooks the effect of health status on retirement decision which is arguably a strong restriction, though it might be defended considering the computational time required to solve such structural models.

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. I focus on non-disabled single males who are not cohabiting and aged $58-94$ from 2002 to 2008. My 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 ignorable.

Preliminary Examination

This subsection provides a multinomial logit analysis of the labor force participation (LFP) decision of single males beyond normal retirement age, with the purpose of providing an exploratory data analysis before executing a structural labor supply analysis. Given the small size of my sample, I treat the data as pooled in this subsection omitting the panel aspect. Since the normal retirement age had been gradually increasing from age 65 to 66 during the period under study, and the HRS age data is discrete, I consider 66 years as the cutoff age in this analysis. In my sample, LFPR of single males aged 66 to 69 is 31.3 percent, aged 70 to 74 is 23.0 percent whereas the same statistic is 8.2 percent in the age group 75+ years. I do not distinguish unemployment and out of the labor force states, like Rust and Phelan (1997), as the unemployment rate is only 0.9 percent in my sample.

Tables 1 and 2 provide summary statistics for select variables by labor force status in the age groups $66-74$ years and 75+ years, respectively. I define part-time work as working less than $1,600$ hours in a given year.[10] As seen from these tables, people in the labor force are younger, more educated and healthier on average. Blacks are more likely to participate in the labor force in the age-group $66-74$ years though this disappears in the age group 75+ years. Full-time workers are less likely to have Medicare and more likely to have private health insurance. There is a question in HRS, directed to only a subset of the respondents, inquiring about the primary health

[10] This assumption causes me to assign elderly people who work full-time (more than 32 hours a week) but only part of a year, and end up working less than $1,600$ hours as part-time workers. This is the case for only 4.1 percent of the workers in my sample. I stick to this definition in the rest of the paper.

Table 1: Sample Means (Std. Dev.s) of Select Variables by Labor Force Participation Status: Single Males Aged 66-74

Variable	Full sample	Full-Time Workers	Part-Time Workers	Out of Labor Force
Age	69.982	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
Private Health Insurance	0.478	0.580	0.534	0.451
Health Expenses - last 2 years	$1,139$	$1,088$	$1,101$	$1,155$
	$(3,403)$	$(1,892)$	$(2,806)$	$(3,691)$
Assets (in $1,000)	325	377	480	287
	(658)	(816)	(989)	(535)
Number of Children	2.599	2.732	2.404	2.614
	(2.225)	(2.479)	(1.738)	(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	178	945

insurance plan. In my sample, 14.3 percent of the respondents in the age group $66-74$ who answer this question identify 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 this age group. Labor force participants are wealthier; nevertheless, only a small fraction of the non-participants receive Supplemental Security Income (SSI) signifying that either their unearned income or financial resources are above the SSI program limits.

The next step is to formulate a multinomial logit analysis. For that purpose, let i denote individuals, j labor force participation status, with $j = 1$ denotes full-time work, $j = 2$ part-time work and $j = 3$ out of the labor force, and y_{ij}^* the unobserved utility individual i derives from the choice of labor force status j. I then consider the following latent utility model:

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

Table 2: Sample Means (Std. Dev.s) of Select Variables by Labor Force Participation Status: 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
Private Health Insurance	0.552	0.700	0.538	0.548
Health Expenses - last 2 years	2,043	1,328	1,146	2,116
	(8,024)	(2,612)	(1,774)	(8,342)
Assets (in $1,000)	354	765	799	316
	(856)	(1,360)	(1,919)	(715)
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

where z_i is the vector of explanatory variables given in Tables 1 and 2 excluding the endogenous variables, θ_j's are the corresponding vectors of unknown coefficients, and η_{ij}'s are the random disturbances. Letting $r = \max\,(y_1^*,\, y_2^*,\, y_3^*)$, the labor force participation status can be characterized via the following categorical variable:

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

I assume that the random disturbances (η_j's) are independently and identically Gumbel distributed, independently of the vector of explanatory variables. McFadden (1974) proves the selection probabilities are given by the Multinomial Logit model:

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

Table 3: Multinomial Logit Estimates of Labor Force Participation Decision: Single Males Aged 66-74

Variable	Full-Time		Part-Time	
	Coef.	Std. Err.	Coef.	Std. Err.
Age	-0.160***	0.036	-0.033	0.033
High School Graduate	0.187	0.219	0.432*	0.228
University Graduate	0.547**	0.274	1.517***	0.255
"Fair" Health	-0.393*	0.242	-0.349	0.219
Very Good Health	0.437**	0.209	0.087	0.199
Black	0.672***	0.207	0.302	0.214
Health Expenses (in $1000)	0.002	0.029	-0.010	0.028
Has a Child	-0.070	0.213	0.367*	0.214
Constant	9.139***	2.508	-0.206	2.342
No. of observations	1,280			
Log-likelihood w/o covariates	-967.3			
Log-likelihood with covariates	-913.7			

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Good health is the reference group for health status. Having no high school diploma is the reference group for education. Year dummies are included in the regression.

Since $\sum_{j=1}^{3}\pi_j = 1$, I choose out of the labor force as the reference group and set $\theta_3 = 0$. I then obtain the consistent estimates of 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 $66-74$.[11] Log odds of staying in the labor force decrease with age, but increase with education level and health stock. While probability of working full-time is on average higher for blacks (with an average marginal effect of 0.064), having a child on average increases part-time participation probability (with an average marginal effect of 0.043) for which I do not have a good explanation.

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

[11]Multinomial logit estimates for the age group 75+ can be found in Table C.3 in the Appendix. Suest-Based Hausman tests provide evidence in favor of the IIA hypothesis in both age groups.

applied for SS benefits. Consumption (c_t) and hours worked (h_t) are continuous variables obtained via splines after using discretizations.[12] b_t denotes the dummy variable indicating whether the individual applied for SS benefits.

