Life Cycle Portfolio Choice with Human Capital and Social Security*

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Abstract

Target date funds – which initially invest a large share of retirement savings in stocks and shift gradually towards bonds over the life cycle – are designed to provide a "one stop shop" for retirement investing. The rationale for this pattern is that human capital, which is highest at the start of a worker's career, is "bond-like." Thus, utility is maximized when financial wealth is initially invested primarily in stocks, with the investment mix shifting towards bonds as the present value of future labor income declines. We revisit this logic in a dynamic model in which shocks to labor income are correlated with the stock market, and in which Social Security replaces a higher share of income for lower-income individuals. In line with empirical evidence, lower-income individuals in the model experience a higher degree of correlation between labor earnings growth and stock returns. We find that utility-maximizing retirement portfolios can vary greatly across individuals, deviating substantially from the pattern of a target date fund for lower-income individuals.

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I. Introduction

In recent decades, academic research has increasingly drawn attention to the fact that individuals do not always make rational choices about saving over the life cycle. For example, present biased preferences may lead to undersaving for retirement (Laibson 1998; O'Donoghue and Rabin 1999); inertia may cause individuals to stick with the default options (including participation, non-participation, and investment mix) offered in a defined contribution (DC) plan (Madrian and Shea 2001); and a lack of financial literacy may hinder the ability to prepare for retirement (Lusardi 2009). In response to these concerns, policy makers have taken steps to encourage employers to automatically enroll employees in DC plans like 401(k)s, requiring an active decision to opt out. At the federal level, starting in 2025, the Secure 2.0 Act will require new DC plans to automatically enroll employees. In addition, many state governments have implemented – or are in the process of implementing – "auto-IRA" policies requiring employers that do not offer a retirement savings plan to make automatic contributions to state-facilitated Individual Retirement Accounts (IRAs) on their employees' behalf. A large body of research, starting with Madrian and Shea (2001), has shown that automatic enrollment appears to substantially boost participation rates, although the impact on overall saving is less clear (e.g., Choukhmane 2024).

Historically, individuals with DC plans have tended to have higher-than-average incomes (Bureau of Labor Statistics 2023). However, as automatic enrollment becomes more prevalent, individuals with lower incomes are increasingly likely to be included in DC plans or state auto-IRAs. In light of this development, it is important for employers and policy makers to understand whether the default options offered – including the investment options – serve the growing

number of participants. Many DC plans and state auto-IRA programs use target date funds (TDFs) as the default investment for contributions.[1] A typical TDF invests most retirement wealth (roughly 90 percent) in stocks at the start of a worker's career. Over time, the TDF is rebalanced to shift towards corporate and government bonds. Over the long term, bonds tend to earn lower returns than stocks; however, they are less risky and provide better protection against economic downturns. TDFs exist for a multitude of alternative target retirement dates, and the trajectory of a TDF's investment allocation over time is referred to as a glidepath. In this paper, we examine whether the typical TDF glidepath is consistent with a life cycle model under a range of assumptions about income level, Social Security, and the relationship between labor earnings and the stock market. We show that the typical TDF glidepath does not maximize utility for many workers, especially those with lower incomes.

TDFs are often marketed as a "one-stop shop" for retirement investing. As TDFs typically invest in stock and bond mutual funds, their fees reflect both the fees of the underlying mutual funds and the expenses involved in managing the TDF. Thus, investing in a TDF is usually more costly than buying the underlying mutual funds directly (Elton et al. 2017). However, an important feature of TDFs is that they do not require the investor to make any active choices. Thus, TDFs may be appealing when individuals suffer from inertia, cognitive constraints, financial illiteracy, or other obstacles to manually rebalancing their retirement portfolio. According to Investment Company Institute (2021), TDFs have grown in popularity over the past

[1] Investment Company Institute (2021); see also https://www.oregonsaves.com/savers/investments (OregonSaves), https://saver.calsavers.com/home/savers/investments.html (CalSavers), https://saver.ilsecurechoice.com/home/savers/investments.html (Illinois Secure Choice), https://myctsavings.com/savers/investments (MyCTSavings), and https://marylandsaves.com/savers/investments (Maryland Saves).

decade. By the end of 2018, 79 percent of 401(k) plans offered TDFs as an option, and TDFs accounted for around 27 percent of assets held in 401(k)s.

The pattern followed by the typical TDF glidepath emerges from the literature on optimal portfolio choice over the life cycle (a classic paper is Bodie, Merton, and Samuelson 1992; see Gomes 2020 for a survey). In this literature, human capital is generally assumed to be more "bond-like" than "stock-like" – i.e., any shocks to labor income are relatively uncorrelated with the stock market. Thus, it is optimal for an early-career worker to invest financial wealth primarily in stocks. As the present value of labor income declines over a worker's career, however, the optimal mix of financial assets shifts towards bonds.

On the other hand, some analyses of optimal portfolio choice have considered the relationship between earnings and stock returns. For example, Campbell et al. (2001) note that labor income is correlated with the one-year lag of stock returns. The authors incorporate this assumption into their model, which also features a Social Security system in which workers contribute a constant fraction of their income while working and receive an actuarially fair annuity upon retirement. They still derive a glidepath in which a declining share of financial assets are invested in stocks over an individual's working years.[2] Li and Webb (2024), Smetters and Chen (2010), and Maurer et al. (2010) show that optimal investment allocations generally depend on the correlation between labor income (which they also allow to impact Social Security benefits) and stock returns. Maurer et al. (2010) establish that, for workers with risky labor income, the optimal equity share may increase over the life cycle (in contrast to a

[2] Bodie, Merton, and Samuelson (1992) also present a version of their model in which labor earnings are risky and potentially correlated with stock returns. In this scenario, optimal investment in the risky asset is lower.

standard TDF). Li and Webb (2024) further estimate welfare losses from standard TDFs and more personalized investment strategies that utilize information available to an employer (e.g., earnings level, savings rate, and retirement wealth). Smetters and Chen (2010) build a realistic life cycle model that allows earnings to be correlated with stock returns. They argue that such a model can rationalize observed household portfolio choices, which tend not to follow the standard TDF glidepath.

We build on this work by exploring why the logic behind the standard TDF glidepath may not apply to individuals with lower incomes. First, as previous authors have noted, labor earnings are correlated with stock returns over periods of a few years. During economic downturns, both stock returns and labor earnings fall – the latter in part because of an increase in unemployment. This correlation can vary across the population, leading to different optimal investment strategies. In his financial planning book entitled *Are You a Stock or a Bond? Identify Your Own Human Capital for a Secure Financial Future*, Milevsky (2012) argues that individuals should consider the unique properties of their human capital risk – and specifically the correlation between their human capital and market returns – when making portfolio choice decisions. We use data from the Current Population Survey to demonstrate empirically that the correlation between labor earnings and stock market performance is stronger for individuals with lower incomes, even after accounting for safety net programs like unemployment insurance, disability insurance, and means-tested transfers.

Second, we carefully model the connection between Social Security income and lifetime wages and show how this relationship impacts optimal life cycle portfolios. Compared to Smetters and Chen (2010), our stylized model that allows us to highlight, in a simple and

transparent way, exactly which assumptions are driving our conclusions about the optimal glidepath. This approach additionally allows us to derive key insights about the role that specific aspects of the Social Security benefit formula play in optimal portfolio choice over the life cycle. In our model, Social Security wealth, which is based on the history of labor earnings through the Social Security benefit formula, becomes safer over the life cycle, as uncertainty around future labor earnings gets resolved. In addition, Social Security income represents a much larger share of retirement income for lower-income individuals than for higher-income individuals. Our simulations suggest that, on average (across the path-dependent trajectories of investment shares), optimal glidepaths for higher-income workers qualitatively resemble those used by TDFs, with a declining share of the portfolio invested in stocks over the life cycle. However, the optimal share of stocks for lower-income individuals is much lower at most ages. Moreover, the optimal stock share increases over the life cycle, especially in the period immediately before retirement, as uncertainty about Social Security income resolves.

