Asymmetric Labor Income Risk: Implications for Risk-Taking in Financial Markets*

Tai Lo Yeung†

August 10, 2025

Abstract

How does the shape of labor income risk influence households' demand for risky assets? I exploit the Survey of Income and Program Participation (SIPP) to construct a state-dependent measure that interacts the variance of individuals' labor income growth with its skewness. Conditional on having the same income volatility, households facing right-skewed income shocks (opportunity risks) raise their equity share, whereas those subject to left-skewed shocks (disaster risks) cut back sharply. This suggests that the counter-intuitive positive link between earnings volatility and stock holdings documented in the literature is driven almost entirely by the upper tail of the earnings distribution. These results show that higher-order moments of labor income risk shape portfolio choice, highlight the limitations of variance-based uncertainty metrics, and offer micro-level support for more robust portfolio choice models.

Keywords: Stock market participation, household finance, labor income risk, risk aversion, investment decisions

JEL Codes: G11, G50, D14

*I would like to thank Lorenz Kueng for his guidance. For suggestions, I also thank Giovanni Pica, Raphael Parchet, Darrel Duffie, Moritz Kuhn, Petra Todd, Harald Uhlig, Sylvain Catherine, Jessica Wachter, as well as seminar participants at USI Lugano, as well as conference participants at the 2nd Workshop on Applied Macroeconomics and Monetary Policy, Frankfurt Summer School 2024, Macro Finance Research Program (MFR) 2024 Summer Session for Young Scholars, Gerzensee Alumni Conference 2024, and RES PhD Conference 2024 for their helpful comments. All errors are my own.

†Università della Svizzera italiana, Via Giuseppe Buffi 13, tai.lo.yeung@usi.ch.

1 Introduction

A vast body of research examines the link between labor income risk and portfolio choice[1]; yet, due to data limitations, only a small fraction can directly assess the connection between human capital risk and risky asset investments of individuals, let alone incorporate higher moments of the labor income process into the analysis. In this study, I advance the methodology for identifying individual labor income risks by removing parametric assumptions and incorporating the distribution of risks. Additionally, I leverage comprehensive household-level panel data from the Survey of Income and Program Participation (SIPP) to quantitatively examine how labor market risks shape portfolio decisions.

Under a Gaussian assumption the risk distribution is symmetric, implying each worker is equally likely to experience a positive or negative deviation from trend. This symmetry is analytically convenient – it lets models summarize risk with a single variance term – but it is rarely realistic. In practice, upside and downside shocks occur with very different probabilities and magnitudes, so relying on a normal approximation masks the skewed risks households actually face. This paper emphasizes the pivotal role of distribution of risk in shaping household portfolio decisions in financial markets, as households derive varying levels of expected utility depending on the specific characteristics of the distribution. A growing strand of research explores how higher-order moments of labor income risk influence financial decisions – for example, Catherine, Sodini and Zhang (2022) examine how the covariance between labor income skewness and stock market returns shapes the cyclical component of portfolio choice[2]. By contrast, this paper isolates the *direct* effect of higher-order labor income risk itself, adding skewness-adjusted volatility to the analysis rather than relying on

[1]For related research on the interplay between labor income risk and household portfolio choice, see, inter alia, Guiso, Jappelli and Terlizzese (1996), Cocco, Gomes and Maenhout (2005), Benzoni, Collin-Dufresne and Goldstein (2007), Angerer and Lam (2009), Betermier et al. (2012), Bonaparte, Korniotis and Kumar (2014), Chang, Hong and Karabarbounis (2018), Gomes and Smirnova (2021), and Catherine (2022).

[2]They employ a *cyclical skewness* metric–defined as $\frac{cov(\mu_3, g(\varepsilon), r_s)}{var(r_s)}$–which tracks how third moments co-move with the business cycle. My skewness measure targets an entirely different object, so the two approaches are not directly comparable.

its comovement with financial market returns.