The observed heterogeneity is captured via a five dimensional vector of state variables: assets, wages, Principal Insurance Amount (PIA) – what provides the basis for monthly SS benefit amounts[13]–, health status, and education. I use 11 asset states denoted by A_t, 6 wage states denoted by w_t, and 5 PIA states.[14] 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 categories and call it as "fair." Including mortality among health status categories, with the purpose of shrinking the state space, I end up with 4 health status categories (hs_t): "very good," good, "fair," and dead. I have 3 education (ed) categories: 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).[15] I use a projection method to accommodate the 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. Denoting the control variables by d, state variables by x, and preference parameters by θ, the flow utility function for health status category $hs_t \in \{$"very good," good, "fair"$\}$ is given by:

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

where

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

[12] 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.

[13] Section 4.3 provides a concise explanation of how SS benefits are determined.

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

The coefficient of relative risk aversion is denoted by υ. θ_{C,hs_t} and θ_{L,hs_t} measure the consumption and leisure weights for health status category hs_t, respectively. $I(.)$ is the indicator function. $\theta_{P,f}$ is the fixed cost of work, and $\theta_{P,good}$ and $\theta_{P,\text{"}fair\text{"}}$ are the additional participation costs depending on health status categories, with $\theta_{P,\text{"}very\ good\text{"}}$ normalized to zero. $\theta_{P,age}(age_t - 57)^{\gamma}$ measures the participation cost explained by age.

Following De Nardi (2004), elderly who die value bequests of assets, A_t, according to the function:

$$b(A_t) = \theta_B \frac{(A_t + K)^{\theta_{C,good}(1-\upsilon)}}{1-\upsilon}, \tag{7}$$

where K measures the curvature of the bequest function. With $K > 0$, the disutility of leaving negative bequests in the amount of less than $-K$ dollars becomes infinite. Since the elderly face mortality uncertainty every period, the curvature implicitly sets a borrowing constraint.

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

Log wages[16] in the current period depend on age, education – with having no high school diploma being the reference category, PIA, and wages in the previous period (through the autoregressive error term):

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

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 value of 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 an increasing function of Average Indexed Monthly Earnings (AIME), which is calculated averaging the earnings for the highest 35 years; with zeros thrown into the calculation for the years without earnings in case an elderly person has a working history of less

[16] Missing wage observations in the sample are imputed using the solution methodology for double selection problems provided by Tunali and Yavuzoglu (2012). The details are provided in Appendix B.

than 35 years. Section 4.3 elaborates on the relationship between AIME and PIA.

Health status next period (including being dead) depends on the current health status, age, and education:[17]

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

Out of pocket health expenses depend on age, health status – with "very good" health being the reference category, Medicare, and asset levels:

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

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 to control for the positive correlation between wealth and the quality of care demanded. Besides, poor people might be covered by Medicaid when confronted with high out-of-pocket health expenses.[18]

The asset accumulation equation is given by:

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

where r is the interest rate, τ_1 is the Federal Insurance Contributions Act (FICA) tax rate, $Y_1(w_t h_t, \tau_1)$ is the level of post-FICA tax wage earnings, τ_2 is the combination of federal and state income tax rates, and $Y_2(G_t, \tau_2)$ is the level of tax amount paid out of gross taxable earnings, G_t,

[17] The functional form employed is laid out in Section 4.1.

[18] The standard deviation of the out of pocket health expenses corresponds to the 97.6^{th} percentile of its distribution in my sample. Most elderly would not face extreme out-of-pocket health expenses unless they choose to have exceptional care (which would pertain to consumption, c_t, in my model). As I do not model out of pocket health expenses as a choice variable, I trim the top 4 percent of the expenses in generating the data moments required for the estimation.

which is generated via:

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

where τ_3 denotes the portion of SS benefits that are taxable and $Y_3\left(b_{t-1} ss_{t-1}, \tau_3\right)$ is the taxable amount of the SS benefits.

In my model wage decrease, health deterioration, and increasing fixed cost of work associated with aging are the determinants of the non-participation decision of the elderly. Nonetheless non-participation is not a permanent decision as 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.[19] My model accounts for this through wage, health status and health expenses shocks.

The Bellman equation is given by

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

where j denotes the health status categories "very good," good and "fair", $F(.|.)$ 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 age 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 is

[19] Dropping the age condition, 3.3 percent of all the non-participants return to work within 2 years and 4.7 percent within 4 years in my sample.

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 variables x_t.

The model is 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. Then, I estimate the following parameters using simulated method of moments $\phi = \{\theta_{C,hs_t}$'s, θ_{L,hs_t}'s, $\theta_{P,f}$, $\theta_{P,\text{“}fair\text{”}}$, $\theta_{P,good}$, $\theta_{P,age}$, γ, and v in the flow utility function, ς_0, ς_1, ς_2, δ_{high}, δ_{uni}, δ_{PIA}, ρ_{AR}, and σ^2_η in the wage determination equation, φ_0, φ_1, φ_2, δ_{fair}, δ_{good}, $\delta_{Medicare}$, and δ_{assets} 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 for joint identification of intertemporal discount factor, β, and relative risk aversion, v, as discussed by Guvenen and Smith (2014).[20] Consequently, I set the discount factor, 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 Medicare premium, mp, equal to the standard yearly Medicare Part B premium in 2006, $\$1,062$.