II. Human Capital and the Stock Market

In this section, we examine the riskiness of the non-investible components of wealth, namely human capital and Social Security wealth (which is driven by human capital through the Social Security benefit formula). We do this by estimating the relationship between individual earnings, the economy-wide average wage index, and stock market returns.

a. Data

Our stock market index derives from the nominal S&P 500 total return index reported by Damodaran (2025), who provides the value of $100 invested at the beginning of 1928 in all

years from 1928-2024. The value of the initial investment reflects both stock price appreciation and dividends. We convert this index to 2024 dollars using the Consumer Price Index for All Urban Consumers (CPI-U). Economy-wide average wages are represented by the Security Administration's average wage index (AWI), also expressed in 2024 dollars.

For individual wages, we use data from the Current Population Survey Annual Social and Economic Supplement (CPS-ASEC), a nationally representative repeated cross-sectional survey, to construct earnings profiles for a set of stylized workers who differ in their sex and education levels.[3] For each adult, the CPS-ASEC includes data on total labor earnings, hours and weeks worked, and transfer payments received during the previous calendar year. Data on all these three variables are available for calendar years 1987-2023 (corresponding to survey years 1988-2024). We convert income measures to 2024 dollars using the CPI-U. We compute a measure of labor earnings plus transfer payments by adding labor earnings and income from unemployment benefits, Social Security disability benefits, other disability benefits, supplemental security income, and public assistance programs. As these transfer payments are received precisely when labor income falls or the individual experiences an unemployment spell, they may offset the correlation between labor income and the stock market. A worker's earnings may change because their hourly wage changes, or because the number of hours they work changes. To explore the role of these factors in determining earnings, we compute a measure of total hours worked during the year by multiplying the number of weeks each respondent reports working during the year by their reported usual weekly hours. The CPS-ASEC also includes demographic and educational information for each respondent. We use this

[3] We obtain our data from the harmonized IPUMS CPS (Flood et al. 2025).

information to classify individuals into two educational groups: individuals who have a high school diploma or less and individuals who have some college education.

To explore correlations between earnings and stock returns, we consider male and female workers, with and without college education, who are born between 1944 and 1990. For each sex, education group, and birth year, we construct stylized age-earnings and age-hours profiles between the ages of 25 and 50 by averaging CPS-ASEC earnings (plus transfers) within each sex, education, birth-year, and age cell. For example, for college-educated men born in 1960, we compute earnings (plus transfers) and hours at age 30 by averaging earnings (plus transfers) and hours across 30-year-old men with some college education in 1990. Because earnings in the CPS-ASEC are top coded, and because top coding varies from year to year, we compute median earnings (plus transfers) in each cell. For hours, however, we calculate the mean in each cell. We apply CPS-ASEC weights to compute the means and medians in each cell.

In all, we construct profiles for 47 birth cohorts in each sex and education group. Our stylized 1944-born workers are only observed between ages 43 (in 1987, the first year of data available) and 50 (in 1994), and our stylized 1990-born workers are only observed between ages 25 (in 2015) and 33 (in 2023). However, those born between 1962 and 1973 are observed at all ages between 25 and 50. Since, because our model is based on three-year periods, we keep only observations for ages 25, 28, 31, 34, 37, 40, 43, 46, and 49. In the remainder of this section, we refer to these ages as model ages $a = 1, 2, \ldots, 9$. That restriction leaves us with 309 observations in each sex and education group (high-school-educated men, college-educated men, high-school-educated women, and college-educated women). Figures 1 and 2, respectively, show stylized earnings (with transfers) for selected birth cohorts of men and

women in the two education groups. Earnings profiles for less educated individuals are generally lower and flatter than for more educated individuals. Men with some college education, in particular, experience significant earnings growth over their careers.

b. Individual Earnings and Stock Returns

For each sex and education group, let y_{ca} represent the earnings (plus transfers) of individuals in birth cohort c at model age a. We calculate the growth in the natural log of earnings over this (three-year) period as $\Delta\log(\mathrm{y}_{ca}) = \log(y_{ca}) - \log(y_{c,a-1})$. Letting S_{ca} denote the S&P 500 total return index when birth cohort c is model age a, we calculate the growth in the natural log of the stock index over this period as $\Delta\log(S_{ca}) = \log(S_{ca}) - \log(S_{c,a-1})$. We then estimate the following regression separately for each sex and education group:

$$\Delta\log(y_{ca}) = \beta_1\Delta\log(S_{ca}) + \beta_2\Delta\log(S_{c,a-1}) + \delta_a + \mu_c + \epsilon_{ca} \quad (1)$$

That is, we regress log growth in real earnings on log growth in the stock index during the most recent period and the previous period. (Note that $\Delta\log(S_{c,a-1}) = \log(S_{c,a-1}) - \log(S_{c,a-2})$.) We also include age-specific intercepts (δ_a) and cohort-specific intercepts (μ_c). Standard errors are clustered by birth cohort. The coefficients β_1 and β_2 tell us the degree of correlation between a worker's earnings (the return on their human capital) and the stock market. These coefficients represent the correlation that remains after controlling for a baseline age-earnings profile and any constant shifts in this age-earnings profile across cohorts. In other words, they tell us the extent to which an above-average stock market return predicts wage growth that is above what would be expected based on age and cohort alone. Because the dependent variable is the growth of log earnings over the past period, the regressions do not include the first

observation for each education-sex group. Thus, each regression includes 309 – 47 = 262 observations. The first two columns of Table 1 show the results from this regression for the high-school and college groups of men; corresponding results for women are shown in the first two columns of Table 2.

c. The Role of AWI and Hours Worked

High-school and college-educated workers also experience different earnings growth relative to AWI. To explore this relationship, we begin by estimating

$$\Delta \log(y_{ca}) = \zeta \Delta \log(\mathrm{AWI_{ca}}) + \lambda_a + \tau_c + \epsilon_{ca} \quad (2)$$

Here $\Delta\log(\mathrm{AWI_{ca}}) = \log(AWI_{ca}) - \log(AWI_{c,a-1})$, and this change represents the growth in the natural log of the AWI over the three-year period. Next, we examine how individual wage growth relative to the AWI is correlated with stock returns:

$$\Delta \log(y_{ca}) - \Delta\log(\mathrm{AWI_{ca}}) = \gamma_1 \Delta \log(S_{ca}) + \gamma_2 \Delta\log(S_{c,a-1}) + \theta_a + \phi_c + \epsilon_{ca} \quad (3)$$

Estimates of ζ are shown in the third and fourth columns of Tables 1 and 2. Estimates of γ_1 and γ_2 are shown in the fifth and sixth columns of Tables 1 and 2, for the high-school and college groups of men and women.

Overall, the results suggest that wage growth is positively correlated with stock returns over the past three years. It is also positively correlated with the lag of the three-year growth rate of the stock index. Generally, the correlation between stock market performance and earnings growth is greater for less educated individuals. Much of this difference can be accounted for by hours worked (including unemployment spells). To illustrate this relationship, the final two columns of Tables 1 and 2 replace the dependent variable in equation (1) with the three-year growth in the log of hours worked. The results suggest that hours worked are

strongly correlated with stock returns, particularly for less educated people. That is, stock market declines are associated with economic downturns, which in turn result in employment and hours reductions that are concentrated among less educated workers.

