Why Are Older Americans Working More Nowadays? *

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Abstract

Since the mid-eighties, both labor force participation and hours per worker of seniors, individuals above age 62, in the US have been growing steadily after a long period of decline. This paper uses data from the Health and Retirement Study to estimate a life-cycle model in order to contrast the labor supply behavior of two cohorts of in the US: individuals born after World War I ("the Great Depression Kids"), and those born after the World War II ("the Baby Boomers"). The paper focuses on the differences between these two cohorts in earning and health dynamics as well as policies that they face, a gradual increase in Normal Retirement Age and the elimination of the Earnings Test in 2000, as the potential sources of changes. The results show that the effects of policies and policy-unrelated factors are of similar magnitude. The elimination of the Earnings Test had the biggest impact of all policies. The joint effect of the rise in out-of-pocket medical expenditures and the increase in life expectancy seems to be dominant among other, non policy-related factors.

Key Words: retirement, labor supply

JEL Classification: J14, J22, J26

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1 Introduction

Around three decades ago labor force participation rate of seniors in the US hit a historical minimum.\textsuperscript{1} Since then it has been growing steadily and nearly doubled by 2014. This striking trend was accompanied by the rise of annual hours per worker of seniors, which increased by about 50% during the same time period (Figure 1 summarizes these patterns). The clear understanding of factors behind such a significant behavioral change, as well as its economic implications, are very important from various perspectives.

First, the trend is the aggregate result of the policies implemented by the US government, and policy-unrelated factors. The key policy changes were a gradual increase of the Normal Retirement Age (NRA) for younger cohorts and the elimination of the Earnings Test at the NRA in 2000. The non-policy factors include, among others, the increase in life expectancy of younger cohorts, and changes in aggregate economy that are reflected in wage structure. The relative importance of these forces and interactions between them are ambiguous (see, e.g., a recent review by Blundell et. al 2016) and disentangling their contributions remains an open question.

Second, the large cohort of Baby Boomers is currently either approaching or are in their sixties. Together with the fact that the labor force participation rate of prime-age individuals has been declining since the beginning of the new millenium, the seniors will constitute increasingly significant part of the US labor force.\textsuperscript{2} The effect of this change on the aggregate savings behavior and welfare of the elderly is unclear. Hand in hand with this problem goes the continuing debate about the effect of increase in Normal Retirement Age on the welfare of the poorest sections of population (e.g. Biggs (2016), Klein (2015), Mermin and Steuerle (2006)). Hence, it is crucial to be able to assess how policy changes affect the labor supply behavior of the elderly.

Finally, some argue that the working seniors can alleviate the increasing cost of the social security system costs posed by population ageing.\textsuperscript{3} Working seniors pay income taxes, and social security benefits of workers are subject to Earnings Test. This means that pressure of aging population on social security system is alleviated by seniors who choose work instead of retirement. As a result, it is critical to understand factors behind the labor supply decisions of the seniors.

The goal of this paper is to quantify the relative effect of the factors driving the increase in participation rate and labor supply of the US seniors. The model economy has a life-cycle structure and distinguishes between agent of different cohorts and genders. Every

\textsuperscript{1}Particularly, I refer to individuals of 62 years of age and above.
\textsuperscript{2}See, for example, https://www.bls.gov/emp/ep_table_303.htm
\textsuperscript{3}See, for example, https://www.ssa.gov/policy/docs/ssb/v66n4/v66n4p37.html
period agents choose how much to work, how much to save and whether or not to claim social security benefits if they eligible. There is no aggregate uncertainty in the model, but there are several sources of idiosyncratic uncertainty. Individual health, wage and medical expenditures are subject to stochastic shocks. Furthermore, every period individuals face a risk of death. I use this model to implement two important exercises. First, it makes possible to study the effect of each factor in isolation through the means of counterfactual exercises. Second, it helps to uncover the interactions between the driving factors. Here, I focus on two relatively large cohorts of individuals: those born between 1915 and 1934 (post-WWI period and Great Depression, "Great Depression Kids") and those born between 1945 and 1964 ("Baby Boomers"). Figure 2 shows the differences in annual labor supply and participation

**Figure 1:** Labor force participation rate and mean annual hours of the seniors aged 62 and older. Data sample is taken from the March supplement of the US Current Population Survey (CPS) for the years from 1980 to 2014. The access to the data is provided by the Integrated Public Use Microdata Series (IPUMS), hosted by the Minnesota Population Center.
rates between the two chosen cohorts as observed in the March supplement of the Current Population Survey. In particular, both men and women of the Baby Boomers cohort have higher participation rates and work longer hours than the Great Depression Kids of the same age.

![Figure 2](image-url)

**Figure 2:** Mean hours per worker and labor force participation rates of the two cohorts of the seniors: those born after World War I ("Great Depression Kids"), and those born after World War II ("Baby Boomers"). Data sample from the IPUMS-CPS, March supplement, 1980 to 2014.

So what is different about current seniors that makes them work more than their predecessors few decades ago? This paper focuses on several potentially important explanations of the labor force participation trends that have been put forward in the literature.

First, the government policies that are aimed at, directly or indirectly, keeping the seniors in the labor force include the increase in the Normal Retirement Age, changes in the early retirement penalty and increase of delayed retirement credit, the elimination of the Earnings Test at the NRA in 2000, and changes in the effective income taxes. Wedges created by these changes provide Baby Boomers with additional incentives for staying in the labor force longer. The quantitative results suggest that the elimination of the Earnings Test plays the most significant role among the policies. Indeed, the Earnings Test creates an artificial earnings threshold, and both in the data and in the model the bunching of individuals with earnings just below the threshold is observed. That is, many individuals choose to work...
the amount of hours which will ensure their annual earnings do not exceed the threshold imposed by the Earnings Test.

Second, the life expectancy of the current pre-retirees is higher. From individual prospective this means longer post-retirement years to finance, which increases the risk of running down individual savings to maintain the desired quality of life. Furthermore, one might perceive that living longer bears higher risk of severe health conditions at older ages, which is inevitably tied to very high medical spendings. I find this to be the most important factor driving the change in the behavior of the Baby Boomers as compared to Great Depression Kids. Indeed, the quantitative results of the baseline model suggest that increase in the survival rate together with the rise in medical spendings seem to be the most important driving factor.

Third, the changes in real wage structure may capture structural changes in the economy. One good example of such a change is job polarizaton, which led to shrinking of american middle class. The baseline model shows the quantitative importance of this change. The extension of the baseline model that takes into account the individual educational attainment (namely, the presence or absence of a college degree) reflects that income effect associated with college premium plays a very important role.

The rest of this section places this study in the existing literature.

1.1 Literature

The paper relates to the two major strands of literature.

First, it draws on empirical literature that investigates the increase in labor force artici- pation of elderly in US since mid-80’s. A number of papers overview and document the trend and put forward possible explanations of the observed facts, e.g. Clark and Quinn (2002), Friedberg (2007), Juhn et al. (2006), DiCeccio et al. (2008), Maestas and Zissimopoulos (2010). Blau and Goodstein (2010) claim social security changes can account for up to 18-20% of the effect. Hurd and Rohwedder (2011) use HRS data to study the effect of pensions (in particular, moving from DB to DC pension plans) on labor force participation of elderly, and find it to be modest, at around 2.5% of overall increase. Schirle (2008) identifies a coordination in retirement schedule among spouses as another important reason and finds that husband’s response to wives’ labor force participation can explain up to 25% of the increase in married males’ participation.

Second, it is closely related to the papers that use life-cycle models to explore various aspects of behavior of seniors. The excellent review of this literature is Blundell et.al. (2016). The models of the first wave were concerned primarily with timing of retirement
(e.g. Gustman and Steinmeier (1986), Burtless (1986)). In these models, retirement was an abrupt process, and they abstracted from any uncertainty. The models failed to replicate early retirement puzzle. Rust and Phelan (1997) resolved the puzzle by introducing realistic uncertainty and individual inability to save and borrow, but they also abstracted from the individual choice of hours to work.

French (2005) extends these models by allowing agents to save, borrow to a certain limit and choose hours to work. He finds that the tax wedge embedded in the Earnings Test to be one of the most important determinants of the early retirement. Yavuzoglu (2016) provides very similar result. Similarly, I find the elimination of Earnings Test at the NRA to be the most important policy change that affected the increase in labor force participation of Baby Boomers aged 62-67. However, I still find that joint effect of increase of out-of-pocket medical expenditures and increase in longevity is dominating, and this effect can’t be attributed to any policy.