4.1 Health Status

It is not viable to estimate health status determination equation given in Equation (10) non-parametrically as that would involve estimating a forward transition matrix for every education and age combination.[21] I indeed estimate a parametric model of transition rates via maximum likelihood following Robinson (2002). Let

$$p(j|i) = \Pr(hs_{t+1} = j|hs_t = i, age_t, ed) = exp\left(a_{ij,ed} + b_{ij,ed}(age_t - 57) + c_{ij,ed}\frac{(age_t-57)^2}{100}\right)$$

$$\text{for } i \in \{\text{"very good", good, "fair"}\},\ j \in \{\text{"verygood", good, "fair", dead}\}, \text{ and } i{\neq}j. \quad (16)$$

[20] Guvenen and Smith (2014) estimate their model for various values of v in their Appendix D.6. 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 is possible only if there is an additional channel like defined contribution plan participation decision, the case studied by Lucchino and de Ven (2013).

[21] Such a non-parametric procedure would require estimating 111 health transition matrices with a total of 999 probabilities.

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

	$\hat{a}_{ij,ed=high\ school\ graduates}$			
$i \diagdown j$	"very good"	good	"fair"	dead
"very good"	–	-2.028 (0.089)	-3.868 (0.147)	-5.617 (0.237)
good	-1.608 (0.096)	–	-2.170 (0.089)	-4.957 (0.216)
"fair"	-3.009 (0.154)	-1.558 (0.112)	–	-4.025 (0.223)
	$\hat{b}_{ij,ed=high\ school\ graduates}$		$\hat{c}_{ij,ed=high\ school\ graduates}$	
$i < j$ (recovery)	-0.030 (0.014)		0.054 (0.045)	
$j = 4$ (death)	0.073 (0.021)		0.034 (0.049)	
$i > j$ (deterioration)	0.010 (0.012)		0.045 (0.038)	

While there is no restriction on $a_{ij,ed}$ values, the age adjustment parameters, $b_{ij,ed}$ and $c_{ij,ed}$, are restricted to 3 values: one for health recovery, one for mortaility, and one for health deterioration. I utilize the implied biannual transition rates from the model, consistent with the structure of the HRS, to obtain the maximum likelihood estimates. The parameters estimates for high school graduates can be found in Table 4.[22]

Table 5 provides observed biannual forward transition rates along with the implied rates from the model for quartiles of the age distribution. I assess the performance of this estimation using χ^2 goodness of fit tests for forward transition frequencies. It passes the goodness-of-fit tests for each age quartile and initial health status category (with $p-values > 0.306$).[23]

[22]The estimates for high school dropouts and university graduates can be found in Tables C.4-C.7 in the Appendix. As the log likelihood of such an exponential formulation is linear, the regularity conditions of the Fisher information matrix are not satisfied. Standard errors are obtained using a bootstrap procedure with $1,000$ replications.

[23]The same result holds for high school dropouts (with $p-values > 0.216$) and university graduates (with $p-values > 0.138$). In conducting these tests, I compare the corresponding counts in the sample with the implied counts from the model.

Table 5: Observed and Fitted Biannual Health Status Forward Transition Matrices: Male High School 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"	70.4%	23.4%	4.4%	1.7%	70.5%	22.6%	5.5%	1.4%
good	24.2%	54.4%	19.3%	2.1%	25.6%	53.1%	18.7%	2.6%
"fair"	9.4%	25.9%	57.4%	7.4%	9.3%	25.8%	59.2%	5.8%
Around the Median Age (68 – 70)					At the Median Age (= 69)			
"very good"	66.1%	24.6%	7.9%	1.4%	67.2%	24.4%	6.2%	2.2%
good	22.1%	55.7%	18.5%	3.6%	23.0%	52.5%	20.5%	4.0%
"fair"	7.8%	20.0%	65.1%	7.2%	8.1%	23.5%	59.8%	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%	60.8%	27.6%	7.6%	4.0%
good	21.8%	51.2%	21.4%	5.6%	20.2%	49.1%	23.5%	7.2%
"fair"	6.1%	24.8%	54.7%	14.4%	7.1%	20.9%	56.7%	15.3%

4.2 Taxes

Federal Insurance Contributions Act (FICA) tax is a federal payroll tax imposed both on employees and employers. It has two components: Social Security tax and Medicare tax. During the period from 1990 to 2010, the Social Security tax rate was 12.4 percent of an employee's wages up to a threshold of earnings known as the Social Security Wage Base,[24] and the Medicare tax rate was 2.9 percent of an employee's wages without any cap. Employees and employers split these taxes equally, so each party paid 7.65 percent of wages as long as wages were less than the threshold. I use only the employee portion in setting τ_1.

The second portion of the tax structure, τ_2, includes federal and state income tax rates. I use the 2006 federal income tax brackets and account for standard deduction, including the additional deduction for the elderly aged 65 or above, and personal exemption, which is subject to phase-out after an income threshold. For the state income taxes, I use the 2006 Rhode Island tax rate schedule following French and Jones (2011).[25]

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

[25] The taxation of self-employed workers, 35.0 percent of workers in my sample, is similar to that of wage earners. Differently, self-employed workers pay both the employee and employer portions of the payroll tax but only on their earnings from self-employment (which corresponds to 92.35 percent of their earnings, obtained after substracting the employer-equivalent portion of the payroll tax). To make the situation more equitable, self-employed workers are allowed to deduct the employer-equivalent portion of the payroll tax from their taxable income as well as some other expenses such as the cost of health insurance and retirement plan contributions. For the purpose of computational

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 above-the-line deductions adjusting gross income and nontaxable interest since my model does not accommodate them.

4.3 Social Security Benefit Levels

Monthly SS benefit levels are calculated using Average Indexed Monthly Earnings (AIME), which is the average monthly earnings in the 35 highest indexed earnings years.[26] In doing this calculation, contribution from any year is limited by the Social Security Wage Base of that year (consistent with the Social Security portion of FICA tax), and zeros are thrown in for the years without earnings in case an elderly person has a working history of less than 35 years. Next, a progressive formula is applied on AIME to compute Primary Insurance Amount (PIA) which gives the basis for monthly SS benefit levels. In 2006, PIA was calculated 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.[27]

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 AIME values for this subsample through an inverse function of the benefit levels.[28] I impute the AIME values for the rest of the respondents.

