The Role of Demographic Change in Explaining Declining Labor Force Participation*

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Abstract

The labor force participation rate has been declining in the United States since the late 1990s. Decomposing the aggregate labor force participation rate by age reveals that this decline is being driven by reduced participation among relatively young individuals, those aged 16 to 24. In fact, participation among older individuals, age 55 and above, has been increasing. In this paper, we develop a model in which individual decisions regarding schooling and retirement, in view of empirically observed changes in mortality, can simultaneously explain these three labor force participation trends. Furthermore, a counterfactual scenario that accounts for the observed demographic trends but does not account for agents' endogenous schooling and retirement response is found to contradict the observed trends.

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1 Introduction

The labor force participation rate (LFPR) in the United States has declined since the late 1990s/early 2000s (Figure 1). One possible explanation for this trend is an increase in retirements resulting from the aging of the baby-boom generation. However, decomposing the LFPR by age reveals that adjustments in the labor supply of young individuals, those age 16 to 24, not the old, is a main driver of the overall decreasing trend. In fact, the LFPR among older Americans, those age 55 plus, has actually increased over this period as Figure 2a shows[1]. In the period from the late 1990s to 2019, life expectancy in the U.S. increased due to declines in the mortality rates among older Americans (Figure 3)[2]. In this paper, we investigate the extent to which these empirically observed changes in mortality during later stages of life can explain trends in the U.S. labor force participation observed in the past two decades for both the young and old cohorts respectively.

The changes in mortality observed in recent decades have the potential to affect the labor force participation of young and old age groups by influencing individuals' schooling and retirement decisions. The relatively strong observed increase in survival rates for older individuals can simultaneously increase the return to education (through an extended working life) and create the need for larger private savings for retirement. Therefore, we focus on agents' human capital and retirement decisions and examine how these individual choices influence the economy-wide LFPR and its behavior at the two extremes of the working age distribution. While the compositional effect of increased life expectancy alone reduces the LFPR on average, we demonstrate that it is unable to capture the changes observed at the two extremes of the age distribution, highlighting the importance of the endogenous schooling and retirement decisions proposed in this paper.

The observed decrease in the economy-wide LFPR over the past two decades could, in principle, be due to a decline in trend or variation in cyclical factors (or both). However, according to the empirical literature the change in LFPR is primarily driven by a decrease in the trend (see survey papers by Perez-Arce and Prados, 2020, and Abraham and Kearney, 2020). Furthermore, papers by Aronson et al. (2014) and Kruger (2017) find that

[1]Figure 2a presents the LFPR by age group for the U.S. from 1980 to 2019. Inspection of this figure reveals a strong decrease in the LFPR rate among those age 16 to 24 and a strong increase in the participation rate for those age 55+. This pattern can be more easily seen in Figure 2b which normalizes the series to start at 0 in 1980 and includes a series for the average LFPR. From Figure 2b, it is easy to see that the LFPR for young individuals (16 to 24) fell faster than average, while the LFPR for older individuals (55+) increased faster than average.

[2]We consider data only up to year 2019, prior to the onset of the COVID-19 pandemic, which is still a very recent shock whose full impact on labor participation trends will be better analyzed in the future.

demographic changes, specifically the "aging of the population," explain half to two-thirds of the trend decline in the LFPR. Aronson et al. (2014) and Kruger (2017) find that the shares of the population in older age groups have increased in the past 20 years, thus partly accounting for a lower trend in the LFPR. Our paper focuses on a related demographic change, the reduction in the mortality rates of adults which of course affects the aging of the population. However, our model also incorporates the ability of individuals to change both their savings decision and their labor force participation decision. Younger individuals may decide to acquire more human capital through education, requiring them to delay entry into the workforce, while older individuals may decide to remain in the workforce longer and delay retirement.[3] These decisions could then reduce the LFPR beyond the mechanical reduction due to the "aging of the population" alone.

While our paper focuses on demographic change due to lower mortality, there are several other factors that have been studied in the empirical literature that may also cause the LFPR to decline. These factors may affect labor supply or labor demand and some of them have been found in the literature to have empirical support.[4] Our paper, however, focuses on the effects of demographic changes which have been found to empirically explain over half of the decline in the trend in the LFPR. Moreover, while there have been important differences in the behavior of LFPRs of males and females on average over this period, the pattern for young (ages 16 to 24) and old (55+)—the primary focus of this paper—is very similar across genders. Specifically, panels a and b of Figure 4 presents the LFPR by age for males, with panel a reporting the data in levels and panel b reporting the data with all initial observations normalized to 0, along with the series for average LFPR. Inspection of panel b reveals that the LFPR for young males age 16 to 24 declined by more than the average and the LFPR for older males age 55+ increased by more than average over the time period considered. The same pattern is observed in panels c and d, which report the age-specific LFPRs for females. Moreover, exactly the same patten is also observed in the overall age-

[3] de Brey et al. (2021) and Current Population Survey (U.S. Department of Commerce, various years) provide evidence consistent with predictions for the young and U.S. Department of Health and Human Services (2021) presents supporting evidence for the old. These data are presented later in Table 2.

[4] In particular, some of the labor supply-related factors that have been studied include: the increased use of social insurance programs like disability and SNAP (Eberstad, 2016); the increased availability of opioid drugs (Kruger, 2017); the increase in entertainment options at home (Aguiar et al., 2021); the increased cost of child care (Kleven, 2014); and the increase in immigration (Blau and Mackie, 2016). There are also a number of factors that are related to labor demand that have been studied including: the increase in trade which lowered demand for manufacturing jobs (Autor, Dorn and Hanson, 2013; Acemoglu et al. 2016); the improvements in automation which may have also reduced demand for labor (Acemoglu and Restrepo, 2020; Autor, Dorn and Hanson, 2015).

decomposition as shown in Figure 2b. Therefore, we abstract from gender-differences in the remainder of our work.

In the theoretical literature, Cervellati and Sunde (2013) investigate the connection between increases in life expectancy and optimal schooling. However, while we focus on the U.S. experience from the late 1990s to today, Cervellati and Sunde (2013) focus on the 1840 to 1930 period when the nature of improvement in mortality was different. Specifically, while in our time period a majority of the increase in life expectancy occurs late in life, most improvement in mortality in the 1840-1930 period was in the working-ages, leading to the "rectangularization" of the survival probability profile. Cervellati and Sunde (2013) find that this reduction in age-specific mortality, even without increasing longevity, can lead to increases in schooling. Similar effects were found in the theoretical literature by Soares (2005) and Cervellati and Sunde (2005), among others.

Echevarria (2004) also finds that longer life expectancy leads to higher education and delayed retirement patterns in a calibrated OG model. Our paper, however, provides a more elaborate and realistic quantitative assessment of changes in life expectancy in the following respects. First, we allow for within-cohort heterogeneity in ability (and resulting accumulation of human capital). Second, our agents face uncertain, rather than certain lifetime horizons, thus allowing for the precautionary saving motive to operate in our model. Third, Echevarria (2004) abstracts from public expenditure on education and mandatory social security, both of which are accounted for in our quantitative analysis and are important for a more realistic quantitative assessment as mentioned above. Finally, Echevarria (2004) focuses on the growth implications of increases in life expectancy which operate through an externality in human capital accumulation (also see Lucas 1990 and Einarsson and Marquis, 1996), while we focus on consequences for labor force participation.

There is also empirical evidence, at both the microeconomic level (Hurd, McFadden, and Li, 1998) and at the macroeconomic level (Bloom et al., 2003), that higher life-expectancy increases the saving rate. However, Bloom et al. (2007) show that, in a simple life-cycle model, a longer life span need not affect the savings rate. An optimal response can result in a proportional increase in the length of agents' working lives, while the savings rate remains fairly steady over time.

In this paper, we develop a perfect foresight overlapping generations model with discrete choice to determine how improvements in mortality late in life, as observed over past few decades, affect individuals' human capital accumulation and retirement decisions, and, hence, the overall LFPR and its distribution over age in the economy.[5] Agents are assumed to be heterogenous in their ability to accumulate human capital through schooling. They face age-cohort specific mortality risk every year, so survival to the next year of life is uncertain for all agents. As stated earlier, the empirical literature finds that changes in LFPR are primarily changes in trend. Therefore, we abstract from labor market search, which is useful for understanding labor market dynamics over the shorter horizon of the business cycles. Furthermore, by making agents' schooling and retirement decisions endogenous within our model, we account for the two primary margins of adjustment in labor force participation, a feature on which most labor market search models remain silent.[6]

At the beginning of each period, all agents must make a discrete choice regarding their labor market status. They are able to choose between being a student, worker, or retiree. Students are assumed to not work, and they must finance their consumption through borrowing in the market. Time spent in school augments an agent's human capital; more for the individuals with higher ability. Workers supply labor to the firm in exchange for a wage. The returns to labor supply increase with human capital, thus more highly educated workers command higher wages. Besides consuming, workers must repay their debt (taken on as a student) and save for retirement. Retirees simply live off of their private savings and the social security benefit they receive after age 65.

We first solve our model assuming a fixed age-specific survival function. This scenario is set to reflect demographic conditions in the pre-1990's U.S., and is used to ascertain the dispersion in individual ability by matching the broad schooling, labor force participation, and retirement patterns observed in the data during this time period. Next, we re-solve our model, holding fixed the distribution of individual ability, but now allowing the age and cohort specific survival probabilities to adjust in a similar way to what is empirically observed in the U.S. from 1990 to 2015. To calibrate other features of our model, we make use of both aggregate and individual-level data. The most notable feature of our calibration

[5] Echevarria and Iza (2006) examine growth implications of changes in mortality in a simple growth, overlapping generations model in which individuals choose the length of education, and the age at retirement, and where unfunded social security pensions depend on workers' past contributions. An increase in life expectancy lowers the per capita growth rate due to an interaction between the social security system and changes in mortality, which reduces the active population.