De Nardi, French and Jones (2010) model savings of retired singles under uncertain medical expenditures and heterogenous life expectancies and find that risk of extreme medical spendings at older age to be one of main reasons why seniors decumulate their assets slowly. Kopecky and Koreshkov (2014) name the expectation of extreme medical spendings at old age (namely, nursing home risk) as the main determinant of slow asset decumulation of US seniors. Lockwood (2010) investigates the relative effect of precautionary and bequest motives on speed of asset decumulation of seniors, and finds it to be of relatively the same magnitude. This is also the case in the current paper. French and Jones (2011) study the effects of employer-provided health insurance, Medicare, and social security on retirement behavior. Casanova (2010) studies the effects of leisure complimentarity in spousal retirement decision. However, these papers abstract from differences in behavior of different cohorts, which are in the core of current paper. I provide direct comparison between the two different cohort of seniors. Furthermore, to my limited knowledge, this paper is the first attempt to disentangle and quantify the effects of the potentially relevant factors on both extensive and intensive margins of labor force supply decisions of seniors.

2 Model

I consider a partial equilibrium life-cycle model with a focus on labor supply decisions in old ages. Individual of age $t$, with $t = 59, 60, \ldots, 100$, chooses consumption $c_t$, savings $a_{t+1}$, hours of work $l_t$, and an age $\alpha \in \{62, \ldots, 100\}$ at which to apply for social security benefits. Let the amount of social security benefits of an agent of age $t$ who has claimed them at age $\alpha$ to be denoted by $b_t^\alpha$. There is a chance of death every period. Individuals can choose to
work zero hours and claiming social security benefits doesn’t prevent them from working.

The agents are of different genders $g \in \{m, f\}$, belong to one of the two cohorts $c \in \{1, 2\}$, and can be healthy or unhealthy, indicated as $h_t \in \{0, 1\}$, respectively. As I detail below, belonging to a particular cohort determines the set of government policies related to retirement and social security structure (such as Normal Retirement Age), effective income tax, and risk-free saving rate. I focus on the two cohorts of individuals: those born between 1915 and 1934 (post-WWI period and Great Depression, which I label as ”Great Depression Kids”) and those born between 1945 and 1964 (which I label as ”Baby Boomers”). Combination of cohort, gender and health status determines average life-cycle profiles of wages $\bar{w}_t^{g,c}(h_t)$, out-of-pocket (OOP) medical expenditures $\bar{m}_t^{g,c}(h_t)$, and survival probabilities $s_t^{g,c}(h_t)$ for an individual. Furthermore, health status $h_t^{g,c}$ is stochastic and follows a Markov process that depends on cohort and gender. Both wages and out-of-pocket medical expenditures are a combination of a respective life-cycle profile and a persistent idiosyncratic shocks, which also follow a Markov process that do not depend on gender and cohort. Therefore, each individual is subject to four sources of idiosyncratic uncertainty at any given age: survival probability, health shock, wage shock and medical expenditures shock. There is no aggregate uncertainty.

### 2.1 Preferences

Agents maximize expected lifetime utility. The expectation is taken with respect to agent’s survival probability, wage, health status and medical expenditure shocks. Future is discounted by a common discount factor $\beta$. Individuals derive utility from consumption, leisure and leaving bequests. Starting from the Early Retirement Age of 62, individual can irreversibly apply for social security benefits. If one applies for the benefits at age $\alpha$, then the actual annual amount of social security transfers at age $t \geq \alpha$ is denoted by $b_t^\alpha$.

The survival probability $s_t^{g,c}(h_t)$ depends on individual’s current health status $h_t$, cohort and gender. Surviving agent enjoys consumption and leisure. Upon death, individual derives utility from leaving a bequest $B(a_t)$, which depends on asset level at the time of death. Labor force participation is costly, and the cost of participation increases with age. Each period agents have an opportunity to work and potential individual wage at any given age is determined exogenously. Retirement is modeled as a form of non-participation, i.e. choosing zero hours, with individuals being able to re-enter labor force. In what follows, I suppress indices of cohort and gender unless necessary.

Per-period utility function takes the form

$$u(c, l, h, t) = \frac{[c^\gamma (L - \delta h - l - I_{t>0}(\kappa + \xi t^\mu)^\gamma)]^{1-\sigma}}{1 - \sigma},$$
where $\bar{L}$ is annual hours endowment of an agent, $h \in \{0, 1\} = \{\text{good, bad}\}$ is binary health status, and $\delta$ is a leisure penalty associated with poor health. Furthermore, $I_{>0}$ is an indicator that takes value of 1 if an individual participates in the labor market, and 0 otherwise, $\kappa$ is the fixed cost of participation, and function $\xi^{i\nu}$ reflects the increase of participation cost with age. Finally, $\gamma_c$ and $\gamma_l$ are consumption and leisure weights, respectively, and $\sigma$ is relative risk aversion.

Bequest function $B(a)$ is defined as

$$B(a) = \eta \frac{(a + d)^{(1-\sigma)\gamma_c}}{1 - \sigma},$$

where $\eta$ is the magnitude of the bequest motivation, and $d$ characterizes the extent to which bequests are luxury goods. If $d$ relatively large, an individual only gets significant utility gain if he or she leaves a sizeable bequest. According to Lockwood (2016), bequest motives for the seniors are roughly as important as precautionary motives in explaining slow wealth decumulation at old age.

### 2.2 Budget Constraint

The timing of the model is as follows. At the start of each period, health, wage, and out-of-pocket medical expenditure shocks are realized and individuals observe the realizations. If an individual is at least 62 and hasn’t applied to social security benefits yet, then he or she chooses whether to apply now or wait and choose again in the following period. Next, individuals decide how many hours to work, works and receives corresponding salary and transfers, pays taxes. Finally, consumption and saving decisions are made. At the very end of the period, survival shock realizes. Agents who die derive a utility from bequeathing their current assets.

Current health status $h_t$ of an individual of age $t$ is determined by age and health status in previous period. It takes on two possible values, $h_t \in \{0, 1\}$, and the transition between the states is described by a two-state age-specific probability matrix.

Individual hourly wage is exogenous and modeled as a combination of life-cycle profile and a persistent Markov process:

$$\log w^{g,c}_t (h_t) = \log \bar{w}_t^{g,c} (h_t) + \tilde{\varepsilon}_t^w,$$  \hspace{1cm} (2.1)

with $\bar{w}_t^{g,c} (h_t)$ being an average life-cycle profile of individual wages, and $\tilde{\varepsilon}_t^w$ is corresponding stochastic process represented by a Markov chain. Similarly, annual out-of-pocket medical
expenditures are given by
\[ \log m_t^{g,e}(h_t) = \log \bar{m}_t^{g,e}(h_t) + \varepsilon_t^m, \quad (2.2) \]
with the notation being analogous to that of wage process. I provide a detailed explanation of how these objects are constructed in the sections \[3.3\] and \[3.4\].

Consider a person of age \( t \) with wage rate \( w_t \) (defined as in \[2.1\]) and savings \( a_t \) who chooses to work \( l_t \geq 0 \) hours. His or her total taxable income net of transfers, \( y_t \), is given by the sum of labor income and return on savings
\[ y_t = w_t l_t + r^e a_t, \quad (2.3) \]
where \( r^e \) is cohort-specific riskless rate of return. Let period-\( t \) medical expenditure of this individual \( m_t \) be determined as in equation \[2.2\]. Then, the budget constraint for this person is given by
\[ c_t + a_{t+1} + m_t = a_t + T(y_t + \mu(y_t, b_t^\alpha)) + (1 - \mu(y_t, b_t^\alpha)) + b_t^{ma}, \quad (2.4) \]
with
\[ a_{t+1} \geq 0, \]
where \( c_t \) is period-\( t \) consumption and \( a_{t+1} \) is savings choice that must satisfy borrowing constraint. Gross individual taxable income is sum of \( y_t \) and a taxable portion of social security benefits \( \mu(y_t, b_t^\alpha) \). Tax function \( T(\cdot) \) maps individual taxable income into a disposable income. A taxable share of benefits \( \mu(\cdot, \cdot) \) depends on \( y_t \) and level of benefits \( b_t^\alpha \). Social security transfer \( b_t^\alpha \) is modelled following the actual rules of the Social Security Administration, hence it’s a complex object. The next section of the paper is devoted to the description of the retirement benefits calculation in the US and it’s implementation in the model. It includes the definition of taxable share of retirement benefits and function \( \mu(\cdot, \cdot) \) associated with it.