I assume that AIME values are constant, so working another year does not affect its value. For people having at least 35 years of work history, the incremental increase in AIME level is either zero 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 of working history.

tractability, my model does not distinguish between self-employed and wage earners.

[26] The index used for the AIME calculation is called the "national average wage index," which is calculated annually by the SS Administration based on the nation-wide average net compensation subject to federal income tax.

[27] Bend points are adjusted each year using the national wage index, but percentages remain the same.

[28] 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.

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_η^2.
- 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}.
- 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_ξ^2.

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.[29] 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.

The curvature estimate implies that the elderly can have unsecured debt up to $\$11,990$,[30] which can be thought as maxing out credit cards rather than borrowing against SS benefits. Figure 2 provides the participation cost due to age.

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

[30]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 $-\$11,990$.

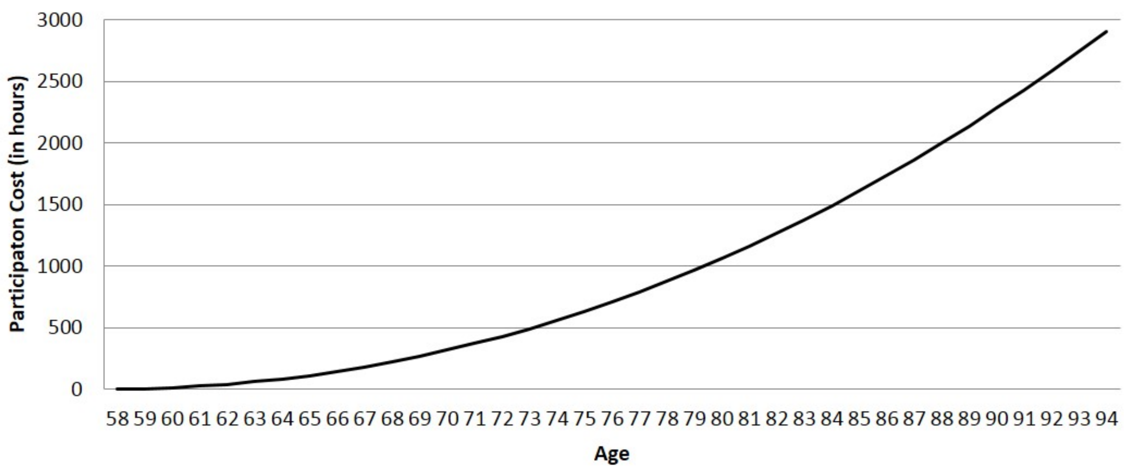
Table 6: The Estimates of the Structural Parameters

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.

Figure 2: Participation Cost Explained by Age



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

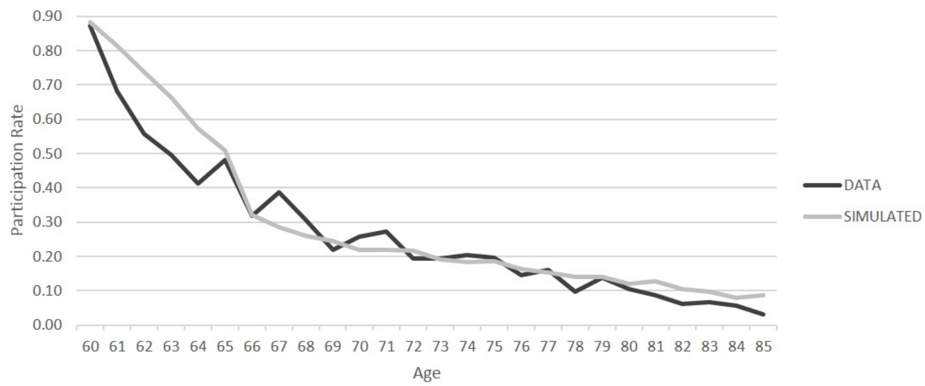


Figure 4: Model Fit - Mean Hours Worked for Participants by Age

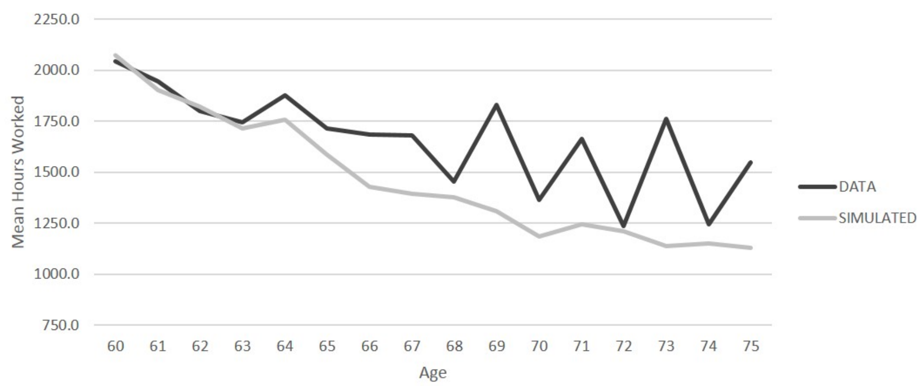


Figure 5: Model Fit - Mean Wages for Participants by Age

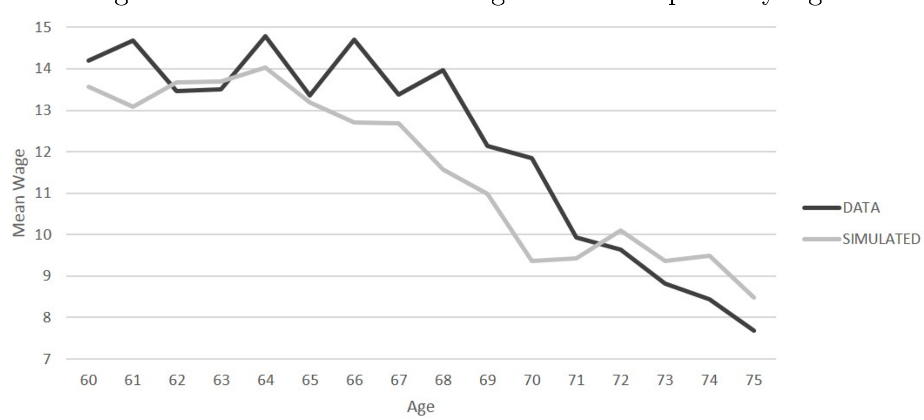


Table 7: Model Fit - Average of Mean Wages of Each Age Between $61-70$ by Education

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.[31] "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 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."