[6] It should be noted that prime-working age agents have full labor force participation within our model. This follows because we abstract for idiosyncratic events that influence labor force participation, such as health emergencies, family planning, etc., and focus instead on long-term life events such as schooling and retirement. While there is variation in the labor force participation rate among this age group in the data, its participation rate is much higher and much more stable than that observed for the young or old age groups (see Figures 2 and 4).

strategy is how we handle the computation of age-cohort specific survival rates. We recover age-cohort specific survival rates from the Human Mortality Database (HMD) which uses Census population and Center for Disease Control (CDC) data to generate reliable and consistent estimates for the population above age 80. As such, we are able to compute smooth survival functions for individuals age 0 to 110 born between the years 1933 and 2015.

The primary mechanism operating in our model is as follows. Increased survival probabilities late in life impinge on individuals' optimal decisions in very different ways depending on their current position in the life-cycle. Younger individuals will react to these demographic adjustments by delaying entry into the labor market in order to accumulate more human capital and boost life-time earnings. In contrast, older individuals who need to increase retirement savings in order to plan for longer and more expensive retirements, will find it optimal to delay retirement and extend their working life. As such, the key mechanism of our model is broadly consistent with an economy-wide decline in the LFPR that is driven primarily by reductions in the labor force participation of young agents. Furthermore, we find a strong incentive for older agents to increase their labor force participation, which is also observed in the data.

To test the above mechanism, we consider a counterfactual scenario that allows only for demographic change, holding fixed agents' schooling and retirement decisions. This exercise allows us to isolate the compositional effect of the observed changes in mortality that is highlighted in the empirical literature discussed above from the endogenous response of the agents through changes in schooling and retirement choices. The results of this counterfactual experiment contradict the observed trends in labor force participation described above. In particular, the results fail to be consistent with the observed decline (rise) in labor force participation among young (old) agents. In fact, this counterfactual analysis not only demonstrates the inability of the compositional effects to explain observed labor force participation trends but also reinforces the importance of the endogenous transmission mechanism through human capital accumulation highlighted in the paper. Specifically, this mechanism is necessary to first reverse the underlying trends, which move in the wrong direction due to the compositional effects, before pulling those trends in the right direction.

The remaining parts of the paper are organized as follows. Section 2 lays out the overlapping generations model with heterogeneous ability and endogenous schooling and retirement choices. Section 3 outlines the calibration and technique for solving the model. The results are presented in Section 4 and Section 5 concludes the paper.

2 Model

We consider a standard discrete time life-cycle model with overlapping generations where agents face age-specific mortality risk. They value consumption and leisure, and in each period (corresponding to a year) allocate their time to one of the three activities: acquiring human capital (student), working for the firm (worker), or enjoying leisure (retiree). Thus, along with a standard consumption-savings decision, each agent must make a discrete choice regarding their labor market position at the start of each period. In particular, this choice depends on their ability to acquire human capital which is heterogeneous across the agents within a given birth cohort. Agents can switch between being a student, worker, or retiree in response to aggregate and individual conditions. The model also includes a representative firm and a government. The next several subsections detail the structure of our model.

2.1 Life-Cycle Structure

The agents are assumed to enter the economy at age 16 and they may live to a maximum of 100 years old, implying a maximum (economic) life-span of 85 years. As each period in the model corresponds to a year, the age, a, of an agent varies from 16 to 100. A unit measure of agents enter the economy at age 16 every period and they face an age-specific survival probability, $\pi(a)$. Given the arrival of new agents and the presence of $\pi(a)$, the mass of agents of arbitrary age, $a > 16$, in a stationary economy, is given by:

$$M_a = \prod_{\tau=16}^{a-1} \pi(\tau) \tag{1}$$

Using equation (1), the total population each period in the economy is given by:

$$Pop = 1 + \sum_{a=17}^{100} M_a \tag{2}$$

With a view to normalize the size of the total population in the economy to 1, let us define the proportion of agents of each age in the economy as:

$$norm_a = \frac{M_a}{Pop} \tag{3}$$

Thus, in the normalized economy, $\frac{1}{Pop}$ agents of age $a = 16$ enter the economy each period.

Given that agents face age-specific survival probabilities, $\pi(a)$, agents of age a will die with probability $1-\pi(a)$ each period. The accumulated savings of agents who die unexpectedly will be treated as an accidental bequest, AB, and rebated in lump-sum to all surviving agents in the economy, regardless of their age and cohort. We provide a detailed expression for AB in our definition of equilibrium (see Section 2.5).

2.2 Schooling and Human Capital Accumulation

The decision to attend school is one of the three discrete and mutually exclusive choices that an agent makes every period. Although, an agent can potentially go to school in any period, schooling forms a continuous, uninterrupted period of time at the beginning of agent's entry into the economy, due to the absence of idiosyncratic income shocks. This is broadly consistent with the real world, although it does not capture the observed occasional retooling/schooling later in life.

All agents are born with the same initial level of human capital, h_0, but they are assumed to differ in terms of their innate ability, ϵ_h^i, which they draw from a known distribution, $G(\epsilon_h)$. This innate ability, which determines the rate at which an individual accumulates human capital, is the only source of within-cohort heterogeneity in our model.

The process of human capital accumulation via schooling is similar to that presented in Glomm and Ravikumar (1992) and follows:

$$h_{a+1}^i = h_a^i + A\epsilon_h^i q^\alpha [h_a^i]^{1-\alpha} \tag{4}$$

where the impact of schooling on an individual, i's, level of human capital is seen to depend on their innate ability, ϵ_h^i, as well as their current level of human capital, h_a^i, the provision of a schooling input by the government, q, and the total efficiency term, A. In particular, an agent's human capital at age $a+1$, h_{a+1}^i, depends both on their human capital at age a, h_a^i, when attending school as well as their innate ability, ϵ_h^i, which determines the actual benefit he or she is able to derive from attending school.

2.3 Labor Productivity

While variation in ϵ_h across agents is the only source of within-cohort heterogeneity in our model, there is also heterogeneity across cohorts, based on age, in terms of their labor productivity. We include this life-cycle variation in labor productivity in the model as it matters for the response of schooling and retirement decisions to the changes in the age-specific mortality profile and the resulting change in life expectancy. Specifically, let $\epsilon_l(a)$ denote the labor productivity of an agent of age a. As is standard in the literature, we assume that $\epsilon_l(a)$ rises initially, peaks near the end of an agent's prime working age, and then declines sharply through an agent's traditional retirement years.

Overall, the differences within age-cohorts in terms of innate ability, as well as variation across agents of different ages in terms of labor productivity, and survival probabilities will impact the agents' primary decisions in the model (e.g., how they choose to allocate time between schooling, market work and retirement, and how they allocate resources to savings in the form of capital). We will discuss the specifics of these decisions in the next subsection.

2.4 Agent's Problem

Agents in our model economy differ in four main ways; their age, a, their innate ability, ϵ_h, their current holdings of physical capital, k, (which defines their level of savings), and their current stock of human capital. Agents also differ in terms of their labor productivity, $\epsilon_l(a)$. However, this value can be computed directly once the agent's age is known. Therefore, the state vector for individual i is given by $(a^i, \epsilon_h^i, k^i, h^i)$. In what follows, we will suppress the i superscript for an individual agent for brevity.

All agents in the model economy choose to devote their time exclusively to one of the three activities each period: acquiring human capital as a student, earning income as a worker, or enjoying leisure as a retiree. Along with this discrete choice, all agents also choose how to allocate their resources between current consumption and savings in the form of physical capital, which they rent to the representative firm in exchange for the market clearing rental rate, r. An agent's decision to save/dissave is motivated by their need to accumulate human capital and acquire assets that can be used to finance expenses during their retirement. Agents face an income tax, τ, levied by the government. The revenue generated by this tax is used to fund schools, q, and provide retirement benefits, b, to retired agents who are at least 65 years of age.[7]

When agents allocate their time to schooling, they must delay market work and finance their current consumption through borrowing or dissaving, should they have accumulated savings in the past. However, schooling is beneficial in that it increases the agent's human

[7]We keep b fixed across all agents in a cohort for simplicity. While allowing b to depend on ability or earnings may potentially affect the *level* of labor force participation for both cohorts, it will have a second-order impact on the *change* in the participation rate across cohorts due to changes in longevity, and it is this change that we seek to quantify in the present paper.

capital, as described in equation (4), which raises the efficiency of their labor hours once they become a worker.

Agents who engage in market work supply their time inelastically to the firm in exchange for the market clearing wage rate per unit of human capital, w. At this stage, agents benefit from their accumulation of human capital as it determines their total wage income, which also depends on the exogenous life-cycle profile of labor productivity. This income allows agents to finance their current consumption and pay-off previous loans as well as build up savings for future retirement.

Retired agents receive a utility bonus, η, which accounts for additional leisure time during retirement. If the retired agent is sufficiently old ($a \geq 65$), they will receive a transfer payment from the government, denoted by b. If they have not yet reached age 65, then they must finance their entire consumption out of the savings they accumulated while working until they reach the minimum age to receive the retirement benefit.

It is important to reiterate that we do not put any direct restrictions on the order in which agents must move through these phases. So, agents are free to move directly from being a student to being a retiree, or agents may exit retirement to return to work or schooling in later years. However, as shown later, such behavior is not an equilibrium outcome in the calibrated model. We now turn to the the optimization problems faced by an agent conditional on their current choice of being either a student, a worker, or a retiree.