Finally, I follow Hubbard, Skinner, and Zeldes (1995) and include a government transfer \( b_t^{ma} \) as a mean to provide poor or impoverished individuals with a minimal level of consumption, a consumption floor \( z \), so that
\[ b_t^{ma} = \max\{0, z + m_t - (a_t + T(y_t + \mu(y_t, b_t^\alpha)) + (1 - \mu(y_t, b_t^\alpha)))\}. \quad (2.5) \]
A way to think about the transfer \( b_t^{ma} \) is as of Medicaid-type insurance: one becomes eligible to it if and only if all other resources are exhausted due to a high medical expenditure shock.
2.3 Social Security

This section provides details on the construction of social security benefits $b_t$ in the equation 2.4 as well as the description of earnings test rules, and details on taxation of social security benefits, i.e. function $\mu(\cdot, \cdot)$. An individual becomes eligible for social security benefits upon reaching Early Retirement Age of 62. Benefit application is irreversible: as soon as one have started to receive benefits, one can’t stop it. The benefits are then paid until death. There are four major factors that affect actual amount of benefits that individual receives.

First, the base for benefit calculation is the Average Indexed Monthly Earnings ($AIME$) of individual, which is the average of earnings over the 35 highest earning years in the labor market. Second, based on the AIME, the amount of benefits that one would get at Normal Retirement Age, Primary Insurance Amount ($PIA$), is calculated. In what follows, I denote $te PIA as $bt$, treating it as a potential amount of benefits that individual is entitled to. Third, the PIA is reduced or increased according to early retirement penalty or delayed retirement credit, respectively. Fourth, if an individual elects to receive benefits and works at the same time, the benefits might be subject to the earnings test or income tax.

2.3.1 Average Indexed Monthly Earnings

The amount of social security benefits one is entitled to is based on the history of individual earnings, adjusted for inflation. I use the following formula to calculate calculate the AIME within the model:

$$\begin{align*}
AIME_{t+1} = \begin{cases}
AIME_t + \frac{\min\{wct, 90000\}}{35}, & T < 35 \\
AIME_t + \max\{0, \frac{\min\{wct, 90000\} - AIME_t}{35}\}, & T \geq 35
\end{cases}
\end{align*}
$$

(2.6)

where $T$ is the actual number of the total individual working years prior to age $t$.

Essentially, it implies that the AIME is strictly increasing as long as an individual has less than 35 years of job experience, and nondecreasing afterwards. Notice also that time-$t$ contribution to the AIME is actually limited from above. The limit, known as the contribution and benefit base, is set annually by the federal Old-Age, Survivors, and Disability

\footnote{The model currently does not distinguish between individual savings and employer-provided pensions, despite the illiquidity of the latter until certain age plays a potentially important role.}
Figure 3: The dependence of the annual Primary Insurance Amount on the individual annualized Average Indexed Monthly Earnings and the two AIME bendpoints, expressed in 2005 US dollars.

Insurance (OASDI) program\textsuperscript{5}. All monetary terms in the model are expressed in 2005 US dollars, so any dollar amounts I’m going to present in the paper are already converted to USD\textsubscript{2005}, unless it is explicitly stated otherwise. In 2005, contribution and benefit base was 90000\textit{USD}, therefore I use this value as contribution cap, i.e. if individual earnings \( w_t \) exceed 90000\textit{USD}, I use this limit in the AIME calculations instead of the actual earnings.

### 2.3.2 Primary Insurance Amount

Next step is to calculate the \textit{Primary Insurance Amount} (PIA) at age \( t \) as a function of the AIME and the two \textit{AIME bendpoints}

\[
PIA_t \equiv b_t = \begin{cases} 
90\% & \text{of the first } 7524 \text{ of annual } AIME_t, \text{ plus} \\
35\% & \text{of annual } AIME_t \text{ over } 7524 \text{ and through } 45348, \text{ plus} \\
10\% & \text{of annual } AIME_t \text{ over } 45348 \text{ and through the cap of } 90000.
\end{cases} \tag{2.7}
\]

The graphical representation of this formula is shown on Figure 3.

By definition, the PIA is a value of pre-earnings test social security benefits for those who

\textsuperscript{5}More detailed information on construction of these values can be found on the US Social Security website \url{https://www.ssa.gov/oact/cola/Benefits.html}
claim them exactly at the Normal Retirement Age (65 for Great Depression Kids and an average of 66.3 for Baby Boomers). In the case of early or delayed application the amount is adjusted. For each year before the NRA that an individual first collects benefits, they are reduced by 6.7% per year during three nearest years (e.g. 62 to 65, or 63 to 66), and by 5% for any additional year before that but not earlier than 62 (the latter thus only apply to those whose NRA is higher than 65, e.g. 62 to 63 if the NRA is 66). In particular, penalty or credit adjustment depending on claim age $\alpha$ for the two cohorts is calculated by

$$
\mathcal{P}_\alpha = \begin{cases} 
-(NRA - \alpha) \times 0.0667, & \text{if } \alpha \geq 62, \alpha < NRA, (NRA - \alpha) \leq 3, \\
-0.2 - (NRA - 3 - \alpha) \times 0.05, & \text{if } \alpha \geq 62, \alpha < NRA, (NRA - \alpha) > 3, \\
(\alpha - NRA) \times 0.0425, & \text{if } \alpha \geq 65, \alpha < 70, c = 0, \\
(\alpha - NRA) \times 0.08, & \text{if } \alpha \geq NRA, \alpha < 70, c = 1 
\end{cases}
$$

The baseline pre-earnings test amount of benefits for an individual who claims them at age $\alpha$ is thus

$$
b_{B,t}^\alpha = b_t(1 + \mathcal{P}_\alpha)
$$

Figure 4 exemplify these rules for Normal Retirement Age of 65 and 66.

To interpret (2.8) first consider a Great Depression Kid who applied for the Social Security
at the Early Retirement age of 62, that is, three years short of the NRA of 65, having a particular value of the AIME on the personal record. The PIA of this individual is then calculated by 2.7 This amount has to be reduced by 6.7% per each year of early retirement, that is, by $6.7\% \times 3 = 20\%$ in total. The reduced amount is then represents an annual social security benefit transfer to the individual. Second, consider a Baby Boomers whose NRA is 66, retiring at 62, that is, four years short of the NRA. The PIA of this individual is going to be reduced by $6.7\% \times 3 - 5\% \times 1 = 25\%$. This difference creates an incentive for Baby Boomers as compared to Great depression Kids to delay benefit draw past 62.

Similarly, for each year of delaying benefit claim past the NRA and until 70, the PIA would increase by additional $3 - 5\%$ (averaging at 4.25%) for the Great Depression Kids, which was actuarially unfair, and by 8% for Baby Boomers, which is roughly actuarially fair (e.g. French 2005). Actuarial unfairness of delayed retirement for Great Depression Kids worked against delayed retirement. Since it was actuarially unfair, an individual was losing in total expected social security wealth if the retirement was delayed, whereas it’s not the case for Baby Boomers anymore.