III. Model

To examine the implications of these relationships for portfolio choice, we consider a 14-period life cycle model in which each period corresponds to three calendar years. A stylized worker in the model begins working at age 25 and retires at age 67. There is a riskless and a risky asset (the latter follows a binomial model). An individual receives periodic income (labor earnings or a Social Security benefit) which may be consumed or invested. However, anticipated future income cannot be used as collateral on loans to finance current spending. We also do not allow the individual to sell stocks short or to borrow to purchase stocks. Subject to these constraints, the individual chooses strategies that maximize expected utility. In this context, our goal is to understand how the nature of an individual's income – both its level and riskiness – influences spending and investment.

a. Asset Returns and Utility

Savings can be allocated across two assets: a risk-free asset ("bonds") and a risky asset ("stocks"). In reality, bonds are not risk free; however, as discussed above, they are less risky than stocks. Thus, our model captures the relative riskiness of the two asset classes used in TDFs. The risky asset has a discrete binomial distribution (Shreve, 2004). At time $t = 0$, the risky asset's value is S_0, and one period later at $t = 1$, it either increases to $S_u = R_u S_0$ (an "up" market) or decreases to $S_d = R_d S_0$ (a "down" market). We assume that "up" and "down"

markets occur with probabilities π_u and $\pi_d = (1 - \pi_u)$ respectively. Over the same interval, the risk-free asset's total return is R_f. All returns are total returns and satisfy the no-arbitrage conditions: $0 < R_d < R_f < R_u$. Upon retirement, all wealth is fully annuitized, and there is no further uncertainty.

This setup gives rise to a binomial tree, with each node corresponding to the endpoint of one of a path of length 0, 1, ..., 14. At each node, the individual derives current utility from their chosen consumption level. We assume a constant relative risk aversion utility function $\frac{c^{1-\gamma}}{1-\gamma}$, where c is consumption and γ is the coefficient of relative risk aversion. Lifetime utility at any node can be evaluated by calculating expected utility across all future nodes and applying a time discount factor. At each terminal node, the individual annuitizes their wealth and receives the present discounted utility associated with the associated level of consumption.

Our model is enormously simplified, with stock returns following a binomial process and bond returns treated as risk-free. Within these constraints, we attempt to realistically calibrate the mean and variance of real stock returns, as well as the safe return earned by bonds. Many studies have attempted to estimate asset returns over different periods of time, although data from before 1926 data are of low quality (see Chambers et. al., 2024, for a survey). The Center for Research in Security Prices (CRSP) provides high quality data on asset returns from 1926 onwards. We use the version of the CRSP data provided by Damodaran (2025) to calculate the arithmetic means of the S&P 500 and Baa corporate bond returns. We concentrate on these two indices as they are most comparable to the assets in typical target date funds. We find that the S&P 500 total return averaged 8.55 percent over the 97-year period from 1928-2024, and

9.34 percent over the past 50 years. The Baa corporate bond total return averaged 3.85 percent over 1928-2024 and 5.16 percent over the past 50 years.

We use this information to calibrate the model with the caveat that – as many investment advisors warn – past returns do not necessarily predict future performance. Because the past 100 years may have been a particularly favorable century for the American economy (Chambers et al. 2024), we set the expected real equity return to 5 percent per year. We set the expected premium of equities over bonds to 4 percent, consistent with the difference between the total S&P 500 and Baa corporate bond returns over the past 50 years. Thus, the real return on the safe asset is 1 percent. To reflect these assumptions, we choose $R_u = 1.4048$, $R_d = 0.7118$, $R_f = 1.0305$, and $\pi_u = 0.6367$. Under these parameters, stock returns have an annual standard deviation of around 19 percent, in line with the Damodaran (2025) data.

b. Earnings

In each period, the worker earns labor income and can opt to save any fraction of this income. For each worker category, earnings are influenced by three factors. First, each worker category has an expected life cycle pattern to earnings. Following Scott et al. (2023), wages are either expected to be flat over the working career or exhibit a ramp up between the ages of 25 and 45 followed by flat earnings growth thereafter. The second two factors are market related: earnings are influenced by both contemporaneous and lagged market conditions. This specification is in line with equation (1) from the previous section. In our analysis, the unit of time is 3 years, so earnings growth over the past 3 years correlates with stock market growth over the last three years and stock market growth over the prior 3 years. Our empirical analysis

suggests that lagged market performance is relatively important for higher-educated workers. For lower educated workers, contemporaneous market conditions are more significant, but lagged market conditions are also sizeable. Female workers overall have higher market sensitivity than male workers, with lagged market conditions playing a larger role.

Formally, earnings evolve based on the following equation:

$$\Delta \ln(W_t^C) = \Delta \ln(L_t^C) + b_1^C \cdot \Delta ln(S_t) + b_2^C \cdot \Delta ln(S_{t-1}) \quad (5)$$

In this equation, W_t^C denotes earnings for worker in category C at time t, L_t^C denotes the life cycle wage progression for worker category C at time t, and S_t denotes the real stock market index at time t. Two key model parameters are b_1^C and b_2^C, which denote the sensitivity of earnings growth to contemporaneous and lagged (respectively) stock market growth.

We consider the four worker categories from the empirical analysis above: college-educated men, high-school educated men, college-educated women, and high-school educated women. Our parameterization of equation (5) for each worker category is shown in Table 3. High school educated workers receive a constant baseline level of real earnings. Those with some college or more receive baseline earnings that increase between ages 25 and 45 and then are flat afterwards. For college-educated men, earnings increase by 80 percent between 25 and 45; for women, the increase is 60 percent. These wage profiles are based on the empirical estimates in Scott et al. (2023) for higher-income and lower-income workers. They are also reasonably consistent with the CPS-ASEC profiles in Figures 1 and 2. Initial earnings are based on medians for the 1998 birth cohort in the CPS-ASEC data described above. Under our wage profile assumptions, Social Security benefits – in expectation - replace 72 percent of average lifetime earnings for high-school educated males and 45 percent of final earnings for college-

educated males. Replacement rates are slightly higher for females. (The realized replacement rates in the model depend on how the market evolves.) Finally, we use the estimates of β_1 and β_2 from equation (1), which are shown in the first two columns of Tables 1 and 2, to capture the correlation between earnings and current and lagged stock market returns (b_1 and b_2).

In our binomial model, the stock market experiences either an up market with return R_u or a down market with return R_d. The respective probabilities of up and down markets are π_u and $\pi_d = (1 - \pi_u)$. Moreover, current earnings are related to contemporaneous and lagged stock returns. Thus, in any period, a worker in category C experiences one of four possible market induced earnings growth factors indexed by combinations of i, j in the following equation:

$$G_{i,j}^{C} = e^{b_1^C} \cdot R_i \cdot e^{b_2^C} \cdot R_j \quad i,j \in \{u,d\}$$

The size of these growth factors depends on the stock market assumptions. However, the average life cycle earnings profile has already been captured for each worker category by the L_t^C factor in equation (5). To ensure that stock market shocks induce earnings volatility but not growth, we normalize the earnings growth factors such that the geometric mean of market induced growth is 1. To accomplish this, we calculate a normalization factor for each category, g^C :

$$g^C = \frac{1}{G_{u,u}^{C\ \pi_u \cdot \pi_u} \cdot G_{d,u}^{C\ \pi_d \cdot \pi_u} \cdot G_{u,d}^{C\ \pi_u \cdot \pi_d} \cdot G_{d,d}^{C\ \pi_d \cdot \pi_d}}$$

Here, the denominator represents the geometric growth associated with the raw market- based earnings growth factors. After normalizing these growth factors in this way:

$$\hat{G}_{i,j}^{C} = \frac{G_{i,j}^{C}}{g^C}$$

We are assured that the median earnings growth rate follows the life-cycle induced pattern. This normalization is consistent with the empirical estimates described above. Empirically, the life cycle earnings profile is captured by the age dummies in equation (1). Thus, the estimates of β_1 and β_2 capture the relationship between stock market performance and earnings volatility beyond what is captured by a deterministic age profile.

c. Social Security

Social Security is typically modelled as a riskless annuity. However, since earnings influence the Social Security income calculation, inherent wage riskiness translates into Social Security riskiness. In this section, we describe how Social Security payouts are determined and illustrate their inherent riskiness.