2.4.1 Dynamic Program of Current Students

The agents who choose to be a student in the current period face following dynamic program:

$$V_a^S(\epsilon_h, k, h) = \max_{c,k'} \left[U(c) + \beta\pi(a) \max\left\{V_{a+1}^S(\epsilon_h, k', h'), V_{a+1}^W(\epsilon_h, k', h'), V_{a+1}^R(\epsilon_h, k', h')\right\}\right]$$

s.t.

$$c + k' \leq k + (1-\tau)rk + AB \tag{5a}$$

$$h' = h + A\epsilon_h(q^\alpha h^{1-\alpha}) \tag{6a}$$

where the superscript, S, on the agent's value function (V) denotes their current choice of being a student and the subscript, a, denotes the current age. Current students choose consumption, c, and next period capital holdings, k', to maximize their current utility plus a continuation value. The continuation value is discounted both by the discount factor, β, which is common to all agents, and the survival probability, $\pi(a)$, which denotes the likelihood an agent of age a will survive to age $a + 1$. The agent's continuation value is the maximum of the agent's next period value functions assuming the agent remained a student, $V^S_{a+1}(\epsilon_h, k', h')$, became a worker, $V^W_{a+1}(\epsilon_h, k', h')$, or became a retiree, $V^R_{a+1}(\epsilon_h, k', h')$. The largest of the three value functions will determine the agent's labor market status next period. The agent also faces two constraints when conducting their optimization. Equation (5a) is the agent's budget constraint and simply states that the agent's current consumption and future holdings of capital cannot exceed their after tax income from renting capital and their receipt of accidental bequests, AB. Equation (6a) is an evolution equation for the agent's human capital, which follows from equation (4) above and determines the gain in human capital the agent will receive as a results of their schooling in the current period.

2.4.2 Dynamic Program of Current Workers

For the agents who choose to be a worker in the current period, their dynamic programming problem is given by:

$$V^W_a(\epsilon_h, k, h) = \max_{c,k'} \left[U(c) + \beta\pi(a) \max\left\{V^S_{a+1}(\epsilon_h, k', h'), V^W_{a+1}(\epsilon_h, k', h'), V^R_{a+1}(\epsilon_h, k', h')\right\}\right]$$

s.t.

$$c + k' \leq k + (1-\tau)[rk + w\epsilon_l(a)h] + AB \tag{5b}$$

$$h' = h \tag{6b}$$

The basic structure of the worker's problem is similar that faced by a current student. The primary difference is the constraints, equations (5b) and (6b). Specifically, the worker's budget constraint, equation (5b), includes an additional term which accounts for the labor income the worker earns by supplying their labor services to the firm. Labor income is the product of three terms; the market clearing (per unit of human capital) wage rate, w, the agent's age-specific labor productivity, and the agent's current level of human capital. Furthermore, equation (6b) indicates that since these agents are not currently in school, their level of human capital remains unchanged across periods.[8]

[8] We could extend the current setup to allow for depreciation of human capital. However, since an agent's efficiency units of labor depend on the product of their human capital, h, and their age-specific labor productivity, $\epsilon_l(a)$, such changes are already partially accounted for. Specifically, agents' efficiency wage declines with age. This is important for agents who are nearing retirement and have experienced large declines in their labor productivity.

2.4.3 Dynamic Program of Current Retirees

If an agent chooses to be a retiree in the current period, then their dynamic programming problem is given by:

$$V_a^R(\epsilon_h, k, h) = \max_{c,k'} \left[U(c) + \eta + \beta\pi(a) \max\left\{V_{a+1}^S(\epsilon_h, k', h'), V_{a+1}^W(\epsilon_h, k', h'), V_{a+1}^R(\epsilon_h, k', h')\right\}\right]$$

s.t.

$$c + k' \leq \left\{ \begin{array}{ll} k + (1-\tau)rk + AB & \text{if } a < 65 \\ k + (1-\tau)rk + AB + b & \text{if } a \geq 65 \end{array} \right\} \tag{5c}$$

$$h' = h \tag{6c}$$

Again, the problem faced by current retirees is similar to that faced by both students and workers. Labor income has again been removed from the retiree's budget constraint, equation (5c), and we see that retired agents with $a \geq 65$ also receive the transfer payment, b, from the government. Equation (6c) specifies that retired agents' human capital stock does not change across periods, reflecting the fact that these agents are not currently in school. The only other change is that retirees also receive a utility benefit, η, which reflects the gain in utility they derive from leisure time not present when working or in school.

2.5 Firm's Problem

The production structure of the economy is standard with a representative neoclassical firm that rents capital and hires labor services from the agents in the economy in order to produce output (Y) using the following production technology:

$$Y = \Omega K^{\phi} N^{1-\phi} \tag{7}$$

where Ω denotes an aggregate productivity term and ϕ is the capital's share of income, while K and N denote the aggregate capital stock and efficiency hours (i.e., hours weighted by human capital) in the economy. The firm is assumed to be perfectly competitive, and as such, takes the market clearing wage rate, w and rental rate, r, as given, when maximizing profits. The firm's problem is given by:

$$\max_{K,N} \Omega K^{\phi} N^{1-\phi} - wN - (r+\delta)K$$

and solving this problem yields the standard result that factor prices equal their marginal product:

$$r = \phi\Omega\left(\frac{K}{N}\right)^{\phi-1} - \delta \tag{8}$$

$$w = (1-\phi)\Omega\left(\frac{K}{N}\right)^{\phi} \tag{9}$$

2.6 The Government

Taxes on agents' labor and rental income are the sources of revenue for the government. Given the tax rate of τ, the government's total tax revenue (TR) is given by:

$$TR = \tau(wN + rK) \tag{10}$$

The government runs a balanced budget and allocates its tax revenue to fund schools, to make transfer payments to retirees age 65 and older, and to finance government consumption. Specifically, a fraction, ξ_1, of the government's tax revenue is used to fund schools, q, which impacts the rate at which students acquire human capital. The fraction, ξ_2, is used to provide a social security-type transfer payment for older retired agents in the economy, b, whereas the remaining tax revenue, $(1-\xi_1-\xi_2)TR$, is allocated to government consumption, G.

In order to receive the social-security-type payment an agent must: (i) be older than 65 years of age and (ii) have chosen to retire. As such, the total resources (B) going to fund the social security payment are given by:

$$B = b\int_{\epsilon_h}\int_k\int_h\sum_{a=65}^{100} norm_a(\epsilon_h,k,h)g_a^R(\epsilon_h,k,h)d\epsilon_h dkdh \tag{11}$$

where $g_a^R(\epsilon_h,k,h)$ is the (binary) decision rule for retirement for an agent of age a, which equals 1 when an agent with ability, ϵ_h, physical capital holdings, k, and human capital level, h, chooses to retire, and 0 otherwise, while $norm_a(\epsilon_h,k,h)$ is a modification of the proportion/normalized mass of agents derived in equation (3) to account for variations across ϵ_h, k, and h.

2.7 Equilibrium

A stationary equilibrium for the model economy consists of value functions, $V_a^S(\epsilon_h, k, h)$, $V_a^W(\epsilon_h, k, h)$, and $V_a^R(\epsilon_h, k, h)$, individual decision rules, $c_a(\epsilon_h, k, h)$, $k_a(\epsilon_h, k, h)$, $g_a^S(\epsilon_h, k, h)$, $g_a^W(\epsilon_h, k, h)$, and $g_a^R(\epsilon_h, k, h)$, a vector of factor prices, (r, w), a vector of government policies, $(\tau, \xi_1, \xi_2, q, b)$, and a vector of aggregates, (K, N, C, AB, B), such that:

1. Given prices, (r, w), the decision rules of each type of agent solve their respective dynamic programs (Bellman equations) and their value functions satisfy the maximized Bellman equations.

2. The factor prices are consistent with the firms FOCs (equations 8 and 9).

3. The vector of aggregates are found by aggregating over individual decisions.

$$K = \int_{\epsilon_h} \int_k \int_h \sum_{a=16}^{100} k_a(\epsilon_h, k, h) * norm_a(\epsilon_h, k, h) d\epsilon_h dk dh$$
$$N = \int_{\epsilon_h} \int_k \int_h \sum_{a=16}^{100} \epsilon_l(a) * norm_a(\epsilon_h, k, h) * g_a^W(\epsilon_h, k, h) d\epsilon_h dk dh$$
$$C = \int_{\epsilon_h} \int_k \int_h \sum_{a=16}^{100} c_a(\epsilon_h, k, h) * norm_a(\epsilon_h, k, h) d\epsilon_h dk dh$$
$$AB = \int_{\epsilon_h} \int_k \int_h \sum_{a=16}^{100} [1 - \pi(a)] * k_a(\epsilon_h, k, h) * norm_a(\epsilon_h, k, h) d\epsilon_h dk dh$$
$$B = b \int_{\epsilon_h} \int_k \int_h \sum_{a=65}^{100} norm_a(\epsilon_h, k, h) * g_a^R(\epsilon_h, k, h) d\epsilon_h dk dh$$

4. The government's revenue and spending constraints are obeyed:

$$TR = \tau[wN + rK]$$
$$q = \xi_1 TR$$
$$B = \xi_2 TR$$
$$G = (1 - \xi_1 - \xi_2) TR$$

5. The Goods Market clears.

3 Calibrating and Solving the Model

We calibrate our model using both aggregate and survey-level data. The next several sections detail our calibration strategy and provide a basic overview of the computational methods used to numerically solve the model.