[31] 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

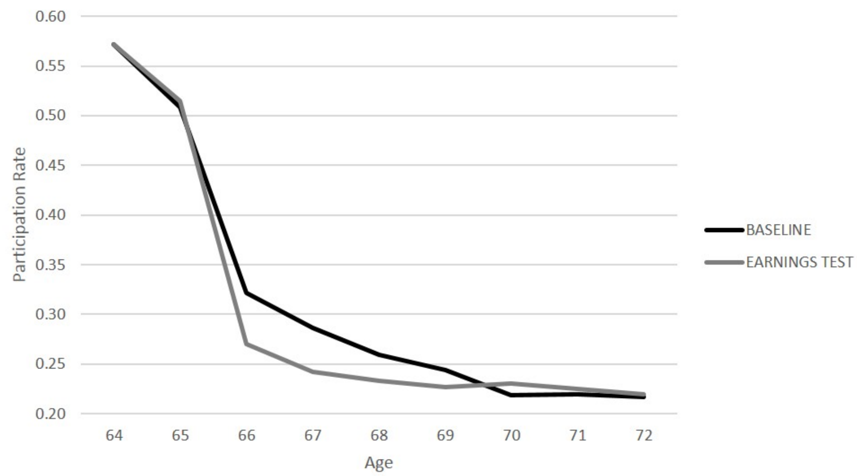
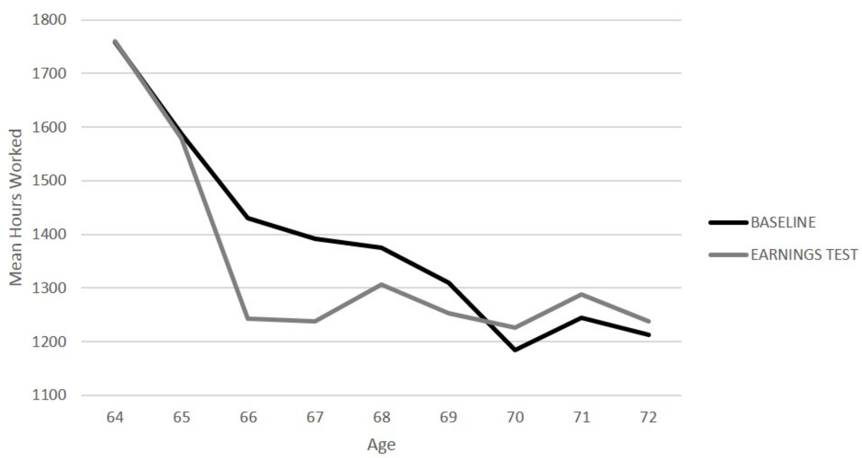


Figure 7: The Effect of The "Earnings Test" - Intensive Margin



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 $66 - 75$.[32] However, there is not a significant response in the intensive margin as presented in Figure 9.

[32] 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.

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

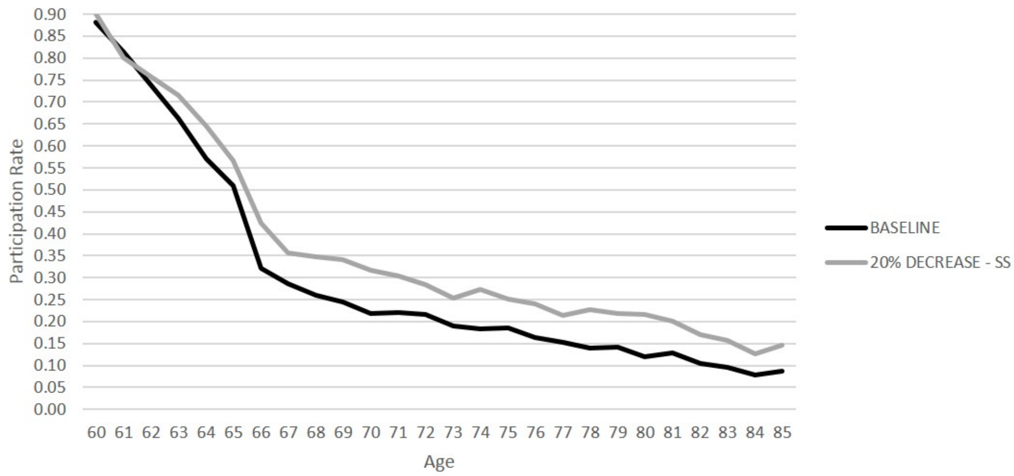
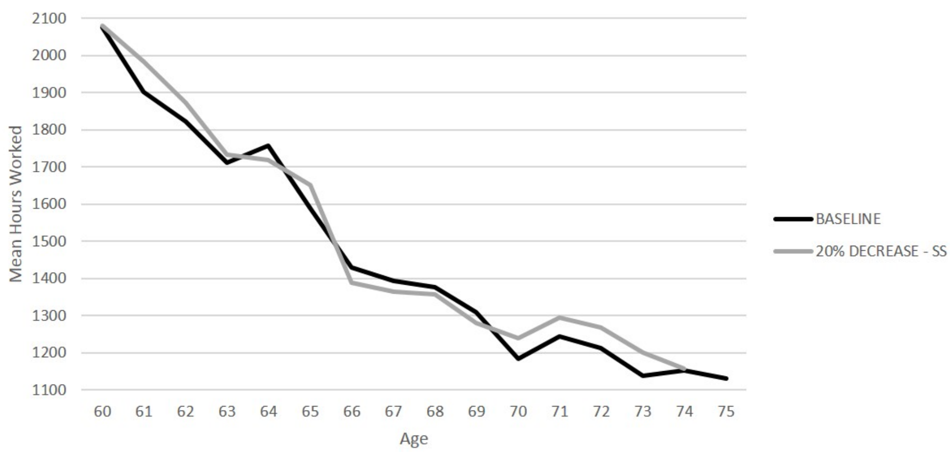