The Social Security benefit formula first calculates average indexed earnings for an individual. (The benefit formula uses the top 35 years of indexed earnings in this computation; in our model, we simplify by using earnings from all periods.) Next, a progressive formula is applied to convert indexed earnings into a monthly benefit. In particular, indexed earnings (I) are given by

$$I = \frac{1}{T} \cdot \sum_{t=1}^{T} \left\{ W_t \cdot \frac{AWI_T}{AWI_t} \right\}$$

where W_t denotes earnings at time t, AWI_t denotes the Social Security Average Wage Index (AWI) at time t, and T denotes the number of periods with earnings. Next, a progressive formula is applied to translate indexed earnings, I, into a primary insurance amount (PIA).

$$\text{PIA} = \begin{cases} P_1 \cdot I, & I \leq B_1 \\ P_1 \cdot B_1 + P_2 \cdot (I - B_1), & B_1 < I \leq B_2 \\ P_1 \cdot B_1 + P_2 \cdot (B_2 - B_1) + P_3 \cdot (I - B_2), & B_2 < I \leq I_{Max} \end{cases}$$

Note, there are three income regions defined by the two bend points, B_1 and B_2. Each of the three income regions is associated with its own payout percentage, P_1, P_2, and P_3. The payout percentages are fixed by law, with P_1=0.9, $P_2 = 0.32$, and $P_3 = 0.15$. The bend points that define the payout ranges are indexed to the AWI:

$$B_i^{t+1} = B_i^t \cdot \frac{AWI_{t+1}}{AWI_t}$$

For 2025, the bend point values B1 and B2 for monthly income were $1,226 and $7,391, respectively. The annual income equivalent bend points are $14,712 and $88,692.[4]

i. Shocks to Average Wage Index

We first consider the simple case where earnings track the AWI. If $W_{t+1} = W_t \cdot \frac{AWI_{t+1}}{AWI_t}$, then any shock to AWI proportionally impacts average indexed earnings. To see this, recall

$$I = \frac{1}{T} \cdot \sum_{t=1}^{T} \left\{ W_t \cdot \frac{AWI_T}{AWI_t} \right\}$$

Recursively substituting in for earnings yields

$$I = \frac{1}{T} * \sum_{t=1}^{T} \left\{ W_{t-1} \cdot \frac{AWI_t}{AWI_{t-1}} \cdot \frac{AWI_T}{AWI_t} \right\}.$$

$$I = \frac{1}{T} \cdot \sum_{t=1}^{T} \left\{ W_0 \cdot \frac{AWI_1}{AWI_0} \cdot \frac{AWI_2}{AWI_1} \cdot \ldots \cdot \frac{AWI_t}{AWI_{t-1}} \cdot \frac{AWI_T}{AWI_t} \right\} = \frac{1}{T} \cdot \sum_{t=1}^{T} \left\{ W_0 \cdot \frac{AWI_T}{AWI_0} \right\}$$

$$I = W_0 \cdot \frac{AWI_T}{AWI_0}.$$

Suppose there is a shock to the path of AWI during the worker's career that cumulatively results in a new final AWI, $AWI_T^* = (1 + \alpha) \cdot AWI_T$. The equation above suggests that indexed

[4] There is also a maximum income allowed by the benefit formula. In 2025, that maximum was $13,689 ($164,268 annually). This is the AIME for a worker earning the taxable maximum income for 40 years prior to retirement.

earnings will fully reflect this shock; that is, $I^* = (1+\alpha)\cdot I$. This proportionality occurs because in any period t, an AWI shock prior to time t is reflected in W_t, whereas an AWI shock after time t is reflected in the indexing term, $\frac{AWI_T}{AWI_0}$.

This shock to average wages is then carried through the PIA formula.

$$\text{PIA}^* = \begin{cases} P_1 \cdot I^*, & I^* \le B_1^* \\ P_1 \cdot B_1^* + P_2 \cdot (I^* - B_2^*), & B_1^* < I^* \le B_2^* \\ P_1 \cdot B_1^* + P_2 \cdot B_2^* + P_3 \cdot (I^* - B_2^*), & B_2^* < I^* \le I_{Max}^* \end{cases}$$

We've established that indexed wages scale with shocked AWI, i.e. $I^* = (1+\alpha)\cdot I$. Recall, that the bend points also directly depend on the AWI, so a shock to AWI results in $B_i^* = (1+\alpha)\cdot B_i$. Thus, *every* term in the PIA formula scales with α, resulting in:

$$\text{PIA}^* = (1+\alpha)\cdot \text{PIA}$$

Thus, for a worker whose earnings generally follow AWI, *any* shock to AWI is fully captured as a shock to their Social Security benefit.[5]

ii. Average Wage Index and Market Risk

Given that shocks to AWI flow directly to Social Security, we next examine how AWI responds to stock market movements. We use data from 1951 to 2023, at three-year intervals, to estimate

$$\Delta \log(AWI_t) = \alpha_1 \Delta \log(S_t) + \alpha_2 \Delta \log(S_{t-1}) + \epsilon_t \quad (4)$$

Here, t indexes three-year time periods. Results from this estimation are shown in Table 4. There are 24 observations in the regression, corresponding to all three-year growth rates from 1954-2023. As the table shows, shocks to AWI depend on both contemporaneous (7.35 percent

[5] There is one important caveat to this result. AWI indexing for earnings only occurs up to age 60. After age 60, shocks to earnings are entirely individual instead of having an aggregate component.

beta) and lagged (5.27 percent beta) shocks to the S&P 500. Thus, we estimate that 12.62 percent of any shock to the S&P 500 ultimately flows through to impact AWI.

iii. Individual Shocks to Earnings

We next consider the case where wages tend to follow AWI but also contain an individual component. Let wages evolve as follows:

$$W_{t+1} = W_t \cdot \frac{AWI_{t+1}}{AWI_t} \cdot \gamma_{t+1}$$

Where γ_{t+1} reflects the individual component of wage growth from t to t+1. Substituting this wage evolution into the equation for average indexed earnings yields:

$$I = \frac{1}{T} \cdot \sum_{t=1}^{T} \left\{ W_t \cdot \frac{AWI_T}{AWI_t} \right\}$$

$$I = \frac{1}{T} \cdot \sum_{t=1}^{T} \left\{ W_{t-1} \cdot \frac{AWI_t}{AWI_{t-1}} \cdot \gamma_t \cdot \frac{AWI_T}{AWI_t} \right\}$$

$$I = \frac{1}{T} \cdot \sum_{t=1}^{T} \left\{ W_0 \cdot \frac{AWI_T}{AWI_0} \cdot \prod_{s=1}^{t} \gamma_s \right\} \quad (6)$$