3.1 Survival Rates

For our measure of age-specific survival rates, $\pi(a)$, we make use of the Human Mortality Database (HMD), which combines information on age-specific cohort size from the U.S. Census (including intercensal population estimates) with death-by-year data (with exact age of the deceased) from the Center for Disease Control (CDC). This data has been used in previous studies (see Bank et al., 2015) and provides a comprehensive estimate of age-specific survival rates. Furthermore, while the Census data is top-coded, the HMD is able to use lagged information from both the Census and CDC to estimate the size of older cohorts and recover consistent survival probabilities for all ages.[9]

Overcoming the top-coding issue present in the Census population estimates is very important. The reason is that most of the gains during our time period of interest were experienced by the individuals in the upper end of the age range and our primary concern is understanding how these changes in mortality impact labor market behavior. While large gains in life-expectancy have been realized for younger age groups, including children and prime working-age individuals, most of these gains were experienced between 1890 and 1930. Restricting attention to the past few decades, we expect that most of the adjustments in survival probabilities have occurred during and near the end of an individual's retirement phase. As such, having detailed age-specific survival probabilities through age 90 (and even higher in some cases) are necessary to properly measure this change.

Figure 3 presents the age-specific survival rates, $\pi(a)$, for two birth cohorts found by averaging HMD data over the 1960s and 1980s.[10] The choice of these cohorts were guided by our interest in explaining labor force participation patterns that begin to shift around the

[9]In many years, all individuals age 80 and older are lumped into a single category, 80+ (with small variation across years in the exact age of the top-code). However, using data from the Census and the CDC in previous years, it is still possible to recover the size of each age cohort. By subtracting the number of 79 year old deaths from the population of 79 year olds in the previous year, we can obtain an estimate of the number of 80 year-olds in the population in the current year. The sizes of the remaining age-cohorts can be recovered in a similar way.

[10]Cohort survival rates move diagonally through a basic mortality table and provide better information for use in a life-cycle model.

year 2000. Specifically, the sustained decline in LFPR that starts in 2000 is also accompanied by a significant decline in the participation rate of young individuals, age 16-19 years old (see Figure 2). Therefore, the 1980s cohorts were chosen to reflect these young agents, as members of the mid-point (1985) birth cohort just reached the age of 16 in 2000, with many cohort members delaying their labor force participation. Similarly, the 1960s cohorts were chosen as the mid-point (1965) birth cohort is in their prime working age by year 2000.

Inspection of Figure 3 makes clear that survival probabilities have increased significantly over this period of time, with the largest changes occurring later in life, as mentioned above. The age-specific survival probabilities are nearly indistinguishable between the two birth cohorts prior to age 50. However, after age 50 the survival probabilities begin to fan out, with very large differences emerging for individuals who reach age 75 to 100. These changes in survival probabilities imply an increase in life expectancy (conditional on surviving to age 16) of 3.27 years—increasing from 71.99 to 75.26.

3.2 Age-Specific Productivity

Agents in our model are also subject to a life-cycle profile in their labor productivity. Specifically, agents' labor productivity is assumed to start low when agents first reach working age (age 16), rise during the prime working years (age 16 to 50), and decline thereafter. This basic life-cycle pattern of age-specific productivity is commonly used throughout the literature. In order to get explicit values for age-specific productivity, we make use of average income by age group reported by the U.S. Census for the year 2000. See Table 1 for a breakdown of average labor income by age group and Figure 5 for a plot of the age-specific labor productivity that is derived from this data.

3.3 Other Model Parameters

With the age-specific survival rates and labor productivity pinned down, we must still assign values to the remaining model parameters. Many of these parameters are standard and can be set following the literature. For example, we set the discount factor, β, to 0.96, which is typical in models with annual frequency. Similarly, the depreciation rate of physical capital, δ, is set to 0.075 and capital's share of income, ϕ, is set to 0.36. The final production parameter, Ω, which determines total factor productivity, is normalized to 1 in the baseline calibration.

As for the government's parameters, we set the tax rate, τ, to 0.3, implying a 30% income tax. This value was chosen so that the government collects tax revenue that is approximately 31% of GDP which is the total (federal, state, and local) revenue raised on average during the period that we are studying (US Treasury, various years; OMB, various years, US Census, various years). This total tax revenue is divided between funding schools, q; providing social security payments, B; and government consumption, G. Both school funding and social security payments are set to approximately 6 percent of GDP, with the remainder of the government's tax revenue being used for government consumption (US Treasury, various years; OMB, various years, US Census, various years). The parameter governing the impact of schools on human capital attainment, α, is set to 0.5 in the baseline case. Rangazas (2002) explores values for this parameter in that range.

Lastly, the agents' innate ability to accumulate human capital, ϵ_h, is approximated by a log-normal distribution. We discretize ϵ_h to 201 nodes that are drawn from a log-normal distribution and spread over 5 standard deviations. We adjust the standard deviation of this process until we recover a realistic wage profile for 45 year olds across education categories. Specifically, we target the relative wage of 45 year olds with less than a high school education, a high school education, some college, and college plus. Even though we only adjust the standard deviation of the process, we are able to fit the data relatively well.[11]

3.4 Computational Methods

We use value function iteration to numerically approximate the invariant/steady state equilibrium of our life-cycle model. This method consists of two repeated steps: (i) backward induction to recover the agents' value functions and optimal decision rules at all ages, and (ii) forward iteration using these value functions and decision rules to recover each agents' life-cycle. The interested reader is directed to Chapter 9 of Heer and Maussner (2009) for additional details.

4 Results

Given the calibration process described above, we solve for two stationary equilibria of our model economy. For the first stationary equilibria we set $\pi(a)$ to the average of the 1960s birth cohort survival probabilities. For the second stationary equilibria we keep all

[11]The relative labor income in the data (model) for less than high school, high school, some college, and college plus is found to be 0.47 (0.78), 0.86 (0.84), 1.04 (1.07), and 1.63 (1.36), respectively. The data comes from the CPS survey (see Flood et al., 2020).

parameters fixed and update $\pi(a)$ to the survival probabilities recovered from the 1980s birth cohorts. By comparing these two stationary equilibria, we are able to isolate the impact of changes in survival probabilities over this period on labor force participation and related decisions of the agents. In particular, are able to determine if this demographic change causes movements in LFPR and other related characteristics of the economy that is qualitatively consistent with that observed in the data. Moreover, we can also determine what proportion of changes observed in the data are explained by improvements in life expectancy later in life. The answers to these two questions will shed light on both the theoretical plausibility and the empirical relevance of the mechanism highlighted in the paper.

4.1 Transmission Mechanism

An increase in life expectancy will alter the labor force participation decision of the agents differently at various ages due to different transmission channels at work in the model. First, the increase in life expectancy results in both a longer work life and a longer retirement, with additional savings from work allowing agents to fund an extended retirement. Second, as they work longer, their retirement, while longer, will be delayed. Third, the increase in work life will increase the return to education causing agents to spend more time in school to accumulate more human capital when young. Thus, the extra years of life will increase not only work life and retirement, as stated above, but also time in school. Moreover, agents will borrow more in the initial periods of their life to finance this extended period of schooling. In short, transitions across all three stages of life will be delayed and each stage will become longer. This will require more borrowing in early periods, followed by more savings later on.

In remaining part of this section, we test this transmission mechanism by matching these predictions with the results of the model. Recall that average life expectancy increases by 3.27 years from 71.99 to 75.26 years across the two cohorts. Consistent with the transmission mechanism's predictions elaborated earlier, the average retirement period increases by 1.83 years from 10.33 years to 12.16 years. Years spent working also rises on average, as predicted. It increases from from 40.87 years to 41.33, implying a modest increase of 0.46 years on average. Finally, as expected, the average years of schooling increases by 0.98 years from 4.79 to 5.77 years across the two cohorts. This increase in schooling years is partially due to more young agents going to school. As a result, the proportion of agents not having any schooling (from year 16 onwards) falls from 28.18 percent to 18.61 percent.

Figure 6 presents the changes described above disaggregated by age. It shows the proportion of agents in each of the three categories, Student, Worker, and Retiree, for both the

1960s and 1980s birth cohorts. Again, the adjustments to these proportions are exactly in line with the model's prediction. As the proportion of students goes up at all school going ages, on average, young agents remain in school longer and delay entry into the workforce following the increase in life expectancy. On the other hand, old agents respond by extending their working years and delaying retirement.

We now consider in more detail the impact of increased life expectancy on the agents' schooling and human capital accumulation decisions. The top panel of Figure 7 shows the years of schooling for the 1960s and 1980s birth cohorts as a function of their type (defined by their ability to acquire human capital, ϵ_h). Most agents that are already going to school increase their years in school by one to two years, the exception being those who are already at the top end in terms of years of schooling. This is how the schooling decision responds to changes in life expectancy on the *intensive margin.* Restricting attention to agents with innate abilities levels, ϵ_h consistent with schooling in the 1960's, we find that the average years of schooling rises from 6.70 to 7.80 years following the increase in life expectancy in the 1980s calibration, implying an increase in schooling of 1.10 years on average.

The schooling decision also responds to changes in the life expectancy on the *extensive margin,* as the increase in life expectancy increases the return to education for many low-ability agents who chose not to attend school under the 1960s calibration. As mentioned earlier, 28.18 percent of agents did not attend school past age 16 under our 1960s calibration and this number falls to 18.61 percent under our 1980s calibration. The average years of schooling for those who did not attend school in the 1960s calibration is 0.69 years for the 1980s calibration. Taking the weighted average between the intensive and extensive margin effects, we find that the average years of schooling increases more modestly by 0.98 years from 4.79 years for 1960s' calibration to 5.77 years for 1980s' calibration, as reported earlier[12].