2.3.3 Earnings Test

Earnings test applies to individuals who receive social security benefits and income from labor at the same time. For those who didn’t yet attain NRA there is an annual exempt amount (e.g. 12000USD in 2005), and for each 2USD of annual earnings on top of this amount 1USD of annual benefits are withheld. That is, for sufficiently high-earning individuals all of their annual benefits could be withheld by the earnings test. However, part of the benefits withheld by the earnings test is not lost for good, but instead individual annual benefits are permanently adjusted upwards to account for the time during which a part of benefits was withheld. The amound withheld by the earnings test at age-$t$ of an individual of cohort $c$ in the model is calculated by

$$b_{i}^{ET}(c, w_{it}) = \begin{cases} \min\{b_{B,t}^{\alpha}, \frac{w_{it}-12000}{2}\}, & \text{if } (t < NRA \cap c = 1) \cup (t < 70 \cap c = 0), \\ 0, & \text{otherwise,} \end{cases}$$

(2.9)

where 12000USD correspond to exempt amount in the year 2005. If part of the benefits $b_{i}^{ET} > 0$ was withheld, the amount of baseline pre-earnings test benefits is permanently adjusted by

$$b_{B,t+1}^{\alpha} = b_{B,t}^{\alpha} + b_{i}^{ET}(c, w_{it})(1 + \mathbb{P}_{t}),$$

(2.10)
where

\[
P_t = \begin{cases} 
0.05, & \text{if } t \geq 62, \ t < \text{NRA}, \ (\text{NRA} - t) > 3, \\
0.067, & \text{if } t \geq 62, \ t < \text{NRA}, \ (\text{NRA} - t) \leq 3, \\
0.0425, & \text{if } t \geq 65, \ t < 70, \ c = 0, \\
0.08, & \text{if } t \geq \text{NRA}, \ t < 70, \ c = 1. 
\end{cases} \tag{2.11}
\]

The dependence on cohort in 2.9 requires clarification. Prior to 2000, individuals were earnings tested until age 70. In 2000, however, earnings test system underwent a significant reform, which eliminated earnings test at NRA, meaning that Great Depression KIDs were subject to earnings test until age 70, whereas Baby Boomers have to take this wedge into account only between the early and normal retirement age. Therefore, this policy difference poses another distinction between the two cohorts. French (2005) and Yavuzoglu (2016) show that this reform is a significant determinant of labor supply of seniors aged 62 and older.

To provide a bit of intuition to 2.10–2.11 consider an individual who have claimed benefits at age 62, thus being entitled to 0.8 PIA in social security transfers, but continues to work on his very well paid job. Imagine that his or her annual earnings at the age of 62 exceed the annual exempt amount by so much that all of the annual benefits he or she is entitled to are fully withheld, that is, \(b^{ET} = b^B_{t}t\). Basically, this individual doesn’t receive any social security this year (despite having applied for it). Next, let this individual quit the job at age 63 and retire in conventional sense. This situation will exactly coincide with the scenario where an individual have applied for the social security benefits at age 63, being entitled to the higher amount of 0.867 PIA for the rest of life.

Finally, the post-earning test benefits \(b^\alpha_t\) received by an individual of age \(t\), claim age \(\alpha\) and cohort \(c\) is just pre-earnings test benefits net the earnings tested amount:

\[
b^\alpha_t = \begin{cases} 
b^\alpha_{B,t} - b^{ET}(c, w, l_t), & \text{if } t \geq \alpha \geq 62, \\
0, & \text{otherwise}. 
\end{cases} \tag{2.12}
\]

This is the formula I use to construct \(b^\alpha_t\) in the model.

### 2.3.4 Social Security Benefits Taxation

This section provides the details about taxation of social security benefits. According to Internal Revenue Service rules, up to 85% of benefits can be subject to income taxation under certain conditions. In particular, this is the case if individual combined income (sometimes
also called provisioned income), $y_t^{cmb}$, defined as the sum of a gross individual income (net of a social security transfers) plus half of a social security benefits (net of the earnings test), $y_t^{cmb} = y_t + 0.5b_t^\alpha$, exceeds either of two statutory thresholds, 25000USD and 34000USD.\footnote{The detailed description and historical background of the corresponding legislation can be found, for example, at https://fas.org/sgp/crs/misc/RL32552.pdf}

If combined income does not exceed the first threshold, one pays no taxes on the social security benefits. In the case when combined income exceeds the first threshold, up to 50% of the social security benefits are subject to income tax. If combined income exceeds second threshold, up to 85% of benefits may be taxable. More precisely, the taxable portion of benefits, $\mu(y_t, b_t^\alpha)$, is given by

\[
\mu(y_t, b_t^\alpha) = \begin{cases}
0, & \text{if } y_t^{cmb} < 25000, \\
\max\{0.5b_t^\alpha, 0.5 \times (y_t^{cmb} - 25000)\}, & \text{if } y_t^{cmb} \in [25000, 34000], \\
\max\{0.85b_t^\alpha, 0.5 \times (y_t^{cmb} - 25000) + 0.35 \times (y_t^{cmb} - 34000)\}, & \text{if } y_t^{cmb} > 34000.
\end{cases}
\]  

\[ (2.13) \]

### 2.4 Dynamic Programming Problem

This section provides a recursive formulation of an individual’s problem. Agent’s state is fully determined by cohort $c$, gender $g$, age $t$, current level of assets $a_t$, health status $h_t$, wage and medical expenditure shocks $\hat{\varepsilon}^w$ and $\hat{\varepsilon}^m$, and social security receipt status. In particular, an agent can be in different states with respect to social security status. First, nobody can apply for social security until the age of 62. During this period, one keeps track of the one’s AIME and the corresponding potential benefits $b_t$. Second, starting from 62, a person faces a choice between drawing the benefits now or face the choice again next year, with higher benefit level. Third situation describes individual who claimed benefits at some age $\alpha$, and currently receives a fixed annual amount $b_t^\alpha$, properly adjusted for the earnings test.

Let $V_t^A(g, c; a, h, \hat{\varepsilon}^w, \hat{\varepsilon}^m, b^\alpha)$ denote a value function of an age-$t$ individual who has already applied for the social security (a superscript $A$ stands for “an applicant”), with age-$t$ social security check $b_t^\alpha$:

\[
V_t^A(g, c; a, h, \hat{\varepsilon}^w, \hat{\varepsilon}^m, b^\alpha) = \max_{c,l,h} u(c, l, h, t) + \\
\beta\left\{s_t^{g,c}(h)E_{t+1} V_{t+1}^A(g, c; a', h', (\hat{\varepsilon}^w)', (\hat{\varepsilon}^m)', (b^\alpha)'), + (1 - s_t^{g,c}(h))B(a')\right\},
\]  

\[ (2.14) \]
subject to
\[ c + a' + m = a + T(y + \mu(y, b^\alpha)) + (1 - \mu(y, b^\alpha)) + b^{ma}, \]
\[ y = w_l + ra, \]
\[ w = \bar{w}^{g,c}(h) \exp(\varepsilon_w), \]
\[ m = \bar{m}^{g,c}(h) \exp(\varepsilon_m), \]
\[ b^{ma} = \max\{0, \zeta + m - (a + T(y + \mu(y, b^\alpha)) + (1 - \mu(y, b^\alpha))\}, \]
\[ a' \geq 0 \]

and equations 2.9 - 2.13. The function \( V_t^A \) describes the phase of an individual life cycle following the social security application and until death. During this phase, the social security base for the individual is only updated due to the earnings test. The expectation is taken with respect to the distributions of wage, medical expenditures, and health shocks. Using the available information, an agent chooses consumption, leisure and annual hours optimally. Notice that the choice of hours in turn determines individual earnings at \( t \), which define the effect of the earnings test and a portion of the benefits subject to income taxation.

Consider now a value function of an individual aged \( t \geq 62 \) who is not currently applying for social security, and has a baseline potential benefit \( b \) ("a non-applicant"):

\[ V_{t}^{NA}(g, c; a, h, \varepsilon_w, \varepsilon_m, b) = \max_{c,l,a'} u(c, l, h, t) + \beta\{ s_{t+h}^{g,c}(h) E_{t} V_{t+1}^{E}(g, c; a', h', (\varepsilon_w)', (\varepsilon_m)', b') + (1 - s_{t+h}^{g,c}(h)) B(a') \}, \tag{2.15} \]

subject to
\[ c + a' + m = a + T(r^c a + w l) + b^{ma}, \]
\[ w = \bar{w}^{g,c}(h) \exp(\varepsilon_w), \]
\[ m = \bar{m}^{g,c}(h) \exp(\varepsilon_m), \]
\[ b^{ma} = \max\{0, \zeta + m - (a + T(r^c a + w l))\}, \]
\[ a' \geq 0 \]

and equations 2.6 - 2.8. Notice that continuation value of the equation 2.15 includes a value function \( V_t^E(g, c; a, h, \varepsilon_w, \varepsilon_m, b) \), which denotes the value of an individual who is eligible for social security benefits and decides whether to draw them now or wait and face the decision next year. This function simply chooses the maximum current expected value of the two functions defined before, namely, between the value of not applying as opposed to applying
to the social security exactly at current age $t$:

$$V_t^E (g, c; a, h, \hat{\varepsilon}^w, \hat{\varepsilon}^m, b) = \max \{ V_t^{NA} (g, c; a, h, \hat{\varepsilon}^w, \hat{\varepsilon}^m, b) ; V_t^A (g, c; a, h, \hat{\varepsilon}^w, \hat{\varepsilon}^m, b) \} ,$$

subject to equation 2.8, which provides an adjustment factor for delayed or early retirement, when $t \neq NRA$. Finally, the value function that closes the system is the problem of an agent who is not eligible for social security benefits yet, that is, for the agent with $t < 62$. Notice that for an an individual of the age up to 60 this function takes form

$$V_t^{NE} (g, c; a, h, \hat{\varepsilon}^w, \hat{\varepsilon}^m, b) = \max_{c, l, a'} u(c, l, h, t) + \beta \{ s_t^{g, c} (h) E_t V_{t+1}^{E} (g, c; a', h', (\hat{\varepsilon}^w)', (\hat{\varepsilon}^m)', b') + (1 - s_t(h)^{g, c}) B(a') \} ,$$

whereas for 61-year-old person, than is, for an individual who becomes eligible at $t + 1 = 62$, it reads

$$V_t^{NE} (g, c; a, h, \hat{\varepsilon}^w, \hat{\varepsilon}^m, b) = \max_{c, l, a'} u(c, l, h, t) + \beta \{ s_t^{g, c} (h) E_t V_{t+1}^{E} (g, c; a', h', (\hat{\varepsilon}^w)', (\hat{\varepsilon}^m)', b') + (1 - s_t(h)^{g, c}) B(a') \} ,$$

subject to 2.1, 2.2, 2.6 - 2.8 and 2.16.

### 3 The Data and Exogenous Profiles

The Health and Retirement Study (HRS) is an individual level panel data collected every two years from 1992 to 2013. It follows individuals from age 50 until their death. The data consists of several waves of respondents starting from age 50, as well as their spouses regardless of age. The dataset contains very detailed individual information on demographic characteristics, employment history, income, medical expenditures, health status and education attainment among others. I use version O of the RAND files of the HRS, which covers 13 waves of respondents from 1992 to 2013.\footnote{http://hrsonline.isr.umich.edu/modules/meta/rand/index.html}

I restrict the sample to individuals born between 1915 and 1934 (post-WWI, Great Depression) and between 1945 and 1964 (post-WWII, Baby Boomers), aged 50 to 90. The choice of these two cohorts is not arbitrary. First, cohorts have to be large enough to be able to capture intended heterogeneity with enough data. Second, they have to be separated in time enough for the between-cohort differences to be significant. In the sample, I observe
the Great Depression Kids between ages 58 and 90, while the youngest Baby Boomers are 50 and the oldest are 68 (however, there are only eight 68-years-old individuals left in the sample).

I further restrict the sample to those individuals for whom I observe either self-reported age of social security application or the age at which social security benefit are first received. I use total non-housing financial wealth of a household from the HRS as a measure of assets.

The RAND version of the HRS imputes a consistent measure of out-of-pocket medical expenditures across all waves of respondents. Out-of-pocket medical spendings combine expenditures on hospital and nursing home stays, doctor visits, home health care, prescription drugs, outpatient and special care that were not covered by medical insurance, and insurance premia paid. In order to make medical expenditures and wages comparable across years, I deflate nominal dollars reported in the data by corresponding Consumer Price Indices, and express all the nominal values in terms of 2005 US dollars. The sample summaries for some important variables are reported in the Table 1. Due to the data limitations the two cohorts are only comparable directly on subsamples restricted to the individuals aged between 57 and 67. Hence, the statistics in the table are presented for both the full sample and the age-restricted subsample.

As seen from the table, Baby Boomers are more educated and somewhat healthier. More of them are active in the labor force, and on average they work longer hours. The increase in the labor force participation rate of Baby Boomers are especially stark for women and unhealthy individuals.

Out-of-pocket medical spendings of the two cohorts is the most interesting feature presented in the table. First, sample means of medical expenditures of Baby Boomers and Great Depression Kids aged between 57 and 67 are almost identical. Second, the distributions of the medical expenditures over the percentile scale are very different. That is, medical expenditures of Baby Boomers in lower, middle and higher quartiles are significantly higher than the expenditures of Great Depression Kids in the same quartiles. In the top expenditure percentiles, from $p_{95}$ and higher, the situation is remarkably different. In particular, there is a small number of Great Depression Kids whose medical bills are extremely high. These few individuals spend significantly more on healthcare than Baby Boomers in their top expenditure percentiles. In fact, they spend so much that the means of medical spendings of the two cohort are similar despite the significantly higher expenditures of the absolute majority of Baby Boomers.

---

8The details of imputation procedure can be found at http://hrsonline.isr.umich.edu/modules/meta/rand/randhrsO.pdf
### Table 1: Sample summary statistics, data from the RAND HRS, 1992-2013

<table>
<thead>
<tr>
<th>Variable</th>
<th>Great Depression Kids</th>
<th>Baby Boomers</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Full sample</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>0.429</td>
<td>0.488</td>
</tr>
<tr>
<td>College degree</td>
<td>0.175</td>
<td>0.336</td>
</tr>
<tr>
<td>Minimum age in sample</td>
<td>57</td>
<td>50</td>
</tr>
<tr>
<td>Maximum age in sample</td>
<td>97</td>
<td>67</td>
</tr>
<tr>
<td>Mean sample age</td>
<td>75.18</td>
<td>56.83</td>
</tr>
<tr>
<td>Normal Retirement Age</td>
<td>65</td>
<td>66.1</td>
</tr>
<tr>
<td>N of observations</td>
<td>73062</td>
<td>33260</td>
</tr>
<tr>
<td>N of individuals</td>
<td>11599</td>
<td>9908</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Individuals of the age between 57 and 67</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
</tr>
<tr>
<td>College degree</td>
</tr>
<tr>
<td>Share of healthy individuals</td>
</tr>
<tr>
<td>Mean annual OOP medical exp</td>
</tr>
<tr>
<td>p25/p50/p75/p99 of annual OOP medical exp</td>
</tr>
<tr>
<td>In labor force</td>
</tr>
<tr>
<td>In labor force, unhealthy</td>
</tr>
<tr>
<td>In labor force, male</td>
</tr>
<tr>
<td>In labor force, female</td>
</tr>
<tr>
<td>Mean (SD) annual hours worked</td>
</tr>
<tr>
<td>Annual hours per worker, male</td>
</tr>
<tr>
<td>Annual hours per worker, female</td>
</tr>
<tr>
<td>N of observations</td>
</tr>
<tr>
<td>N of individuals</td>
</tr>
</tbody>
</table>

One of the reasons behind this phenomenon might be that there are more Great Depression Kids in this age group with medical conditions that require expensive treatment. Indeed, an individual of this cohort, as compared to Baby Boomer, has higher chances to fall victim to age-related health problems relatively early. Figure 5 plots the shares of healthy individuals aged between 59 and 70 in each cohort from the HRS sample. Both profiles demonstrate that the share of unhealthy individuals increase with age. Importantly, Great Depression Kids start to experience rapid age-related health decline as early as at the age of 62, whereas Baby Boomers likely to have a few more years of healthy life. In other words, Baby Boomers have less health problems than Great Depression Kids in the age interval between 57 and 67. Furthermore, if amount of out-of-pocket medical expenditures reflects the seriousness of health condition, then Baby Boomers are unlikely to develop such a condition.
before reaching the age of 67.

The following sections describe the estimation of exogenous life-cycle profiles that are used as the model inputs.

### 3.1 Health Evolution

Health status \( h_t \) of an age-\( t \) individual is one of the state variables of the model, as well as one of the sources of idiosyncratic uncertainty. As a measure of health, I use self-reported health status from the HRS, which is coded into 5 categories: excellent, very good, good, fair and poor. I create a binary variable that takes value of 0 ("healthy") if self-reported health is excellent, very good or good, and 1 ("unhealthy") otherwise. The evolution of individual health status is fully described by the set of \( 2 \times 2 \) transition matrices. Matrices are uniquely defined for each possible age from 59 to 99. The dependence of transition probabilities on age captures age-related health decline. Next-period health status of an individual depends on current health, age, cohort and gender, but doesn’t affected by his or her medical expenditures. The HRS is biannual survey, so for any given individual I observe health status every two years. Therefore, I first estimate biannual rates of transition between

**Figure 5:** Change in the share of healthy individuals for the two cohorts. Data sample from the RAND version of the HRS, 1992-2013.
**Table 2:** Results of the logistic estimation of the health transition rates.