The core task is to characterize the *asymmetric* (non-Gaussian) nature of each worker's income risk. To recover this shape – and trace its impact on portfolio choice – I build on two key assumptions. First, workers in the same industry-education cell share an identical monthly distribution of income risk (Catherine, Sodini and Zhang (2022)). Second, I restrict attention to households' directly held equities – the most liquid segment of their risky portfolios – because they can be converted to or from cash immediately[3]. By imposing the two assumptions, I recover an idiosyncratic labor income *variance* for every worker and then attach a *shape* to that risk by interacting the worker-level variance with the relevant group-level skewness. The interaction yields a state-dependent, worker-specific measure of labor income risk.

The SIPP offers two advantages for studying portfolio choice. First, it is a large monthly panel covering 2013-2023, giving repeated observations on the same individuals across the entire working-age spectrum. Second, it reports both detailed earnings and stock market participation, along with key covariates – age, education, wealth – that standard models require. The high frequency and long span let me estimate individual labor income risk far more precisely than is possible with the Survey of Consumer Finances (SCF) or Panel Study of Income Dynamics (PSID)[4]. Taken together, these features make the SIPP uniquely well-suited for analyzing how earnings risk shapes participation and asset allocation.

The findings indicate that, given the same level of labor income volatility, households are more inclined to invest in risky assets when the right tail of the labor income risk distribution is more pronounced. This tendency is especially evident among households with lower risk aversion and those facing higher income volatility. Conversely, when the

[3]I estimate the main specifications with fixed-effects OLS rather than a Tobit model because the sample is restricted to households that have participated in the stock market at least once. Excluding perpetual non-participants eliminates noise from households whose zero equity share may reflect unobserved factors unrelated to labor income risk, allowing a cleaner identification of portfolio responses among active investors.

[4]For the significance of within-year variation in labor income, please refer to Ganong et al. (2024)

left tail of labor income risk distribution becomes longer, households – particularly those with higher risk aversion – tend to decrease their investments in risky assets. Focusing on working-age households, I find that when unconditional on distribution, one unit increase in the labor income volatility raises their investments in risky assets by 0.057 percentage points. However, this effect varies when accounting for the level of skewness. Once variance is estimated jointly with upper-tail dispersion (L9050×variance), its coefficient on the risky assets share turns negative (-0.084) and remains statistically significant. This suggests that the previously observed positive effect of variance is largely driven by contributions from the upper quantile. Moreover, the estimates indicate that the sensitivity of portfolio choice to downside labor income risk (or Disaster Risk) – captured by the L5010×variance term – rises sharply as human capital accounts for a larger share of a household's total wealth. Households that rely heavily on human capital and possess limited financial buffers are acutely sensitive to downside risks; when labor income risk turns left-skewed, they respond by scaling back their holdings of risky assets. However, they do not correspondingly increase their investments even in the presence of strongly positive skewness. By contrast, households with greater risk tolerance – typically wealthier families and those in mid-career – are less deterred by downside risk. Instead, they tend to expand their equity positions when the prospect of upside shocks (Opportunity Risk) improves.

Related literature and contribution. This paper advances three intertwined literature that link labor income risk to household portfolio choice, and in doing so offers new evidence that non-Gaussian features of earnings shocks are central for understanding equity demand.

The first strand is about the measurements of labor income risk. Classic life-cycle models – from Merton (1969) and Samuelson (1969) onward – assume normally distributed earnings shocks and therefore summarize uncertainty with a single statistic: the variance of (log) income growth. Empirical tests built on this framework proxy risk with volatility alone; for instance, Betermier et al. (2012) and Bonaparte, Korniotis and Kumar (2014) find that Swedish, Dutch, and U.S. households exposed to either greater earnings volatility or a stronger covariance between income growth and stock returns reduce their equity holdings – behavior consistent with hedging motives. A parallel macro literature, however, documents pronounced time-variation in the *shape* of the earnings distribution. Using U.S. Social-Security data, Guvenen, Ozkan and Song (2014) find that skewness is strongly pro-cyclical; Busch et al. (2022) show the same for Sweden and Germany. Bridging the two strands, life-cycle calibrations that allow regime-switching income volatility reproduce the modest portfolio rebalancing seen in administrative data (Chang et al., 2022), and more recent Catherine, Sodini and Zhang (2022) link counter-cyclical skewness to household portfolios. This paper extends that connection. Exploiting publicly available SIPP micro data, I demonstrate that the effect of earnings volatility on equity demand *depends on the sign of skewness*: downside-skewed volatility reduces stockholding, whereas upside-skewed volatility does not. Conditioning on skewness also resolves the long-standing puzzle that higher variance appears positively correlated with risky holdings[5]. Once higher-order moments are accounted for, the variance coefficient flips from positive to significantly negative without invoking unobserved risk-preference sorting.