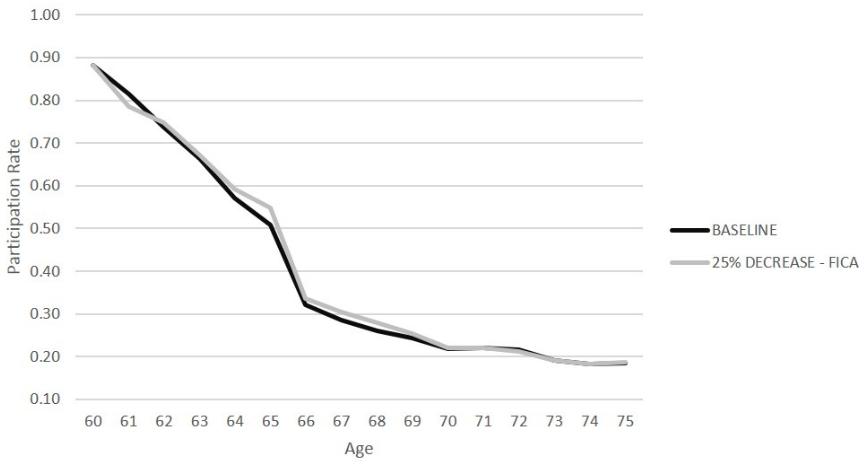
Figure 9: Mean Hours Worked under 20% Decreased SS Benefit Levels



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 at the elderly ages. 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 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 11: Mean Hours Worked under Decreased FICA Amounts for Everyone

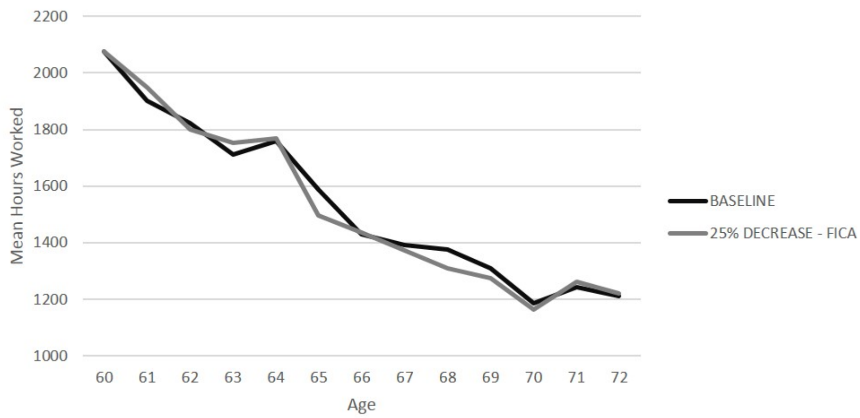


Figure 12: Participation Rates under Decreased FICA Amounts for People Aged 70+

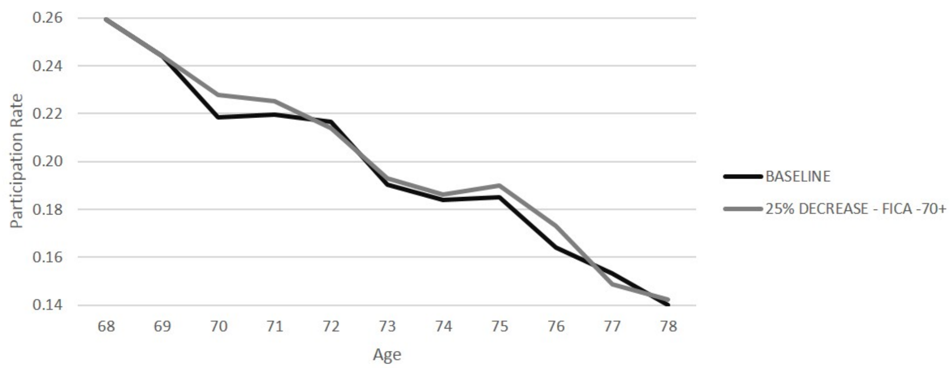
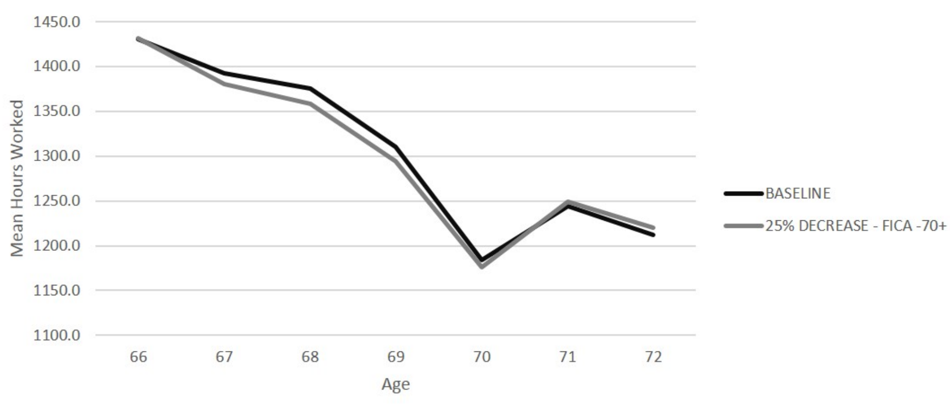


Figure 13: Mean Hours Worked under Decreased FICA Amounts for People Aged 70+



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.