<table>
<thead>
<tr>
<th></th>
<th>Estimated coefficients.</th>
</tr>
</thead>
<tbody>
<tr>
<td>age</td>
<td>0.00600*** (3.44)</td>
</tr>
<tr>
<td>age²</td>
<td>-0.000258*** (-11.46)</td>
</tr>
<tr>
<td>Male dummy, D_m</td>
<td>0.000698 (0.03)</td>
</tr>
<tr>
<td>Cohort dummy, D_c</td>
<td>0.107** (3.28)</td>
</tr>
<tr>
<td>Current health status dummy, D_h</td>
<td>2.654*** (127.94)</td>
</tr>
</tbody>
</table>

Observations 72222

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

healthy and unhealthy states using a logistic regression of the form

$$Pr(h_{t+2} = 1|t, h_t, g, c) = \Lambda(\beta_h h_t + \beta_c D_c + \beta_g D_g + \beta_1 t + \beta_2 t^2),$$

where $\Lambda(\cdot)$ is the logistic function defined at some $x$ by

$$\Lambda(x) = \frac{e^x}{1+e^x}.$$

I annualize health transition rates by finding two stochastic matrices such that their product is equal to biannual transition matrix. Figure 6 and Table 2 provide the results of a logistic estimation. Despite the fact that the estimated health transition profiles of the two cohorts are very close, they do not coincide. The coefficient at cohort dummy is positive and highly significant, meaning that Baby Boomers are healthier.

### 3.2 Survival Rates

In the data, I observe whether a person has died since the previous interview. Individual probability of survival between age $t$ and $t + 1$ depends on $t$, health status at $t$, cohort and gender. I estimate biannual survival rates using a logistic model:

$$(s_{t}^{g,c}(h_t))^2 = Pr(alive_{t+2} = 1|t, h_t, g, c) = \Lambda(\beta_h h_t + \beta_c D_c + \beta_g D_g + \beta_1 t + \beta_2 t^2)$$
Figure 6: Probability of being healthy next year, conditional on gender and current health status, by age. Each panel shows the "raw" number of transitions to "healthy" status, and logistic fit. Data sample from the RAND version of the HRS, 1992-2013.

To construct annual survival rates $s_t$ from biannual $s_{2t}$, I take a square root of biannual rates. Figure 7 and Table 3 summarize the results.

### 3.3 Out-Of-Pocket Medical Expenditures

Out-of-pocket (OOP) medical expenditures are defined as the expenses for medical care that aren’t reimbursed by insurance. They include deductibles, coinsurance, copayments, insurance premia paid, expenditures on hospital and nursing home stays, doctor visits, home health care, dental care, prescription drugs, outpatient surgery and special facility services. I use an imputed measure of annual individual OOP medical expenditures provided by the RAND version of the HRS. This measure is consistent across all interview years and all waves of respondents.

I model OOP medical expenditures as an exogenous stochastic process, conditional on cohort, gender, and health status. Namely, the model is

$$\log m_t^{g,c} = \log \tilde{m}_t^{g,c} + \varepsilon_t^m.$$
The process is the combination of a profile \( \log \bar{m}_t^{g,c}(h_t) \), and a stochastic process \( \varepsilon_t \). I obtain \( \log \bar{m}_t \) from the data running the following regression:

\[
\log m_t^{g,c} = \alpha_m + \beta_m t + \beta_c^m D_c + \beta_g^m D_g + \beta_h^m D_h + \varepsilon_t^m.
\]

The residuals are then given by

\[
\varepsilon_t^m = \log m_t^{g,c} - \log \bar{m}_t^{g,c},
\]

where the life-cycle profile of log OOP medical expenditures \( \log \bar{m}_t^{g,c} \) is defined as

\[
\log \bar{m}_t^{g,c} = \hat{\alpha}_m + \hat{\beta}_m t + \hat{\beta}_c^m D_c + \hat{\beta}_g^m D_g + \hat{\beta}_h^m D_h.
\]

Figure 8 demonstrates the profiles for the two cohorts.

I assume that \( \varepsilon_t^m \sim \mathcal{N}(\mu_t, \sigma_t) \), and use sample average \( \hat{\mu}_t \) and sample standard deviation \( \hat{\sigma}_t \) of residuals \( \varepsilon_t^m \) as the estimators of \( \mu_t \) and \( \sigma_t \). Furthermore, I approximate \( \varepsilon_t \) by a discrete Markov process. Namely, for a given age \( t \) I build a stochastic transition matrix between the five bins. One of these bins represent extreme medical expenditures (I count medical
Table 3: Results of logistic estimation of survival rates.

<table>
<thead>
<tr>
<th></th>
<th>Probability of being alive in two years.</th>
</tr>
</thead>
<tbody>
<tr>
<td>age</td>
<td>0.116***</td>
</tr>
<tr>
<td></td>
<td>(54.76)</td>
</tr>
<tr>
<td>age²</td>
<td>-0.00122***</td>
</tr>
<tr>
<td></td>
<td>(-46.67)</td>
</tr>
<tr>
<td>Male dummy, $D_m$</td>
<td>-0.397***</td>
</tr>
<tr>
<td></td>
<td>(-15.24)</td>
</tr>
<tr>
<td>Cohort dummy, $D_c$</td>
<td>1.420***</td>
</tr>
<tr>
<td></td>
<td>(20.79)</td>
</tr>
<tr>
<td>Current health status dummy, $D_h$</td>
<td>1.341***</td>
</tr>
<tr>
<td></td>
<td>(51.02)</td>
</tr>
</tbody>
</table>

Observations 105256

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As an example, consider an individual with period-\(t\) OOP medical expenditures being such that $\hat{\epsilon}_t^n$ is contained in some bin $j$, one of the five. Based on this information and the estimates of the regression coefficients $\hat{\beta}_{bin_i}$, one can calculate the predicted probability of finding $\hat{\epsilon}_{t+1}$ in any particular bin at $t+1$. Five possible initial bins and five possible resulting bins provide 25 different combinations. The probabilities of each combination result in a $5 \times 5$ stochastic transition matrix. One example of such a matrix is presented in Table 4. The matrices are defined at the ages from 50 to 99. Notably, the resulting autoregressive process defined by these transition matrices is highly persistent.

Initial step of a simulation of individual OOP medical expenditures is to generate a counterfactual “residual” at every age $t$. Next step is summing up the value of predicted profile at $t$ and the simulated residual to obtain a counterfactual OOP medical expenditure. The transition matrices allow to simulate the evolution of OOP medical expenditures only up
to the bin it belongs to. Recall that each of the five bins is defined by a continuous interval and have two well-defined borders. A residual belongs to the certain bin if it’s numerical value lies inside the interval limited by that bin’s borders. Every bin thus covers a range of values of residuals. In order to pick a particular value of the residual form the interval covered by the bin, I make a random draw from a normal distribution that is truncated by the bin borders. The task is simplified by the fact that I already estimated the means and the standard deviations of parental normal distributions at every age \( t \).

### Table 4: Example of OOP medical expenditures transition matrices

<table>
<thead>
<tr>
<th></th>
<th>( age = 59 )</th>
<th></th>
<th>( age = 80 )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Bins</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>.461</td>
<td>.264</td>
<td>.163</td>
</tr>
<tr>
<td>2</td>
<td>.242</td>
<td>.343</td>
<td>.253</td>
</tr>
<tr>
<td>4</td>
<td>.090</td>
<td>.158</td>
<td>.267</td>
</tr>
<tr>
<td>5</td>
<td>.103</td>
<td>.132</td>
<td>.235</td>
</tr>
</tbody>
</table>
Figure 9: Life-cycle profiles of mean hourly wage, in 2005USD (data from the HRS sample, 1992 to 2013).