Average indexed earnings is thus a function of initial earnings, and the evolution of both AWI and individual earnings. In other words,

$$I = I(W_0, AWI_0, AWI_T, \gamma_1, \dots \gamma_t, \dots, \gamma_T)$$

If we assume $\gamma_t \approx 1 \; \forall t$, then we recover the result that:

$$I(W_0, AWI_0, (1+\alpha) \cdot AWI_T, \gamma_1, \gamma_2, \dots, \gamma_T)$$
$$\approx (1+\alpha) \cdot I(W_0, AWI_0, (1+\alpha) \cdot AWI_T, \gamma_1, \gamma_2, \dots, \gamma_T)$$

Now consider a shock to individual income that occurs at time t^*. Using Eq. (6) we can see that

$$I = \frac{1}{T} \cdot \sum_{t=1}^{t^*-1} \left\{ W_0 \cdot \frac{AWI_T}{AWI_0} \cdot \prod_{s=1}^{t} \gamma_s \right\} + \frac{1}{T} \cdot \sum_{t=t*}^{T} \left\{ W_0 \cdot \frac{AWI_T}{AWI_0} \cdot \prod_{s=1}^{t^*-1} \gamma_s \cdot \prod_{s=t*}^{t} (1+\alpha) \cdot \gamma_s \right\}$$

Again, assuming $\gamma_t \approx 1 \; \forall t$, we get

$$I \approx \frac{1}{T} \cdot \sum_{t=1}^{t^*-1} \left\{ W_0 \cdot \frac{AWI_T}{AWI_0} \right\} + \frac{1}{T} \cdot \sum_{t=t^*}^{T} \left\{ W_0 \cdot \frac{AWI_T}{AWI_0} \cdot \right\} + \frac{1}{T} \cdot \sum_{t=t^*}^{T} \left\{ W_0 \cdot \frac{AWI_T}{AWI_0} \cdot \alpha \right\}$$

$$I \approx \left(1 + \frac{T - t^* + 1}{T} \cdot \alpha \right) \cdot I\{\gamma_{t^*}\}$$

Thus, individual wage shocks that occur earlier in the working career are proportionally more impactful on indexed earnings compared to shocks experienced later in the career.

Given this model of earnings and Social Security, how would we expect riskiness of Social Security to evolve over the life cycle? The general answer would be AWI riskiness persists throughout a worker's career while individual riskiness depreciates over their career. For example, assume AWI carries an effective 12 percent stock exposure, and consider a worker whose earnings carry an effective 30 percent stock exposure. Further assume this worker has a 42-year career lasting from age 25 to age 67. Initially, the riskiness of their Social Security is the full earnings exposure of 30 percent. Halfway through their career, the contribution from AWI remains at 12 percent, but the incremental exposure from their individual earnings shocks has dropped to only 9 percent. The aggregate exposure at the halfway point in their career is roughly 21 percent. There is a discontinuity at age 60. Just prior to age 60, AWI shocks fully influence the PIA, but after age 60 AWI is frozen. In our model, one-sixth of the working career is left at age 60. Thus, just prior to age 60, stock exposure is approximately 15 percent, and just after age 60 exposure drops to 5 percent. Essentially, AWI market exposure drops to 0 percent, while the individual component exposure of 30 percent is down-weighted by a factor of one-sixth to reflect the remaining career.

We model the relationship between stock market performance and the AWI by using the correlations in Table 4 to simulate AWI in the model. We normalize the average growth of AWI to 1 percent. Since individual earnings are also related to stock market performance (Tables 2 and 3), we capture differences across workers in exposure to both individual shocks and aggregate AWI shocks.

IV. Results

In this section, we present results from solving the model above for males and females with either some college education or no college education. Parameters are chosen according to Table 4. Starting salaries are calculated from the CPS data as median real earnings for full-time workers born in 1998. We present results for a coefficient of relative risk aversion of five. We considered other coefficients of relative risk aversion (two, four, and five), and while all coefficients resulted in qualitatively similar glidepaths for college plus educated men, a coefficient of five corresponded most closely to actual TDF glidepaths. As described above, our stylized worker is exposed to risk from three sources: (1) stock investments, (2) earnings, and (3) Social Security. All three sources of risk are correlated. The worker's portfolio includes financial wealth and human capital. Human capital includes future earnings and Social Security benefits, and its level and riskiness are beyond the worker's control. The worker can, however, influence the level and riskiness of his financial wealth by making saving and portfolio allocation decisions as described in the model above. Thus, the worker can, to a limited extent, use the allocation of financial wealth to offset human capital risk.

a. Stylized College Educated Worker

Figure 3 summarizes the optimal investment strategy for college-educated men. The vertical axis indicates the share of assets invested in stocks, and the horizontal axis indicates age. As a baseline, the solid horizontal line in Figure 3 shows the worker's Merton fraction – the fraction of wealth that the worker would like to invest in stocks if all wealth (including the present value of earnings) were available and investable at the start of the career. The Merton fraction – 21.9 percent – does not depend on age. However, human capital wealth is not investable. In this scenario, the optimal investment allocation is path dependent. That is, the allocation in any period depends on the history of stock market and earnings growth. Figure 3 depicts this dependency by plotting a "glide cloud" rather than a glidepath. The vertical bars represent the range of realized optimal asset allocations during the period indicated on the horizontal axis. Assets are zero prior to the late 30s. Initially, all savings are invested in stocks. Averaged across states, the proportion of financial wealth invested in stocks declines with age, consistent with a standard TDF glidepath. The temporary uptick in stocks around age 60 corresponds to the resolution of AWI risk. Since AIME is indexed to AWI at age 60, a worker's Social Security risk declines dramatically as they approach that age, leading to an increase in the portfolio share invested in stocks.

In the remainder of this paper, to mimic a standard TDF, we constrain the individual in the model to choose a glidepath in advance. That is, individuals can choose a time-dependent, but not state-dependent, asset allocation. We refer to the resulting optimal solution as a "personal glidepath," as it is a glidepath that is fixed in advance but tailored to the risks faced by the worker. The personal glidepaths for college-educated men and women are depicted as dotted lines in Figure 4. Each stylized worker's Merton fraction is also shown as a solid

horizontal line. Note that the Merton fraction depends only on the distribution of stock returns and risk aversion; thus, it is the same (21.9 percent) for both stylized workers. The personal glidepaths resemble the average glidepaths when path dependency is allowed; they also resemble a standard TDF glidepath. The shapes of the personal glidepaths depicted in Figure 4 are driven by the riskiness of the workers' non- investable wealth (human capital) relative to overall desired stock market exposure. The dashed line in each panel of the figure shows the stock exposure (β) of the worker's human capital relative to stocks. For both men and women, the human capital β starts out at or just below the Merton fraction. It declines starting around midlife as human capital risk is resolved. Thus, when these college-educated workers start saving (in midlife), they use their relatively limited financial wealth to increase the stock exposure of their overall portfolio by investing 100 percent of it in stocks. That fraction declines over their working lives (aside from the small uptick in stocks around age 60) as financial wealth comes to represent a larger share of the total portfolio, thereby requiring a smaller share to be invested in stocks to offset the low risk of human capital wealth.

b. Stylized High School Educated Worker

We next consider a stylized male and female workers with a high school education, with parameters chosen according to Table 3. We present results for a coefficient of relative risk aversion of five. Figure 5 depicts the stylized worker's Merton fraction (solid horizontal line), β of human capital (dashed line), and personal glidepath (dotted line). Compared to the college educated workers described above, the stylized high school educated workers have higher human capital betas. Most significantly, for both men and women, the human capital βs are above the workers' Merton fractions until they are in their 50s. Workers aim to offset that stock

exposure by investing no financial wealth in stocks. As human capital's stock exposure declines, the share invested in stocks rises. By age 61, human capital wealth consists only of Social Security benefits based on already realized earnings; thus, it is completely safe. To move towards the Merton fraction, therefore, workers invest 100 percent of their financial wealth in stocks.