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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, 2006

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 the report "Social Security Programs throughout the World: Europe, 2006" published by the 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. Remark 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, 2006

Country	Life Expectancy at Age 65	
	Male	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: Single Males Aged 75+

Variable	Full-Time		Part-Time	
	Coef.	Std. Err.	Coef.	Std. Err.
Age	-0.173^{***}	0.037	-0.142^{***}	0.024
High School Graduate	0.036	0.346	0.159	0.251
University Graduate	0.582	0.405	0.938^{***}	0.281
"Fair" Health	-1.003^{***}	0.391	-0.721^{***}	0.268
Very Good Health	-0.163	0.332	-0.005	0.237
Black	-0.150	0.462	-0.122	0.332
Health Expenses (in $1000)	-0.004	0.034	-0.021	0.031
Has Children	-0.116	0.402	0.847^{**}	0.406
Constant	10.838^{***}	2.916	8.051^{***}	1.938
No. of observations	1,938			
Log-likelihood w/o covariates	-640.4			
Log-likelihood with covariates	-584.2			

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Good health is the reference group for health status. Having no high school diploma is the reference group for education. Year dummies are included in the regression.

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

	$\hat{a}_{ij,ed=high\ school\ dropouts}$			
$i \setminus j$	"very good"	good	"fair"	dead
"very good"	–	-1.599 (0.149)	-2.830 (0.194)	-5.025 (0.292)
good	-1.862 (0.155)	–	-1.588 (0.134)	-4.969 (0.272)
"fair"	-3.265 (0.201)	-1.968 (0.164)	–	-4.012 (0.250)
	$\hat{b}_{ij,ed=high\ school\ dropouts}$		$\hat{c}_{ij,ed=high\ school-dropouts}$	
$i < j$ (recovery)	-0.023 (0.019)		0.066 (0.058)	
$j = 4$ (death)	0.073 (0.024)		0.021 (0.055)	
$i > j$ (deterioration)	-0.020 (0.019)		0.112 (0.056)	

Table C.5: Observed and Fitted Biannual Health Status Forward Transition Matrices: 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%	49.2%	28.2%	3.2%
"fair"	7.9%	19.6%	64.3%	8.2%	6.7%	18.2%	68.2%	6.9%
	Around the Median Age $(71-73)$				At the Median Age $(=72)$			
"very good"	61.0%	23.9%	9.1%	6.0%	55.8%	27.4%	12.3%	4.5%
good	18.3%	44.5%	32.5%	4.7%	18.2%	47.6%	29.0%	5.2%
"fair"	3.6%	17.5%	65.9%	12.9%	6.2%	17.2%	65.6%	10.9%
	Around the Third Age Quartile $(77-79)$				At the Third Age Quartile $(=78)$			
"very good"	44.3%	25.0%	21.6%	9.1%	48.1%	29.5%	14.5%	7.9%
good	20.6%	42.0%	29.2%	8.2%	17.2%	41.9%	31.6%	9.3%
"fair"	5.3%	14.4%	57.4%	22.9%	6.0%	16.4%	58.9%	18.7%

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

$i \setminus j$	"very good"	good	"fair"	dead
	$\hat{a}_{ij,ed=university\ graduates}$			
"very good"	–	−2.556 (0.130)	−4.968 (0.286)	−5.855 (0.339)
good	−1.539 (0.150)	–	−2.630 (0.149)	−5.078 (0.387)
"fair"	−3.153 (0.318)	−1.534 (0.182)	–	−3.831 (0.370)
	$\hat{b}_{ij,ed=university\ graduates}$		$\hat{c}_{ij,ed=university\ graduates}$	
$i < j$ (recovery)	−0.028 (0.022)		0.055 (0.067)	
$j = 4$ (death)	0.090 (0.034)		−0.040 (0.080)	
$i > j$ (deterioration)	0.033 (0.017)		0.013 (0.052)	

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

	Observed Frequencies				Fitted Frequencies			
	Around the First Age Quartile (63 – 65)				At the First Age Quartile (= 64)			
$i \setminus j$	"very good"	good	"fair"	dead	"very good"	good	"fair"	dead
"very good"	76.6%	19.5%	2.7%	1.3%	80.2%	16.2%	2.4%	1.2%
good	28.4%	57.3%	12.2%	2.2%	29.1%	54.7%	13.7%	2.5%
"fair"	5.3%	28.3%	60.0%	6.3%	9.1%	26.7%	56.8%	7.5%
	Around the Median Age (68 – 70)				At the Median Age (= 69)			
"very good"	77.3%	19.9%	1.6%	1.2%	76.2%	19.0%	3.0%	1.8%
good	26.4%	57.6%	12.0%	4.0%	26.2%	53.7%	16.2%	3.9%
"fair"	7.2%	18.1%	59.7%	15.0%	8.0%	24.4%	56.4%	11.2%
	Around the Third Age Quartile (74 – 78)				At the Third Age Quartile (= 76)			
"very good"	70.8%	22.8%	2.8%	3.6%	69.1%	23.3%	4.3%	3.2%
good	24.2%	48.8%	21.2%	5.9%	23.3%	49.7%	20.0%	7.0%
"fair"	4.5%	21.6%	54.8%	19.2%	7.0%	21.8%	52.2%	18.9%