Figure 8 sheds light on the human capital implications of the schooling decisions. The top panel shows human capital over age for both 1960s cohort (left figure) and 1980s cohort (right figure) for different values (maximum, mean, and minimum) of ability (*i.e.*, ϵ_h). As expected, the graphs for the maximum and minimum ability agents do not change across the cohorts, while there is a sizable change for the mean-ability agents (and for many other agents of non-extreme abilities, not shown in the figure for clarity). The bottom panel presents the same information but now aggregated and averaged over all levels of abilities

[12] This value of 0.98 is recovered by adding the product of the change in years of schooling for school-goers in the 1960s calibration (1.10 years) and the proportion of agents who went to school in the 1960s calibration (0.7182) to the product of the change in years of schooling for the non-school-goers in the 1960s calibration (0.69 years) and the proportion of agents who did not go to school in the 1960s calibration (0.2818).

and shows increased human capital accumulation at all ages.

Next, we compare the impact of increased life expectancy on agents' savings decisions across their lifetime. The top panel of Figure 9 presents the life-cycle profiles of physical capital for agents with select ability levels (i.e., maximum, minimum, and mean), while the bottom panel reports the average for the economy. First, note the substantially different dynamics in physical capital accumulation by age for agents with different ability levels. Those who accumulate human capital by going to school borrow and accumulate debt in the beginning of their life but then rapidly accumulate capital by saving during their working years. For most school-goers, this increased savings is sufficient for them to accumulate more capital than agents who do not go to school. Thus, school-goers typically enter their retirement phase with more savings than their non-school-going counterparts.

We also find that changes in saving behavior across cohorts is consistent with the predictions of the transmission mechanism described above. In the top panel of Figure 9, we see very little change in the saving behavior of those with minimum or maximum ability in their *initial* years as they do not change their schooling decisions in response to change in life expectancy. However, those who respond by increasing their years of schooling, like those with mean ability, see a considerable increase in borrowing (or reduction in saving) followed by increased capital accumulation later on. This increased borrowing to fund additional schooling, coupled with the need for greater savings due to an extended retirement phase, results in a lower trough of average physical capital accumulation in early years of life and a higher peak later on for the 1980s cohort. This pattern can be seen clearly in the second panel of Figure 9. We find that the while the trough in average savings occurs at age 25 for both cohorts, it is deeper for the 1980s cohort by 34.95%, going down from -0.4153 to -0.5729. On the other hand, the peak of average capital by age increases by 9.39% from 1.9835 to 2.1698 and this peak also shifted two years later, moving from age 62 to age 64. Overall, in the economy, average savings/capital increases by 5.97% from 0.6168 to 0.6536.

4.2 Aggregate Effects

Adjustments in aggregate labor force participation are driven by a number of other forces (such as the increased use of social insurance programs, increase in immigration, lower demand for manufacturing jobs, increased female participation in labor force etc.) besides life expectancy, as mentioned earlier in the introduction. Having worked out the implications of the model, we next consider if the magnitude of adjustments in labor force participation that are driven by changes in life expectancy are capable of explaining a significant portion of the changes observed in the data at the two extremes of the working age distribution. This allows us to assess the theoretical relevance and empirical importance of changes in longevity in explaining the declines in the LFPR observed between 2000 and 2019.

The top panel of Table 2 presents the fraction of individuals age 16 to 24 that are enrolled in school, the aggregate labor force participation rate, and fraction of retirees observed in both the new and the old data. The old data corresponds to the enrollment rates in 1985, the labor force participation rate in 2000 and the fraction of individuals who are retired in 2019, while the new data corresponds to the enrollment rates in 2005, the labor force participation rate in 2019 and a projection of the fraction of individuals who are retired in 2040.[13] Inspection of the top panel of Table 2 reveals that the school enrollment for those age 16 to 24 increased from 46.0% to 56.9% (10.9 percentage points), the labor force participation rate fell from 67.1% to 63.0% (4.1 percentage points), and the fraction of retirees increased from 16.9% to 21.6% (4.7 percentage points).

The second panel of Table 2 presents the aggregate results of our model first under two scenarios; (i) The baseline model calibrated and solved using the 1960's survival rates, (ii) the model re-solved using the 1980s' survival rates. We see that our baseline model, calibrated using the 1960s survival rates and corresponding to the old data in the first panel, over-predicts both the labor force participation rate (72.18 percent vs. 67.10 percent) and the fraction retired (19.40 percent vs. 16.90 percent), as well as the percent of individuals age 16 to 24 that are enrolled in school (53.53 vs 46.0 percent). While our baseline model, therefore, does not match the *level* of labor force participation exactly, our focus is on comparing the *changes* resulting from shifting demographics.[14] For this purpose, let's compare the results for scenarios (i) and (ii), i.e., baseline results (for 1960s Cohort) to results with demographic change (1980s Cohort). From the second panel of Table 2, we find that the labor force participation rate falls from 72.18% to 68.95%, a 3.23 percentage point decline compared to 4.1 percentage point decrease observed in the data. The fraction of retirees rises from 19.40% to 21.47%, a 2.07 percentage point increase compared to a 4.7 percentage point increase in

[13]The timing of data was chosen as follows: the old cohort was born in the 1960s, with a mid-point of 1965. As such, an average individual from this cohort is 20 years old in 1985, which is the mid-point of our school-age range of 16 to 24. Furthermore, this individual is 35 (prime-working age) in 2000 and 54 (nearing retirement) in 2019. Similarly our younger cohort is born in the 1980s, with a midpoint of 1985. As such, the average individual from this cohort would be 20 in 2005, 34 in 2019, and 55 in 2040.

[14]Our baseline model over estimates the aggregate labor force participation rate because our model assumes full labor force participation for prime-working age individuals. If the participation rate were lower at 90 percent, then the labor force participation rate in our baseline model would fall to 66 percent, much closer to that is observed in the data. However, given that our focus is on changes in the labor force participation, not its level, we maintain the simplifying assumption of full participation among prime-working age individuals.

the data. Furthermore, the percent of agents age 16 to 24 that are enrolled in school increases from 53.53% to 64.42%, a 10.89 percentage point increase which is virtually identical to the increase observed in the data. Thus, the model replicates the qualitative features of the data and explains a significant portion of the movement in the labor force participation rate, as well as the changes at the two extremes of the working age distribution.

Further support for the mechanism comes from a comparison of the LFPR for various age groups from the model (Table 3) and the data (Figure 2). Figure 2 shows that over time there has been a significant decline in the LFPR of 16-19 year olds, accompanied by a more modest, but still significant, decline for 20-24 years olds and similarly a significant rise in LFPR for those age 55+. Comparison of first two columns of Table 3 shows a similar pattern with a steep decline in the LFPR of the young (age 16 to 24) from 46.47% to 39.72% and a modest rise in the LFPR of the old (age 62+) from 17.99% to 20.17%.

4.3 Testing the Mechanism - A Counterfactual Analysis

The outcomes highlighted in the previous subsection capture both the compositional change that occurs within the age distribution as a result of the shifting demographics (e.g., the aging of the population) and the endogenous response of agents who alter their behavior as demographics shift. In order to better understand the important role played by the endogenous mechanisms of our model, we consider a counterfactual analysis where agents' decision rules are held fixed as the agents' survival probabilities are adjusted. That is, we allow only the exogenous demographic change to operate in the model in the counterfactual experiment and we no longer allow agents to alter their behavior in response to this demographic change. The results of this counterfactual analysis are summarized in scenario (iii) of Table 2, which shows that the labor force participation rate falls from 72.18% to 69.47%. This suggests that demographic change alone accounts for a 2.71 percentage points of the explained 3.23 percentage point decline in the labor force participation rate.

On the surface, this seems to suggest that most of the adjustment we observe is accounted for by the compositional change that follows from the increase in life expectancy. However, we also see from Table 2 that under this counterfactual scenario the fraction of enrolled students remains unchanged at 53.53% while the fraction of retirees increases from 19.40% to 22.57%. The fact that school enrollment remains constant while the fraction of retirees increases raises concerns that the reduction in the LRPR is now occurring for the wrong reasons vis-a-vis the patterns in the disaggregated data as depicted in Figure 2. Table 3 corroborates this concern. As suspected, we find that when the survival rates are changed but the decision rules are held fixed, young labor force participation counterfactually remains almost fixed at 46.47%, while old labor force participation counterfactually falls from 17.99% to 16.08%. This indeed contradicts the empirical observations presented in Figure 2 which show a *strong decline* for the young and a *clear rise* for the old.

The foregoing analysis demonstrates the inability of the compositional effect of the demographic change by itself to accurately capture the mechanism underlying the changes in the labor market outcomes. On the other hand, endogenous choices from our model, including the agents' human capital and retirement decisions, turn out to be critical to address the aggregate data as well as its disaggregated components, particularly the two extreme ends of the working age distribution. Simply put, compositional effects generate a decline in the aggregate LFPR solely by a *reducing* the LFPR of the old whereas in the data the decline is accompanied by an *increase* in the LFPR of the old which is offset by a much larger decline in the LFPR of the young. The endogenous mechanisms of our model are needed to reproduce this disaggregated pattern. In fact, the counterfactual analysis not only demonstrates the inability of the compositional effects to explain observed labor force participation trends but also reinforces the importance of the transmission mechanism highlighted in the paper because the proposed mechanism has to first reverse the underlying trends moving in the wrong direction due to the compositional effects, before moving them in the right direction.