c. Welfare Analysis

We can use our model to quantify the welfare costs of sticking to standard default investment and contribution choices. Suppose our stylized workers are defaulted into a typical TDF that invests 90 percent of its portfolio in stocks initially, reducing that fraction gradually to 48 percent when the worker reaches retirement. This glidepath is roughly in line with the average TDF glidepath (Investment Company Institute 2024). We assume for now that workers optimize their contribution amounts, taking the TDF portfolio mix as given. How much additional lifetime earnings would the worker need (with the additional earnings paid in the same pattern as their baseline earnings profile) to equate their lifetime utility with what could be achieved through a personal glidepath? The present values of these earnings adjustments are shown in the second-to-last row of Table 3; they are expressed in both dollars and as a percent of starting salary. This welfare cost measure is low for college-educated workers, reflecting the fact that these workers' personal glidepaths resemble a standard TDF glidepath. On the other hand, the welfare cost is high for high-school educated workers, whose personal glidepaths deviate substantially from that of the standard TDF. To equalize welfare between the TDF glidepath and the personal glidepath, high-school educated men and would need to receive

lifetime earnings increases equal to roughly 27 and 62 percent, respectively, of their starting salaries.

Now suppose that the worker sticks to the default TDF investment *and* a default contribution rate of 10 percent. In this scenario, welfare cost increases dramatically. The required increase in lifetime earnings now ranges from 1.8 to 3.6 times the starting salary. The default contribution rate causes high-school educated workers to oversave throughout their lives. It also causes college-educated workers to oversave when they are young and undersave later in life. The welfare cost from the mistiming of savings is so large that the overall welfare cost is now larger for college-educated workers than for high-school educated workers.

V. Discussion and Conclusions

Our results suggest that the optimal glidepath in a retirement account depends on the relationship between stock returns and the value of human capital. We establish empirically that this relationship varies across the population. We solve a life cycle model to explore what these results imply about the utility-maximizing share of financial wealth invested in stocks. On average, less-educated workers' earnings tend to have a relatively strong correlation with the stock market. Our model shows that the utility-maximizing portfolio allocation for total wealth (financial wealth and human capital) therefore requires investing financial wealth in safer assets early in life. As retirement approaches, human capital risk is resolved, leading to an increase in the optimal share of financial wealth invested in stocks. In contrast, more-educated workers' earnings tend to be less correlated with the stock market. For these workers, it is optimal to invest a large share of financial wealth in stocks early in life. Because financial wealth is low

compared to human capital wealth at this point in the life cycle, financial wealth must largely be invested in stocks to bring about the desired stock exposure in the overall portfolio. As financial wealth grows and human capital wealth declines, the share of financial wealth invested in stocks can decline to match the desired overall stock exposure.

We have restricted our attention in this paper to four broad demographic groups (defined by education level and gender). Moreover, we only have two financial assets – stocks and the risk-free asset. These simplifying assumptions help us to illustrate the role that human capital and Social Security risk play in determining the optimal portfolio. Of course, there are many other important differences across retirement plan participants that we have not considered, including occupation, industry, marital status, risk aversion, and ownership of other assets (such as housing). Taking these differences into account would almost certainly lead to larger welfare losses than we have calculated for opting for the "one-size-fits-all" solution. For example, renters and homeowners would likely have different optimal asset allocations. Similarly, for married people, the spouse's job and its associated retirement plan is relevant for the optimal asset allocation. Thus, joint optimization is needed. Finally, a coefficient of relative risk aversion of 5 may be appropriate for the average person. However, risk aversion varies across the population. People with risk aversion parameters of 2 or 3 will not have the same optimal asset allocation path as those with values of 5 or 6. Our results suggest that even separating people into broad groups, by gender and education, leads to solutions that deviate substantially from the standard TDF glidepath. Incorporating additional differences will likely increase the welfare cost of sticking to the TDF default.

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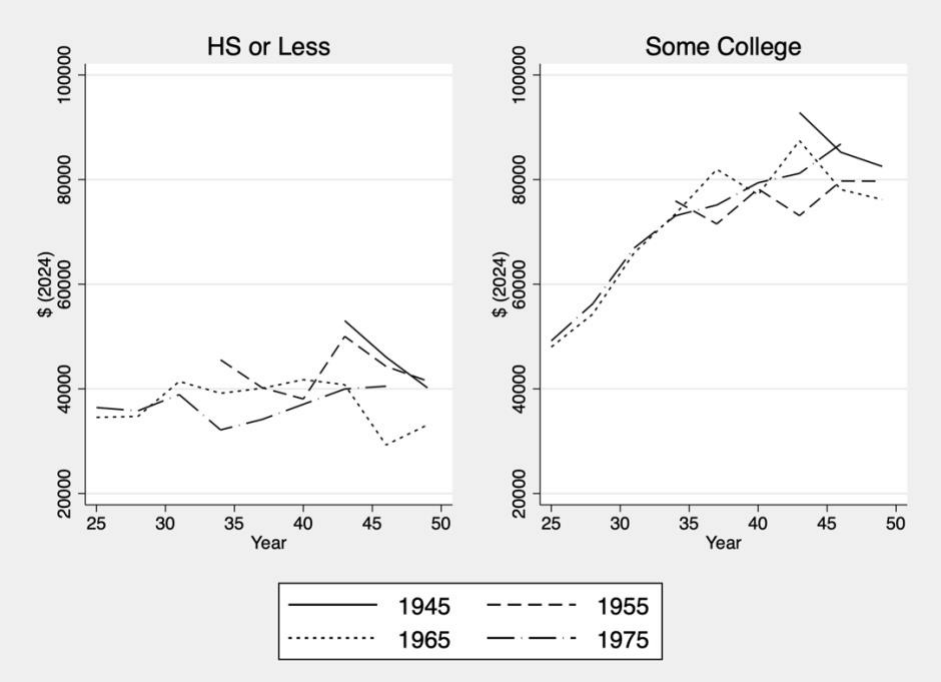
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Figure 1: Earnings Profiles for Stylized Male Cohorts