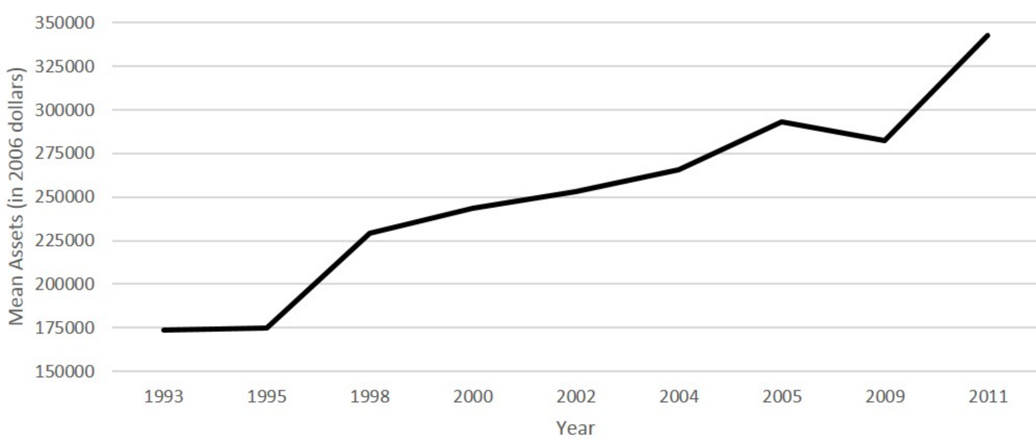
Notes: The observed death probabililty from "very good" health status for the age group 75 – 77 is only 1.1 percent, due to the small subsample encountered. The same probabilities for the 72 – 74 and 78 – 81 age groups are given by 4.4 and 5.9 percent, respectively. To account for that, I compute the forward transition rates around the third age quartile considering a wider age group, 74 – 78.

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

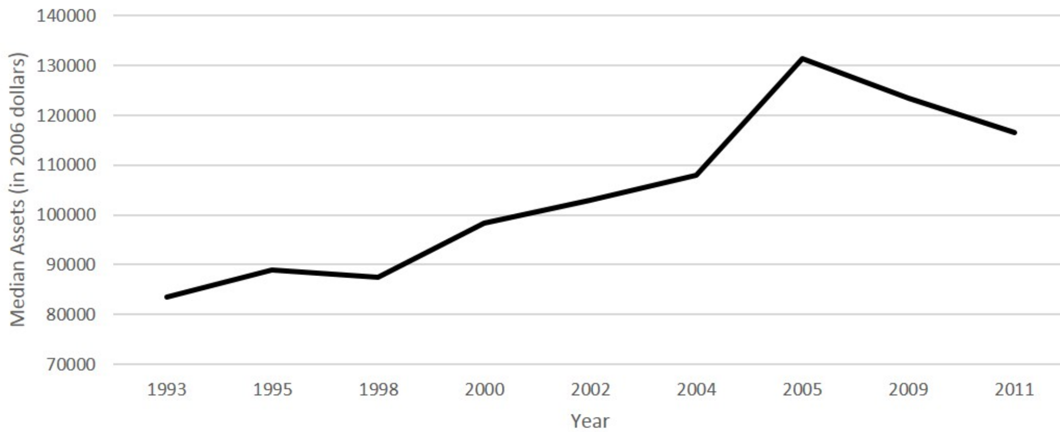
D Figures

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



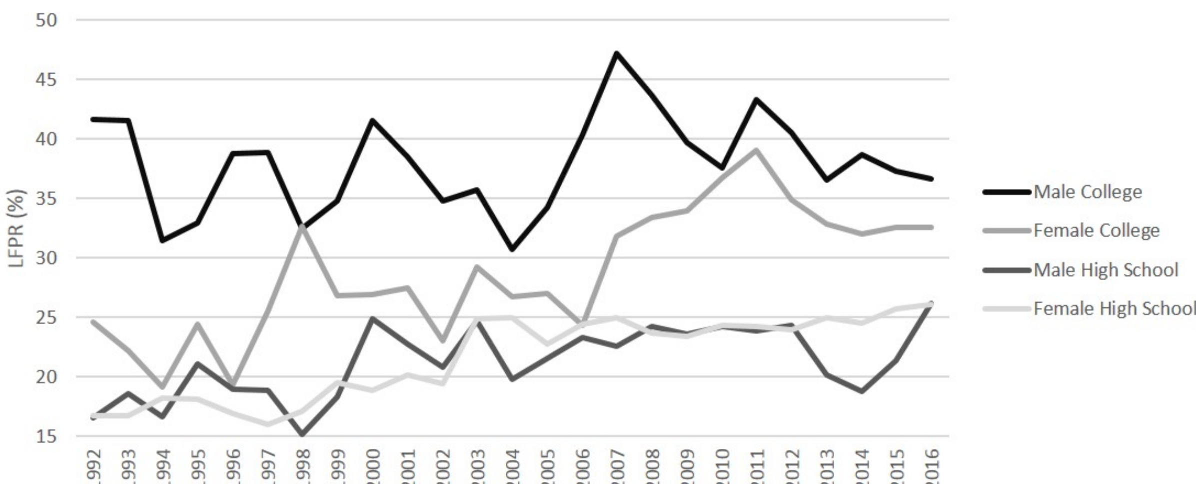
Source: Wealth and Asset Ownership Data from the Survey of Income and Program Participation collected by the U.S. Census Bureau. Asset levels are adjusted to 2006 dollars using CPI-U-RS.

Figure D.2: Median Asset Levels of Elderly Single Males Aged 65+



Source: Wealth and Asset Ownership Data from the Survey of Income and Program Participation collected by the U.S. Census Bureau. Asset levels are adjusted to 2006 dollars using CPI-U-RS.

Figure D.3: Trends in Labor Force Participation Rates of Single Elderly Aged $65-74$ by Gender and Education Level



Source: CPS March Annual Social and Economic Supplement Data.