5 Conclusion

The U.S. labor force participation rate (LFPR) experienced a notable declining trend since the late 1990s (until the pandemic). Examining the data of various age groups, the two major features within this period relate to the two extremes of the working age distribution. They are the decline in the LFPR among the relatively young, those age 16 to 24, and the increase in the LFPR among older individuals, those age 55 and above. Using a life cycle model, we find that individual decisions about schooling and retirement that take into account the recent trends in mortality can explain a large share of both the aggregate and age-specific patterns observed in the labor force participation rate. In particular our model predicts a reduction in the economy-wide LFPR by approximately 3.23 percentage points, which is about 80% of the observed decline in the LFPR in the U.S. economy over the past two decades. Essentially, a longer life expectancy incentivizes the young to acquire more human capital and to earn and save more for a longer expected lifetime. For older individuals, having a longer expected lifetime provides incentives to stay in the workforce longer in order to save for a more lengthy retirement.

Our results are roughly consistent with the empirical findings of Aronson et al. (2014) and Kruger (2017) which find that the "aging of the population" due to people living longer explains up to two-thirds of the reduction in the overall LFPR. We conclude that demographic changes may be the primary driving factor of the LFPR decline, although alternative factors like the increased used of social insurance programs or the increased availability of entertainment options at home have been discussed more prominently in the press than demographic factors. An important caveat to our results is that we do not include the pandemic period which has been a major shock to both life expectancy and labor force participation. As more time passes and additional data becomes available, research will be needed to determine if these recent events influence long-run labor market patterns.

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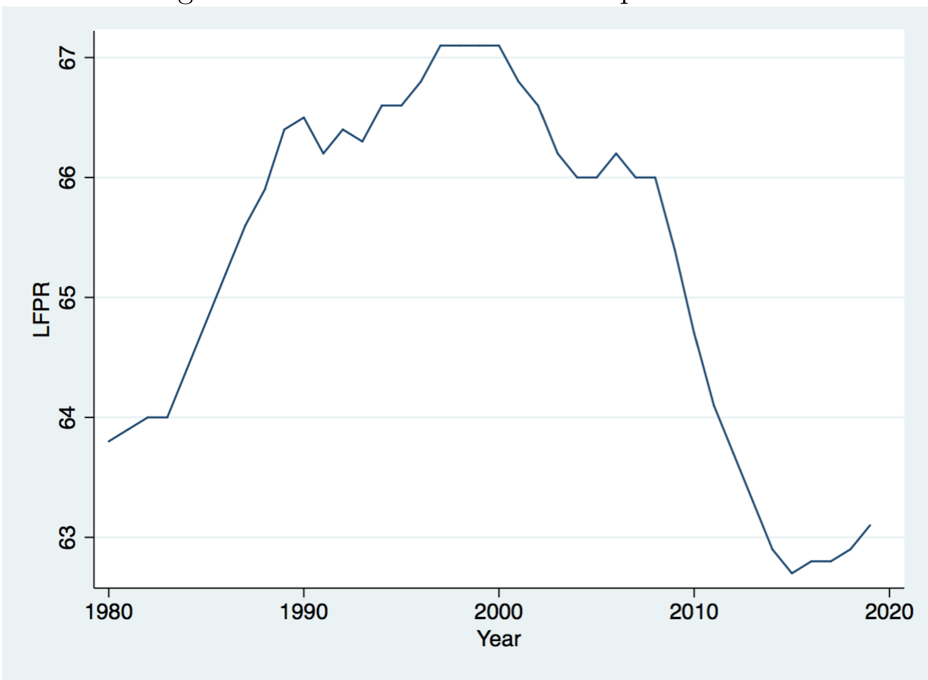
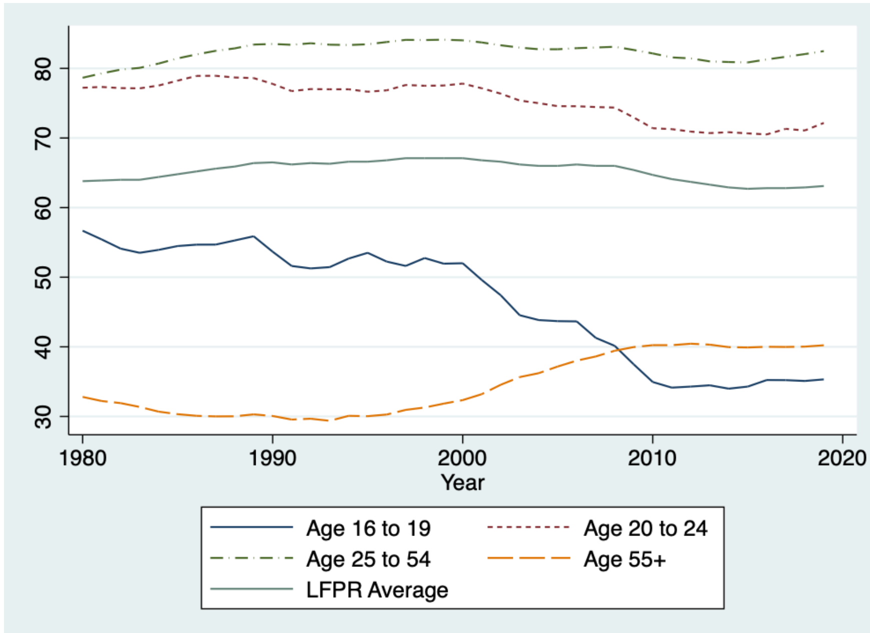
Figure 1: U.S. Labor Force Participation Rate



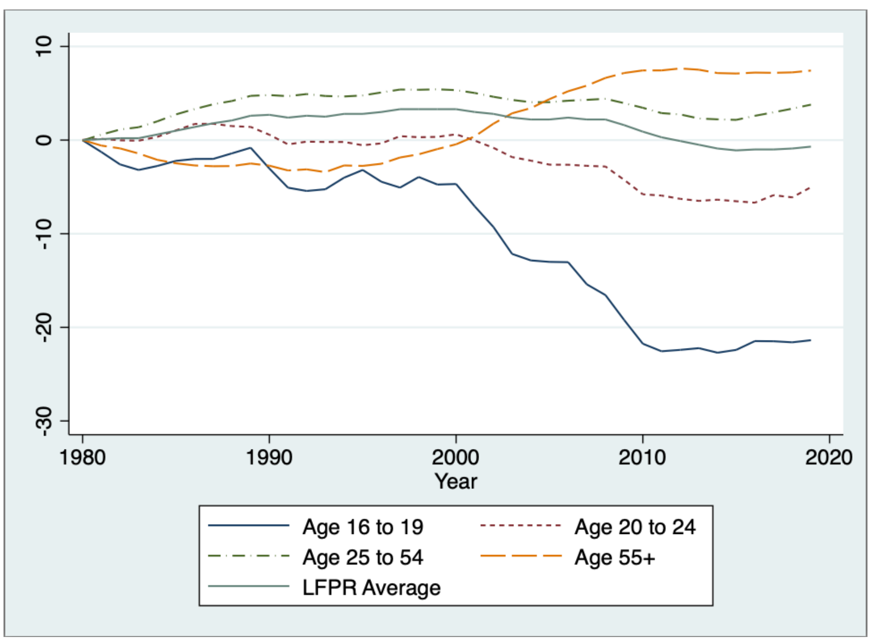
Data Source: Current Population Survey (U.S. Department of Commerce, various years)

Figure 2: LFPR by Age Group

(a) Levels



(b) Normalized Initial Obs. to 0



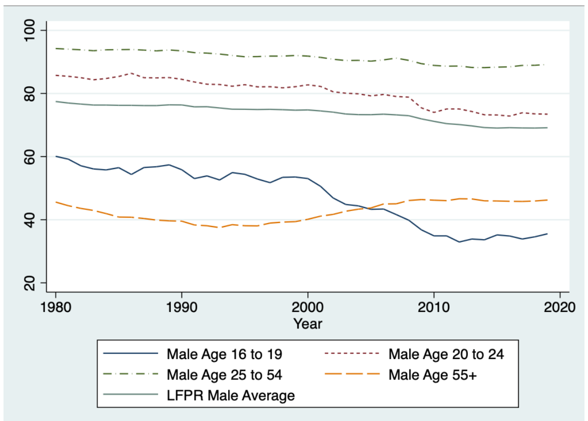
Data Source: Current Population Survey (U.S. Department of Commerce, various years)

Figure 3: Age-Specific Survival Rates: 1955 and 1985 Cohorts

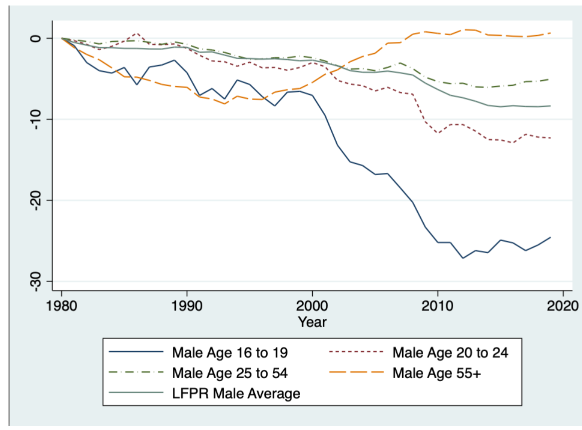
Data Source: Human Mortality Database, various years