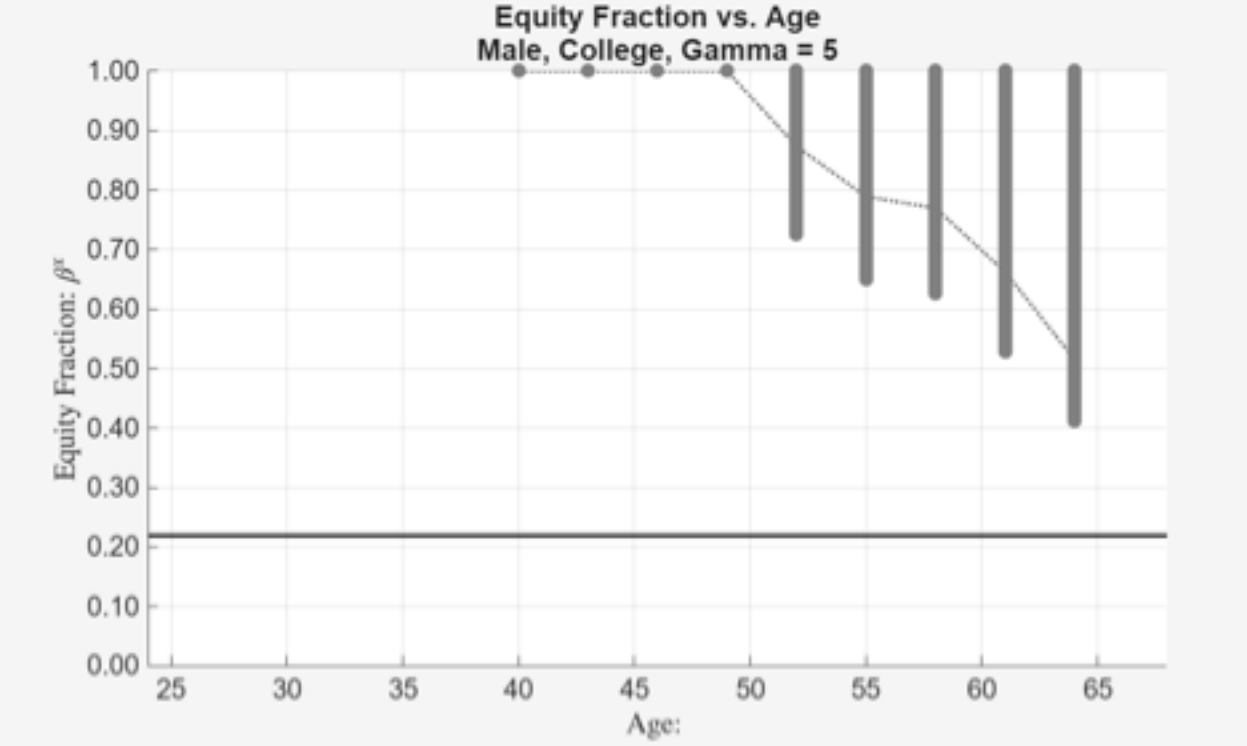
Notes: Authors' calculations from CPS-ASEC data, depicting age profiles of median real earnings plus transfer payments for cohorts of men born in 1945, 1955, 1965, and 1975.

Figure 2: Earnings Profiles for Stylized Female Cohorts



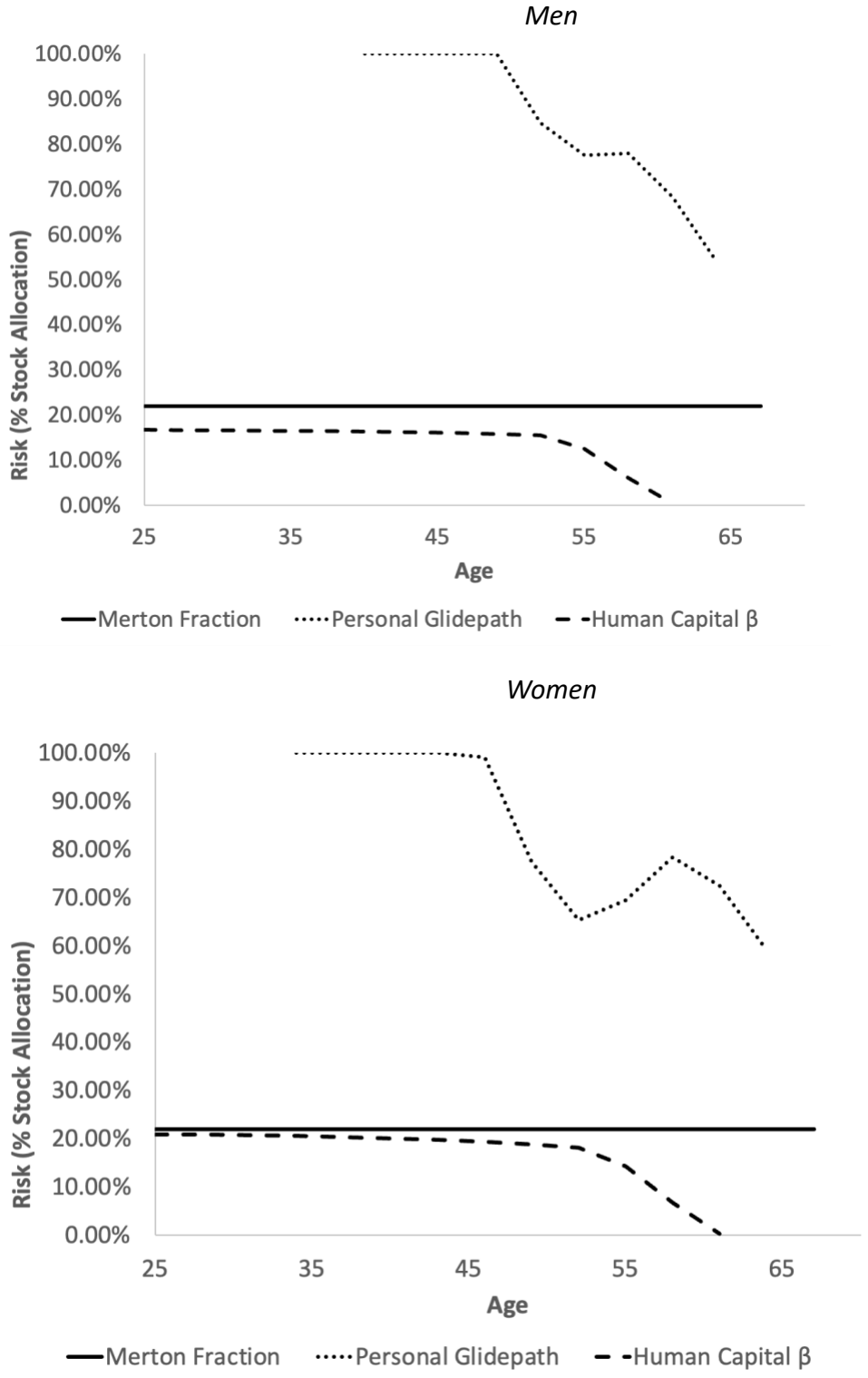
Notes: Authors' calculations from CPS-ASEC data, depicting age profiles of median real earnings plus transfer payments for cohorts of women born in 1945, 1955, 1965, and 1975.

Figure 3: Optimal Path-Dependent Investment Strategy for College-Educated Men



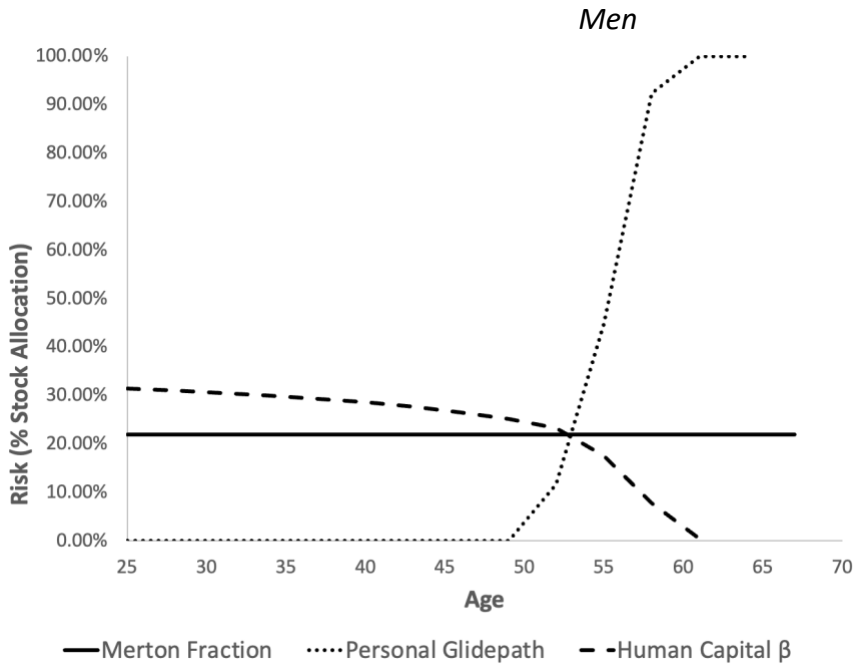
Notes: Authors' calculations based on model described in previous section. Assumes coefficient of relative risk aversion of 5. Horizontal line shows the Merton fraction. Vertical bars indicate optimal allocations across states of the world.