### 3.4 Wages

Wages are constructed by dividing annual labor earnings by annual hours worked. Annual earnings are directly available in the HRS, whereas annual hours worked by individual are computed as a product of weekly hours worked and number of weeks worked during a reference year. Wage profiles and wage evolution is calculated very similarly to the calculation of medical expenditures. I have much fewer observations here, since I only observe wages for those who work, as compared to OOP medical expenditures, which I observe for almost everyone in the sample. The assumed wage process is:

\[
\log w_t = \alpha_w + \beta_{w_t} t + \beta_{2,w_t} t^2 + \beta_{c}^w D_c + \beta_{g}^w D_g + \beta_{h}^w D_h + \varepsilon_t^w.
\]

Figure 9 demonstrates the wage profiles for the two cohorts.

In order to discretize the autoregressive process of wage transitions I sort residuals into 5 quintile bins. Then I calculate the conditional transition probabilities between bins in the same way as for the OOP medical expenditures. Again, the resulting autoregressive process is remarkably persistent.
### 3.4.1 Controlling for Wage Selection Bias

The well-known problem with the type of wage profiles I’m using in this paper is that they are subject to selection bias. In the data we only observe the wages of those who work, and we don’t observe potential wages for non-workers. At older ages, this bias becomes extremely significant, given the small fraction of working individuals. Thus, it is crucial to correct for this bias to get any credible results from the model. I employ the procedure following French (2005).

The main idea is we can observe wages of those who doesn’t work in the model simulated data. The key assumption is that the difference in wages of those who work and those who don’t is similar in the HRS and in the data simulated by calibrated model. I do initial calibration of the model using the biased wage profiles from the HRS. I then use the model to simulate a large number of individual life-cycle decisions. In the simulated data I can observe wage offers and corresponding labor supply decisions for every individual. I use this information to build two life-cycle wage profiles. The first one is constructed using only wages of those who work, so it is analogous to the profile from the HRS. The second profile is constructed using wages of both workers and non-workers. This one represents a potential "true" unbiased average wage profile, which we would like to obtain. The difference between the two profiles provides a sense of an upward bias of the wage profile from the HRS. For example, assume that at a certain age the average wage of simulated workers exceeds the average wage of all simulated individuals by 20%. Then it is likely that the wage in the HRS profile at this age was overestimated by 20%. Therefore, this difference is used to update the HRS profile, decreasing the average wages. This updated profile is then used on the next to produce a new calibration of the model. The updated model is then again used to simulate the two profiles, calculate bias, update the candidate true wage profile again. The procedure is repeated up to the point where the update doesn’t change the profile.

### 4 Calibration and Estimation

First, I fix labor endowment at age 50 to \( L = 5000 \) and time discounting factor to \( \beta = 0.95 \). The ultimate goal is to estimate the set of preference parameters \( \Upsilon = \{ \sigma, \gamma_t, \gamma_l, \delta, \kappa, \zeta, \nu, \eta, d, \xi \} \). Main assumption is that \( \Upsilon \) is similar between the two cohorts, and all the observed differences in behavior come from the exogenous objects, such as survival rates and policies. In order to estimate \( \Upsilon \), I employ the following two-step approach. On the first step, I estimate health transition matrices, survival rates, wage and medical expenditure processes, and joint distributions of AIME, assets, wages, medical spendings and total yeats worked at age 59.
directly from the data. Given these objects and some guess on \( \Upsilon \), I solve an individual
dynamic programming problem backwards to obtain a corresponding optimal savings deci-
sions, labor supply decisions, and timing of social security application. Given these set of
decisions, I can simulate a large number of individuals, and calculate the difference between
observed and simulated labor supply, labor participation, assets and social security timing
profiles under a particular distance measure. I then continue to update \( \Upsilon \) until the simulated
and observed profiles are sufficiently close. I consider the resulting \( \Upsilon \) as a parameters of the
data-generating process for both cohorts.

After this is done, I can simulate a large number of individuals of the two cohorts with
respect to the common \( \Upsilon \) and the set of the exogenous processes specific to the each cohort.
In an ideal case, this will allow me to see which part of the change in labor force participation
decisions can be explained by considered exogenous factors.

4.1 Initial Distributions

Individuals enter the model at age 59. In order to start simulation, I need to know age-59 joint
distribution of AIME, assets, wage, health and medical spendings, and total years worked
prior to this age. I estimate this distribution directly from the data. Launching the model
simulations, for each individual I draw initial values from this distribution. Out of these, in
the sample I directly observe everything apart from AIME for everybody. However, I recover
initial AIME for Baby Boomers from the Social Security payments for retired individuals
and predicted SS wealth at age 62, 65 or 70 for pre-retirees, as well as observing their earning
histories down to age 59. To estimate the distributions, I assume that AIME, assets, wage
and OOP medical spendings and total years worked prior to 59 are jointly lognormal at
age 59, conditional on cohort, gender and having zero assets. I then calculate sample mean
vector and variance-covariance matrices. The estimates are presented in the Table 5.

4.2 Taxation Function

In order to calculate income taxes, I use the parametric estimates of effective tax functions
from Guner et al. (2014). Namely, I use estimates for year 1989 for the Great Depression
Kids cohort (right after Raegan tax cuts) and for year 2000 for Baby Boomers cohort, for
whom effective income taxes were changed in a way that low-income household paid less
taxes that before, whereas richer household paid more.. The average tax rate is \( \tau(y) \), where \( y \)
is income in $2005, \( \tau \) is effective tax rate, and \( m, s \) and \( p \) are cohort-dependent coefficients.
Table 5: Joint initial distribution means: logs of AIME, wage, OOP medical expenditures and assets, and years worked.

<table>
<thead>
<tr>
<th>Cohort</th>
<th>Gender</th>
<th>Positive assets</th>
<th>AIME</th>
<th>Wage</th>
<th>OOP</th>
<th>Years</th>
<th>Assets</th>
</tr>
</thead>
<tbody>
<tr>
<td>BB</td>
<td>Female</td>
<td>No</td>
<td>9.82</td>
<td>2.46</td>
<td>7.09</td>
<td>3.11</td>
<td></td>
</tr>
<tr>
<td>BB</td>
<td>Male</td>
<td>No</td>
<td>10.02</td>
<td>2.75</td>
<td>6.86</td>
<td>3.37</td>
<td></td>
</tr>
<tr>
<td>BB</td>
<td>Female</td>
<td>Yes</td>
<td>10.09</td>
<td>2.75</td>
<td>7.04</td>
<td>3.25</td>
<td>10.45</td>
</tr>
<tr>
<td>BB</td>
<td>Male</td>
<td>Yes</td>
<td>10.55</td>
<td>3.03</td>
<td>6.69</td>
<td>3.45</td>
<td>10.45</td>
</tr>
<tr>
<td>GDK</td>
<td>Female</td>
<td>No</td>
<td>9.11</td>
<td>2.41</td>
<td>6.96</td>
<td>29.77</td>
<td></td>
</tr>
<tr>
<td>GDK</td>
<td>Male</td>
<td>No</td>
<td>9.32</td>
<td>2.35</td>
<td>6.70</td>
<td>36.52</td>
<td></td>
</tr>
<tr>
<td>GDK</td>
<td>Female</td>
<td>Yes</td>
<td>9.44</td>
<td>2.51</td>
<td>6.85</td>
<td>30.57</td>
<td>11.27</td>
</tr>
<tr>
<td>GDK</td>
<td>Male</td>
<td>Yes</td>
<td>9.92</td>
<td>2.92</td>
<td>6.87</td>
<td>40.84</td>
<td>11.44</td>
</tr>
</tbody>
</table>

Table 6: Parameters of the taxation function (from Guner et al., 2014)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>m</th>
<th>s</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Great Depression Kids</td>
<td>0.479</td>
<td>0.0355</td>
<td>0.817</td>
</tr>
<tr>
<td>Baby Boomers</td>
<td>0.264</td>
<td>0.0136</td>
<td>0.964</td>
</tr>
</tbody>
</table>

Thus, the disposable household income is calculated by

\[ T(y_t) = (1 - \tau(y_t))y_t, \]

where the precise functional form of effective taxation function is given by

\[ \tau(y) = m[1 - (sy^p + 1)^{-\frac{1}{p}}] \]

The values of the parameters of taxation function are presented in the Table 6.