Figure 4: LFPR by Age Group and Gender

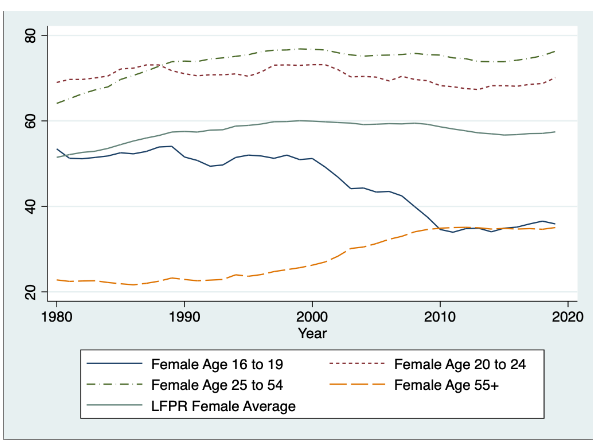
(a) Males - Levels



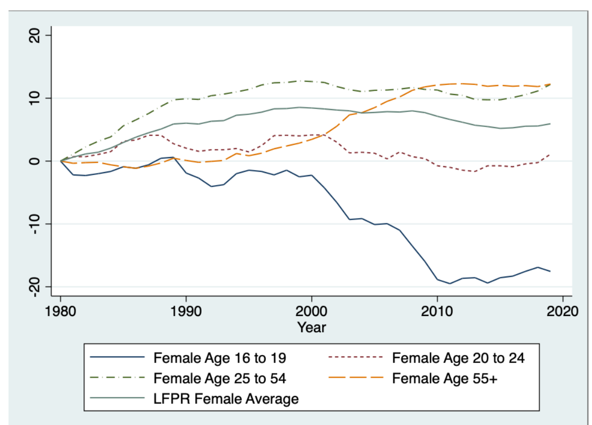
(b) Males - Normalize Initial Obs. to 0



(c) Females - Levels



(d) Females - Normalize Initial Obs. to 0



Data Source: Current Population Survey (U.S. Department of Commerce, various years)

Figure 5: Age-Specific Productivity

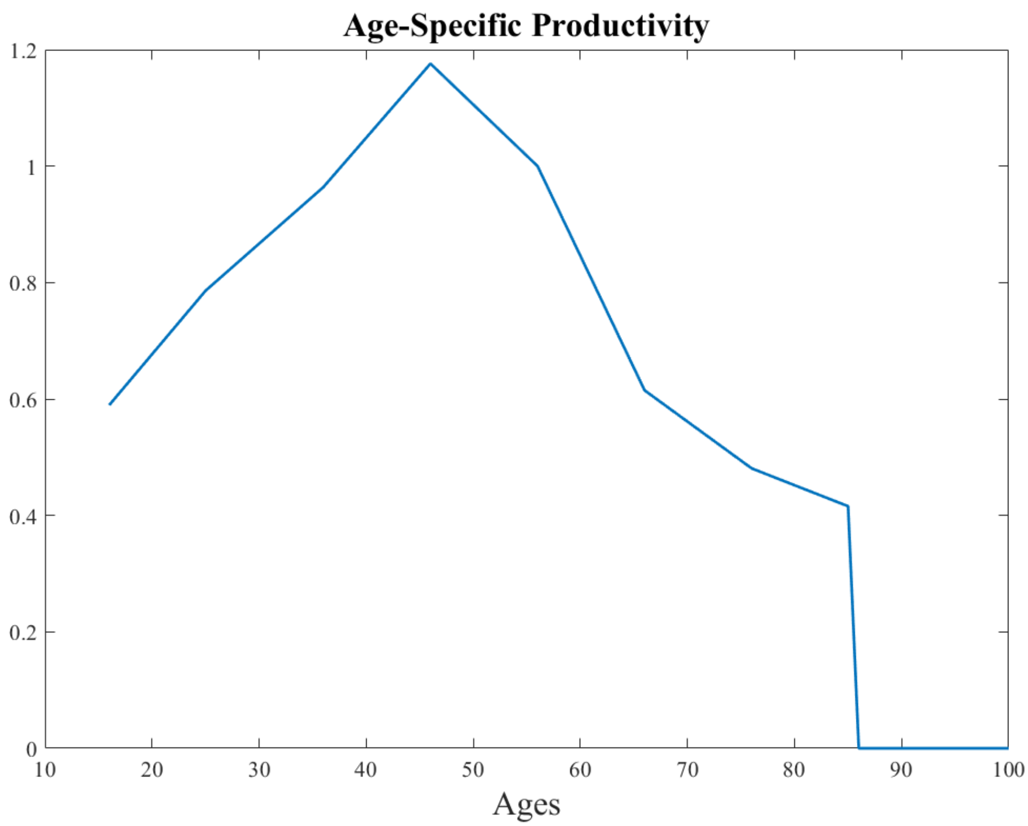


Figure 6: Impact of Increased Life Expectancy on Labor Market Status

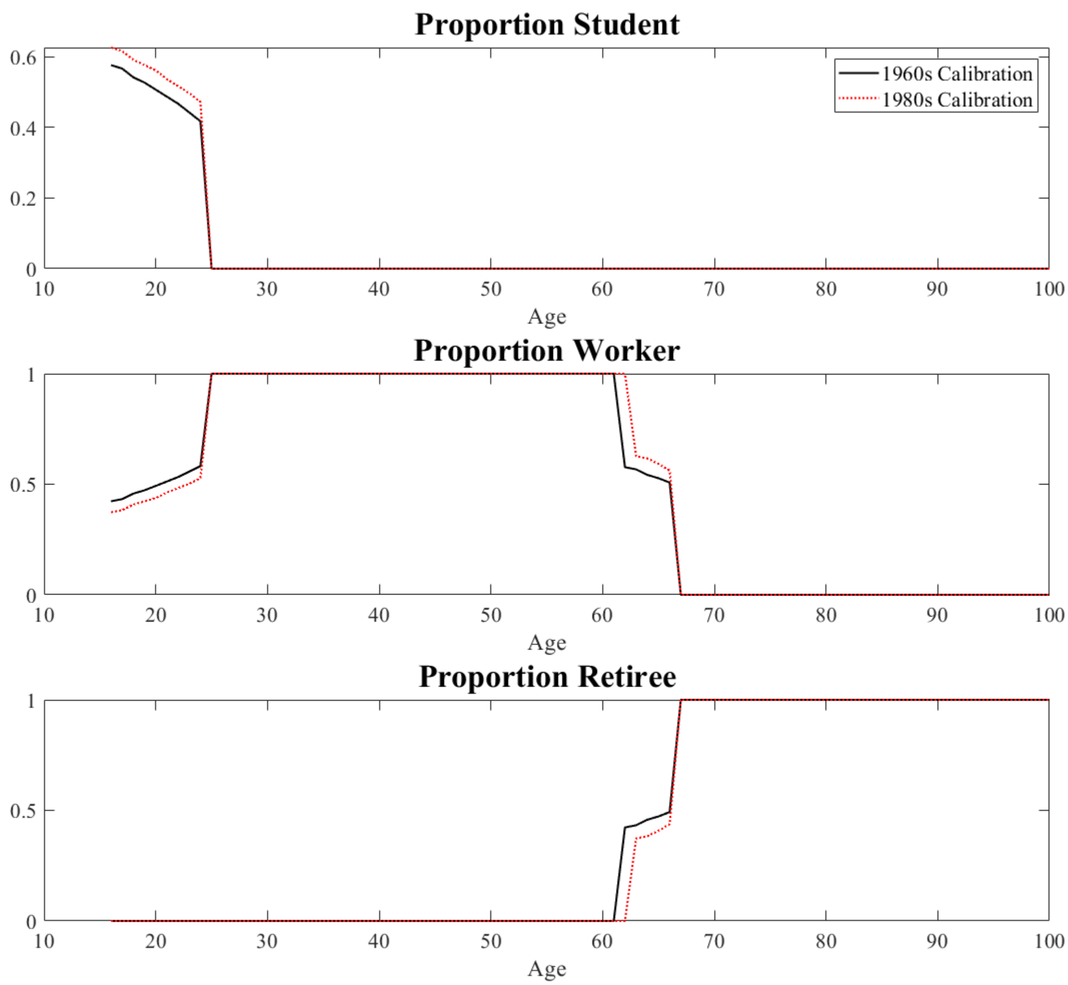


Figure 7: Impact of Increased Life Expectancy on Schooling Decision

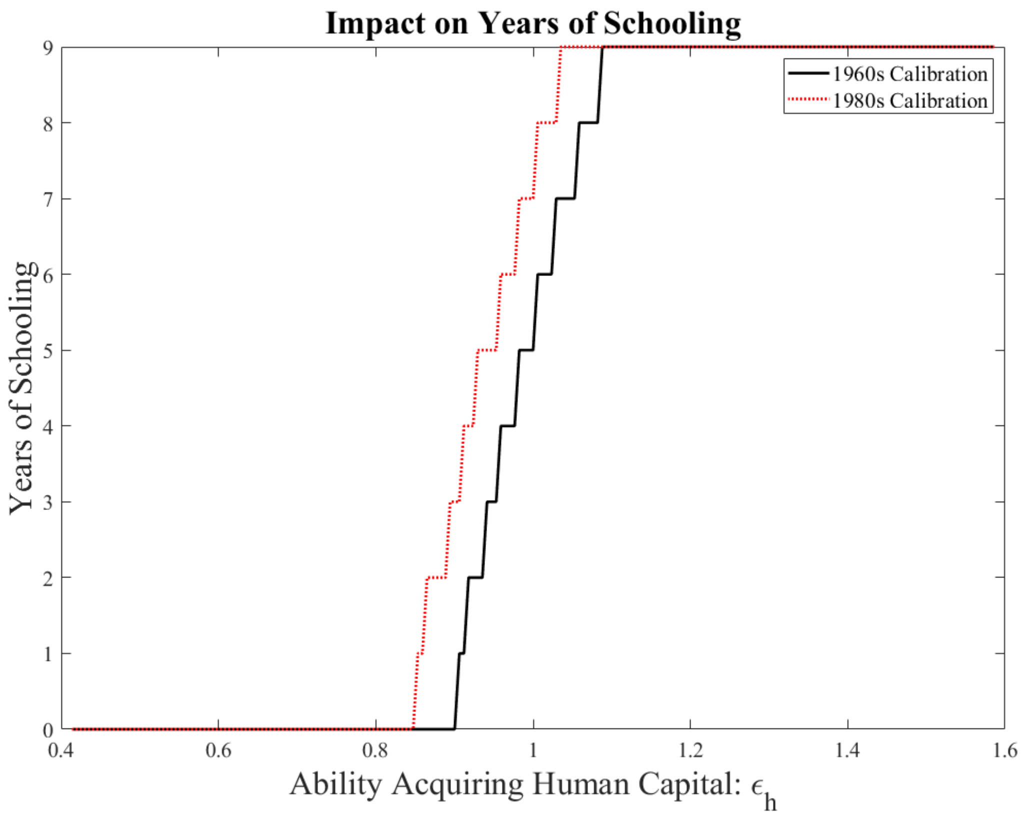


Figure 8: Impact of Increased Life Expectancy on Schooling and Human Capital Accumulation