Low stock market participation remains a central puzzle in household finance (Haliassos and Bertaut, 1995; Vissing-Jorgensen, 2002). Existing models address it with fixed entry costs, habit, or business cycle risk, yet they still over-predict participation rates for the young or under-predict for the old (Catherine (2022)). Using the monthly panel structure of the SIPP, I track households' entry, exit, and portfolio weights over time. The data reveal a pronounced age gradient: conditional on holding stocks, *younger* investors cut their equity share most sharply – and are most likely to leave the market altogether – when hit by downside income shocks, whereas older and wealthier households hardly adjust. Because human capital dominates young balance sheets, disaster risk translates into a larger effective background risk, raising the shadow cost of market participation. Embedding this mechanism

[5]See Ranish (2013) and d'Astous and Shore (2024) for instance.

in life-cycle models helps reconcile the observed age profile of participation with theory and suggests that accounting for income risk *shape* is essential for resolving the participation puzzle.

A long line of theory – beginning with Lucas (1978) and Weil (1992) – argues that uninsurable human capital shocks help explain both the equity premium puzzle and cross-sectional wealth gaps. The micro evidence in this paper sharpens the mechanism: downside earnings risk depresses stock holdings for households whose balance sheets are dominated by human capital, yet leaves the rich virtually unchanged. The result widens average return differentials and accelerates wealth divergence (Fagereng et al., 2019; Mian, Straub and Sufi, 2020; Catherine et al., 2022). Ignoring skewness therefore understates how background risk feeds into inequality dynamics.

By introducing a tractable, state-dependent measure of labor income risk and linking it to both intensive and extensive portfolio margins, this paper (i) reconciles the variance puzzle, (ii) explains why young stockholders are less likely to participate, (iii) provides insights on how downside risk fuels wealth-return inequality, and (iv) offers researchers with a publicly replicable framework for incorporating skewness into empirical and structural analyses. Taken together, the results call for a shift away from variance-only metrics toward richer descriptions of labor income risk when studying household portfolios.

The rest of this paper is structured as follows. Section 2 outlines the background theory related to labor income process and portfolio choice. Section 3 illustrates the background of the U.S. labor market relevant to this research and summarizes the data sources and selection criteria and explains how variables are constructed for empirical studies. Section 4 examines the relation between portfolio choice and labor income risks. Section 5 offers additional insights that extend the core findings. Finally, Section 6 concludes the discussion and suggests avenues for future research.

2 Motivating Framework and Hypotheses

This section develops the theoretical underpinnings for the empirical analysis, closely following the framework from Guvenen, Ozkan and Song (2014), demonstrating precisely how higher-order moments of labor income risk enter optimal portfolio choice. All assumptions, steps, and references are provided in detail. Additionally, I explicitly discuss my theoretical deviations and extensions relative to Guvenen, Ozkan and Song (2014) to rationalize my empirical specification.

2.1 Economic Environment

An infinitely lived household maximizes expected lifetime utility under CRRA preferences (Campbell and Viceira, 2001):

$$u(C_t) = \frac{C_t^{1-\gamma}}{1-\gamma} \quad \gamma > 0 \tag{1}$$

choosing consumption C_t and the portfolio share α_t of financial wealth W_t invested in a risky asset, with return R_{t+1}, subject to:

$$W_{t+1} = R_{t+1}^p (W_t - C_t) \quad R_{t+1}^p = \alpha_t (R_{t+1} - R^f) + R^f \tag{2}$$

The optimization problem is thus:

$$\max_{C_t, \alpha_t} E_0 \sum_{s=0}^{\infty} \beta^s u(C_{t+s}) \quad 0 < \beta R^f < 1 \tag{3}$$

This CRRA utility implies decreasing absolute risk aversion (DARA), ensuring the existence of non-degenerate optimal portfolio choices (Gollier and Pratt, 1996). Note that human capital, denoted by H_t, also contributes to financial wealth W_t; thus, a shock to human capital directly translates into a shock to the household's background wealth.