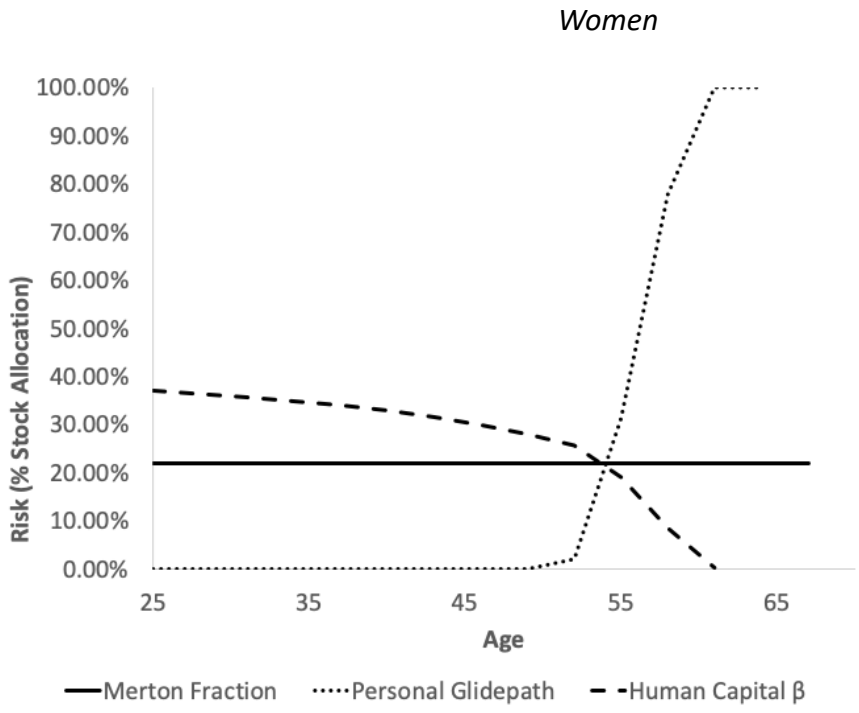
Figure 4: Personal Glidepaths and Human Capital Risk for College-Educated Men and Women



Notes: Authors' calculations based on model described in previous section. Assumes coefficient of relative risk aversion of 5.

Figure 5: Personal Glidepaths and Human Capital Risk for High School-Educated Men and Women





Notes: Authors' calculations based on model described in previous section. Assumes coefficient of relative risk aversion of 5.

Table 1: Relationship between Stock Returns and Earnings Growth for Men

	Δlog(earnings + transfers)		Δlog(earnings + transfers)		Δlog(earnings + transfers) - Δlog(AWI)		Δlog(hours)	
VARIABLES	High School or Less	Some College or More	High School or Less	Some College or More	High School or Less	Some College or More	High School or Less	Some College or More
$\log(S_a) - \log(S_{a-1})$	0.193***	0.0616***			0.122***	-0.00949	0.0870***	0.0487***
	(0.0330)	(0.0224)			(0.0291)	(0.0174)	(0.0255)	(0.0150)
$\log(S_{a-1}) - \log(S_{a-2})$	0.126***	0.100***			0.0742***	0.0483***	0.0158	0.0148
	(0.0319)	(0.0146)			(0.0248)	(0.0121)	(0.0173)	(0.0153)
$\log(AWI_a)$-$\log(AWI_{a-1})$			1.964***	1.106***				
			(0.297)	(0.168)				
Observations	262	262	262	262	262	262	262	262
R-squared	0.367	0.635	0.385	0.661	0.285	0.639	0.232	0.512
Number of Cohorts	47	47	47	47	47	47	47	47

Notes: Authors' calculations based on estimation of equations (1)-(3) using stylized male earnings profiles calculated from CPS-ASEC data, stock returns from Damodaran (2025), and the Social Security Administration's Average Wage Index (AWI). All regressions include age and cohort dummies. Standard errors clustered by cohort and year in parentheses.

Table 2: Relationship between Stock Returns and Earnings Growth for Women

	Δlog(earnings + transfers)		Δlog(earnings + transfers)		Δlog(earnings + transfers) - Δlog(awi)		Δlog(hours)	
VARIABLES	High School or Less	Some College or More	High School or Less	Some College or More	High School or Less	Some College or More	High School or Less	Some College or More
$\log(S_a) - \log(S_{a-1})$	0.164***	0.0692***			0.0929*	-0.00184	0.0945***	0.0416***
	(0.0481)	(0.0207)			(0.0461)	(0.0198)	(0.0206)	(0.0125)
$\log(S_{a-1}) - \log(S_{a-2})$	0.221***	0.136***			0.169***	0.0841***	0.0864***	0.0136
	(0.0279)	(0.0246)			(0.0280)	(0.0149)	(0.0206)	(0.0118)
$\log(AWI_a)$-$\log(AWI_{a-1})$			1.778***	1.104***				
			(0.462)	(0.227)				
Observations	262	262	262	262	262	262	262	262
R-squared	0.279	0.323	0.227	0.295	0.213	0.241	0.273	0.271
Number of Cohorts	47	47	47	47	47	47	47	47

Notes: Authors' calculations based on estimation of equations (1)-(3) using stylized female earnings profiles calculated from CPS-ASEC data, stock returns from Damodaran (2025), and the Social Security Administration's Average Wage Index (AWI). All regressions include age and cohort dummies. Standard errors clustered by cohort and year in parentheses.

Table 3: Parameterization and Welfare Costs for Worker Categories

Gender	Male	Male	Female	Female
Education	High School or Less	Some College or more	High School or Less	Some College or more
Life Cycle Wage Progression	Flat	80% ramp between 25-45	Flat	60% ramp between 25-45
Social Security Rate Replacement	72%	45%	78%	48%
Starting Wage (W_0)	$42,200	$58,700	$39,100	56,600
β_1	19.3%	6.2%	16.4%	6.9%
β_2	12.6%	10.0%	22.1%	13.6%
$\beta_1 + \beta_2$	31.9%	16.2%	38.5%	20.5%
Welfare cost of TDF risk (% of starting salary)	$11,485 27.2%	$1,358 2.3%	$24,126 61.7%	$1,719 3.0%
Welfare cost of TDF risk + 10% contribution (% of starting salary)	$76,068 180.3%	$211,524 360.3%	$117,024 299.3%	$135,392 239.2%

Notes: Authors' choices of parameters for earnings evolution described in equation (5). Welfare cost of default investment mix and contribution rate are calculated as described in Section IV.c.

Table 4: Relationship between Stock Returns and Average Wage Index

VARIABLES	Δlog(AWI)
$\log(S_t) - \log(S_{t-1})$	0.0735***
	(0.0213)
$\log(S_{t-1}) - \log(S_{t-2})$	0.0527**
	(0.0202)
Constant	0.00205
	(0.0111)
Observations	24
R-Squared	0.405

*** p<0.01, ** p<0.05, * p<0.1

Notes: Robust standard errors in parentheses. Authors' estimation of equation (4) based on stock returns from Damodaran (2025) and the Social Security Administration's Average Wage Index (AWI).