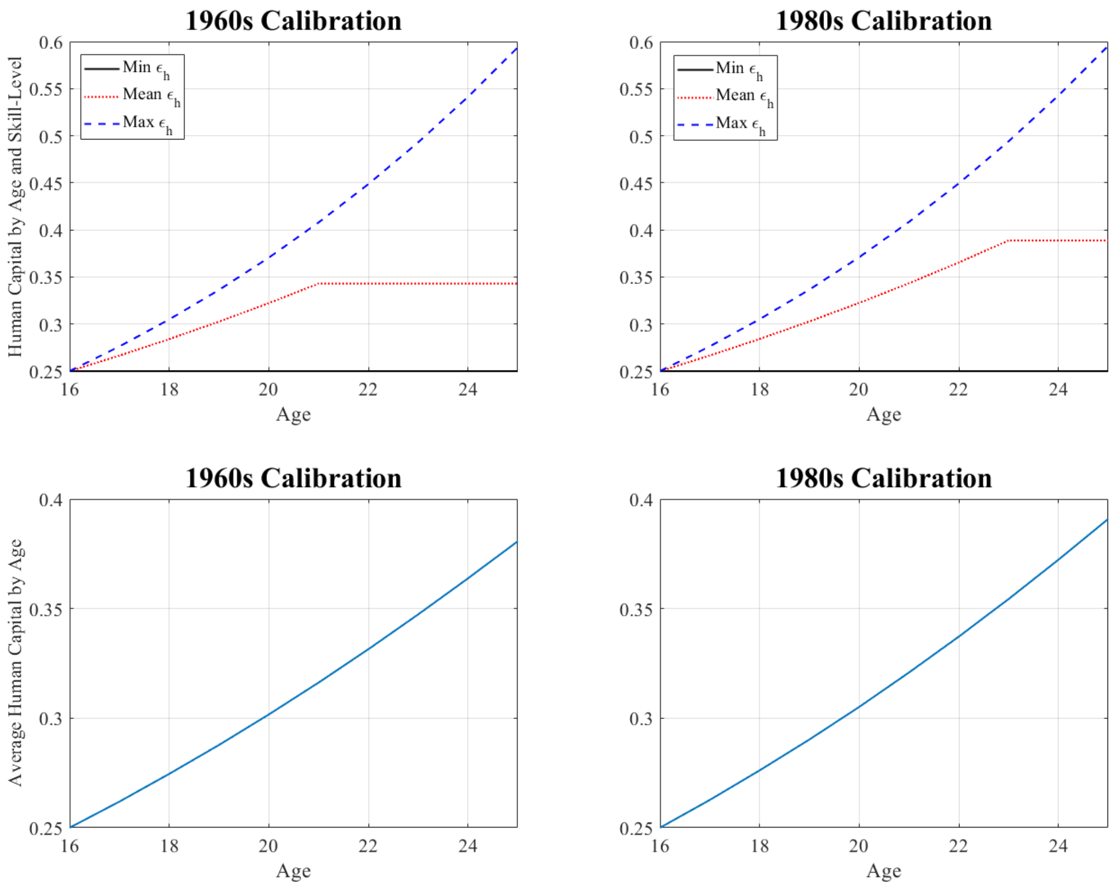


Figure 9: Impact of Increased Life Expectancy on Savings and Physical Capital accumulation

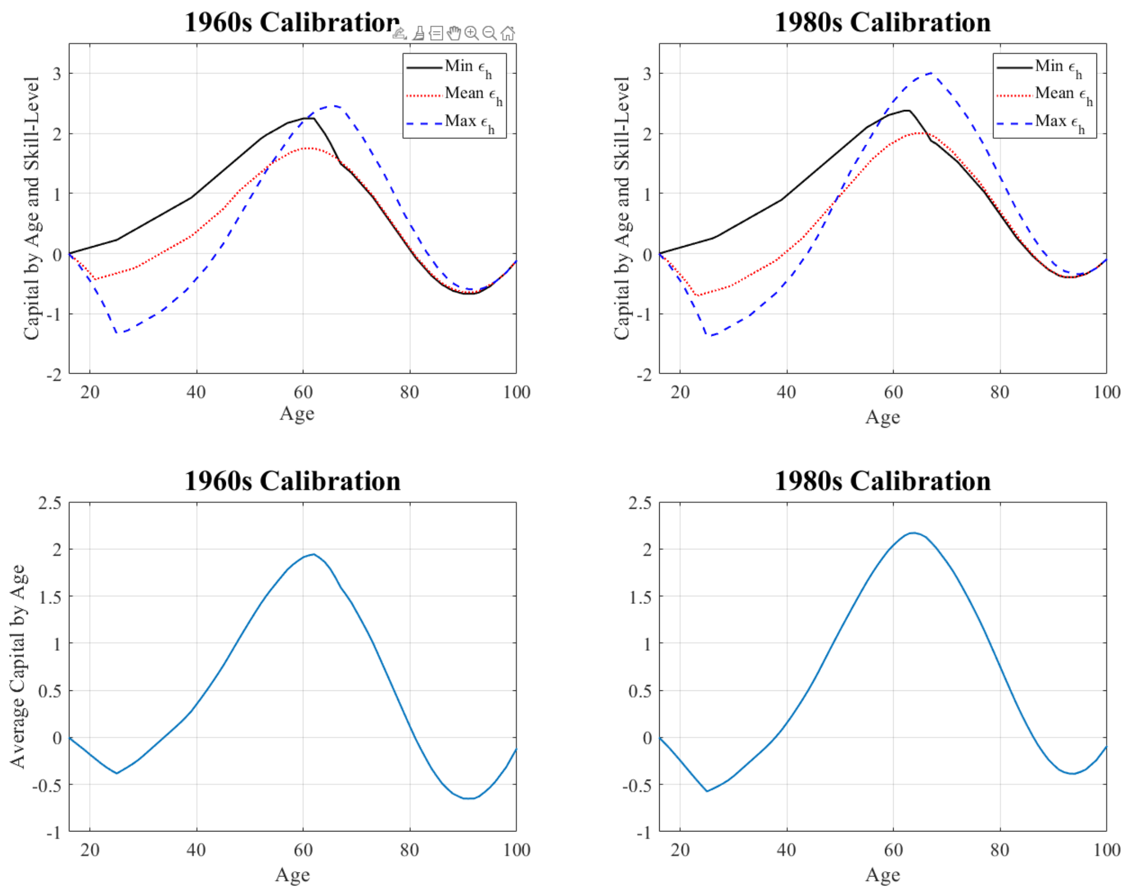


Table 1: Average Income by Age

Average Income[a]	Age Range
$14,255	15 to 24 years old
$17,481	25 to 34 years old
$21,328	35 to 44 years old
$18,136	45 to 54 years old
$11,150	55 to 65 years old
$8,719	65 to 74 years old
$7,410	75 years and over

[a] Source: U.S. Census Bureau (2001). "Money Income in the United States: 2000," Report Number P60-213.

Table 2: Aggregate Impact of Changing Life Expectancy

	Percent Age 16-24 Enrolled in School	Labor Force Participation Rate	Fraction Retirees
Results from Data[a]			
Old Data:	46.0	67.1	16.9
New Data:	56.9	63.0	21.6
Change: New - Old	10.9	-4.1	4.7
Results from Model[b]			
(i) 1960s Cohort: Baseline	53.53	72.18	19.40
(ii) 1980s Cohort: Demographic Change	64.42	68.95	21.47
Change: (ii) - (i)	10.89	-3.23	2.07
(iii) 1980s Cohort: 1960s' Decision Rules	53.53	69.47	22.57

[a] "Old Data" refers to the percent of those age 16-24 enrolled in school in 1985, the labor force participation rate from 2000 and the fraction of retirees from 2019. "New Data" refers to the percent of those age 16-24 enrolled in school in 2005, the labor force participation rate from 2019 and the projected fraction of retirees from 2040.
Sources: de Brey et. al. (2021), Current Population Survey (U.S. Department of Commerce, various years), U.S Department of Health and Human Services (2021).

[b] Our baseline model results come from the steady state solution to our model, calibrated with survival probabilities from the 1960s. The "Exogenous Demographic Change" results hold fixed the decision rules recovered from our baseline model, but use updated survival probabilities from the 1980's. The "Including Endogenous Choice" results resolve the model under the updated survival probabilities, and as such allow both choices and demographics to evolve.

Table 3: Labor Force Participation by Age from Model

	1960s Cohort: Baseline	1980s Cohort: Demographic Change	1980s Cohort: 1960s' Decision Rules
16 - 24	46.47	35.58	46.47
62+	17.99	20.17	16.08