4.3 Moment Conditions

I calibrate the vector of model parameters \( \Upsilon = \{\sigma, \gamma_c, \gamma_l, \delta, \kappa, \zeta, \nu, \eta, d, c\} \) to fit the following set of moments:

- Mean labor force participation, for every age 59 to 90, to identify \( \kappa, \theta_p \) and \( \xi \).
- Mean labor force participation conditional on having zero assets, for every age 59 to 90, to identify \( \zeta \).
- Mean labor supply (in hours), for every age 59 to 90, to identify \( \gamma_l, \gamma_c \) and \( \sigma \).
- Mean labor supply (in hours), by health status, for every age 59 to 90, to identify \( \delta \).
Table 7: Set of calibrated model parameters, male Great Depression Kids

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed parameters</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.95</td>
<td>Time discounting, fixed</td>
</tr>
<tr>
<td>$L$</td>
<td>5000</td>
<td>Annual labor endowment (hours), fixed</td>
</tr>
<tr>
<td><strong>Calibrated parameters</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\kappa$</td>
<td>889 (8)</td>
<td>Participation cost (hours)</td>
</tr>
<tr>
<td>$d$</td>
<td>5.07(0.09)(\times 10^4)</td>
<td>Strength of bequest motive</td>
</tr>
<tr>
<td>$\xi$</td>
<td>2512 (78)</td>
<td>Consumption floor</td>
</tr>
<tr>
<td>$\delta$</td>
<td>517 (50)</td>
<td>Participation cost, bad health</td>
</tr>
<tr>
<td>$\eta$</td>
<td>5.2(0.2)</td>
<td>Bequest motive magnitude</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>3.99(0.1)</td>
<td>Relative risk aversion</td>
</tr>
<tr>
<td>$\gamma_c$</td>
<td>0.471(0.014)</td>
<td>Consumption weight</td>
</tr>
<tr>
<td>$\gamma_l$</td>
<td>0.6782(0.015)</td>
<td>Leisure weight</td>
</tr>
<tr>
<td>$\xi$</td>
<td>2.99 (0.07)</td>
<td>Participation cost due age, magnitude</td>
</tr>
<tr>
<td>$\nu$</td>
<td>1.74(0.01)</td>
<td>Participation cost due age, power</td>
</tr>
</tbody>
</table>

- Mean assets, for every age 59 to 90, to identify $\eta$ and $d$.

As a first step weighting matrix I use the inverse of variance of each moment at each given age. The set of calibrated model parameters is presented in Table 7.

4.4 Model Fit

The calibrated model fits the selected moments reasonably well. Four panels of the Figure 10 demonstrate the model fit. The baseline model successfully replicates annual working hours, participation rate and saving decision of male Great Depression Kids. On top of that, the model is able, at least partially, replicate the surge of Social Security applications at the age of 62.

I furthermore assess the robustness of the model. In order to do that, I use the parameters calibrated to fit the moments of the older cohort and use them to simulate the corresponding moments of the younger cohort, using their exogenous profiles. Then I compare these simulated profiles to the actual behavior of Baby Boomers. Within the frame of this exercise, the model behaves acceptable. Namely, figures 11 and 12 demonstrate the outcomes of this exercise, meaning that model have substantial predictive power. Of course, further robustness checks is on the way. Namely, one of the most important test is the sensitivity of the results to the particular form of utility function.

Table 8 summarizes the results of the robustness check for the age interval from 62 to 67.

30
4.5 Decomposition Exercises

The primary goal of this paper is to quantify the relative importance of the forces that are, potentially, responsible for the increase in labor force activity of US elderly. The factors under investigation can be thought of either as policy-related or "natural" ones. The policy-related factors include the rise in Normal Retirement Age, elimination of the earnings test, changes in the taxation schedule, changes in the rate of social security early retirement penalty and delayed retirement credit. The policy-unrelated factors include the increase in life expectancy, increase in OOP medical expenditures, changes in wages, changes in health. The main objects of interest are differences in labor force participation and average hours worked between the two cohorts. The goal is to measure which shares of these differences can be attributed to each of the driving forces. I focus on the individuals aged between 62 and 67.

As an example, consider measuring the effect of increase of the Normal Retirement Age
on labor force participation rate. In order to isolate the effect, I run the baseline model calibrated to the Great Depression Kids, but use the NRA of Baby Boomers as an input. The simulation results thus reflect the changes in the decisions of agents related to the increase in NRA, while all other factors remain unchanged. I use this approach to assess the effect of every factor of interest. Tables 9 and 10 represent the results of the exercise. It is clear that individuals react to both policies and non-policy factors.

First, the elimination of the Earnings Test at the NRA has a strong effect on both participation and hours worked of individuals between 62 and 67, explaining in isolation almost half of the overall increase in participation and one-third of the increase in hours worked. Increase in the NRA and changes in effective tax rates potentially could significant portions of the increase in participation and hours. The change in Social Security rules, which increased the delayed retirement benefit from 4.25% to 8% per year, has moderate effect,
with some 6% more individuals delaying retirement past the NRA.

The factors not directly related to policies have more ambiguous effects. Increase in longevity and increase in OOP medical expenditures, taken in isolation, can only explain a modest part of the increase in labor supply of seniors. Changes in wage structure of Baby Boomers lead to significant increase in participation rate, but at the same time the decline in hours is observed. If Great Depression Kids are given the health dynamics of the Baby Boomers, the decrease in hours is observed.

A very important result, however, is that some factors interact to produce synergetic effects of high magnitude. One example is a very strong effect that increase in longevity and OOP medical expenditures has on labor force decisions of individuals, as can be seen from Table [11]. That is, if Great Depression Kids had both life expectancy and OOP medical expenditures of the Baby Boomers, the model predicts very large increase in both participation

---

**Figure 12:** Mean hours: data from the HRS sample and the model and model, Baby Boomers.

**Table 9:** Decomposition exercise: policy-related factors, age 62-67

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>NRA</th>
<th>Taxes</th>
<th>Earnings test</th>
<th>SS rules</th>
<th>Baby Boomers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean participation rate</td>
<td>0.521</td>
<td>0.529</td>
<td>0.534</td>
<td>0.552</td>
<td>0.525</td>
<td>0.584</td>
</tr>
<tr>
<td>Mean annual hours</td>
<td>842</td>
<td>859</td>
<td>862</td>
<td>906</td>
<td>851</td>
<td>1056</td>
</tr>
<tr>
<td>% explained, LFP</td>
<td>12.7</td>
<td>20.63</td>
<td>49.2</td>
<td>6.35</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% explained, hours</td>
<td>7.94</td>
<td>9.35</td>
<td>29.91</td>
<td>4.22</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
and hours worked. A potential explanation might lie in the fact that longer life expectancy means higher chances to live up to a very old age, where extreme medical shock is very probable. Thus, seniors continue to work to hoard additional resources to insure against this shock.

5 Conclusions

A life-cycle model is built to assess the changes in labor market activity of two different cohorts of US seniors. A baseline calibration of the model to males of the post-WWI cohort fits the data reasonably well. Initial counterfactual experiments suggest the model is capable of capturing a significant part of observed differences in participation rates and hours per worker. The decomposition exercise suggests that both policies and non-policy factors play a significant role in shaping changes in labor force behavior of seniors. Furthermore, there are hidden interaction between the factors that can lead to significant reinforcement of the effects. One example of such interaction is large effect of increase in longevity tied with increase in OOP medical expenditures.


References


Figures and Tables

A Appendix

A.1 Solving the Model

The model allows to simulate individual life cycle. I solve for value function on multidimensional grid on assets (11 gridpoints, nonequally spaced between $0$ and $1000000$), benefit value (11 gridpoints, nonequally spaced between $0$ and $34670$, the upper value corresponds to AIME cap), 50 gridpoints for joint shock (2 health statuses, 5 wage statuses corresponding residual bin means, 5 medical expense statuses) and $J = 41$ life period. Grid is sparse, so I resort to multidimensional linear interpolation between gridpoints during the simulation.

Furthermore, to pin down a particular value of deviation from the mean, I draw a random value from truncated normal distribution within a particlar quintile bin. I allow transition matrices to depend on age, cohort, health status, gender and (in the extension) education level.

The benefit accumulation (AIME update, PIA calculation, and benefit adjustment) in the model is captured by the function $F(b_t, w_l, t)$. Given current benefit level and age, this function first converts current benefit to AIME, then updates AIME, and then converts AIME back to updated benefits.