Labor Income Risk The household owns human capital worth H_t at the start of period t, and the innovation in log human capital over one period, $\tilde{y}_{it}$, is defined as:

$$\tilde{y}_{it} = \sigma_i, \upsilon_g \tag{4}$$

where:

- $\sigma_i^2 = \text{Var}(\Delta e_{i,t})$ is the worker-specific variance of income growth, capturing idiosyncratic earnings uncertainty. $\hat{\varepsilon}_{i,t} = \Delta e_{i,t}$ denotes the residual from a regression of individual labor income growth on its predictors; by removing the predictable component, it captures the purely idiosyncratic shock to labor income (see Equation 14 for details).

- υ_g captures within-group earnings dispersion (industry–education cells) and is measured by the inter-decile range of income growth, $P90 - P10 = L9010$. For tail–specific analyses, I also report its decomposition into the upper-tail span $P90 - P50 = L9050$ and the lower-tail span $P50 - P10 = L5010$. This closely mirrors the measure used by Guvenen, Ozkan and Song (2014), who emphasize earnings risk through cyclical variations in skewness rather than variance.

Connecting to previous literature The earnings innovation specification of Guvenen, Ozkan and Song (2014) is:

$$\Delta y_{it} = \eta_{s_i t} + \tilde{\varepsilon}_{it}, \quad \text{with} \quad \eta_{s_i t} = m_{s_i t} + \sigma_{s_i t} Z \quad Z \sim N(0,1) \tag{5}$$

with $m_{s_i t}$, $\sigma_{s_i t}$, and ε_{it} respectively capturing state-dependent means, standard deviations, and transitory shocks[6]. Empirical setup in this paper links these concepts explicitly as follows:

- The individual variance σ_i^2 is analogous to the transitory shocks ε_{it}, reflecting idiosyncratic volatility in earnings shocks.

- The group-level skewness υ_g captures asymmetry across economic states, analogous to the state-dependent mean difference $m_{s_{it}}$ and variance difference $\sigma_{s_{it}}$ in Guvenen, Ozkan and Song (2014). Thus, υ_g is a simplified summary measure capturing structural skewness across regimes.

In such a setting, they introduce a state-dependent variance for numerical analysis by simplifying the states to simply good and bad, assigning them probabilities, and enabling non-Gaussian variance. My objective in this study is to recreate a reduced-form setting where the variance has a specific shape rather than being symmetric, and include information that is far more rich than only two states.

Capturing state-dependent Labor Income Risk Critically, the reduce-form approach in this paper employs a multiplicative interaction $\sigma_i^2 \times \upsilon_g$, because this allows for explicit separation and clear identification of the scale (variance) and shape (skewness) components of risk. The multiplicative form explicitly captures how increased idiosyncratic variance amplifies sensitivity to skewness, accurately representing the economic intuition that households facing higher individual volatility are more susceptible to macro-level risks.

2.2 Downside Risk Aversion and the Cost of Risk Bearing

To expand on my motivation, I introduce the concept of downside risk aversion (downside RA)(Hammitt, 2023). In the context of this paper, individuals exhibiting downside RA incur

[6] A detailed proof of this specification is presented in the Appendix A1.

higher costs from bearing risks when they possess lower levels of wealth.

Connecting CRRA Preferences to Downside Risk Aversion Under expected utility, downside RA theories suggest that individuals with greater wealth tend to be less vulnerable to risks. This notion aligns with the empirical evidence presented (See Panel B in Figure 7). While CRRA implies DARA, and DARA implies downside RA, the converse is not necessarily true. Therefore:

$$CRRA \Rightarrow DARA \Rightarrow Downside\ RA$$

Transitioning to downside RA offers greater flexibility, but Constant Relative Risk Aversion (CRRA) is simpler and more cost-effective, even though it involves stricter assumptions. To illustrate the difference between downside RA and CRRA, it is important to note that for CRRA, it must satisfy the condition where $r'(W) < 0$, such that the absolute risk aversion is a decreasing function of W, while the relationship is as follows:

$$r'(W) = r(W)[r(W) - \rho(W)] < 0 \Rightarrow r(W) < \rho(W)$$

Here, $\rho(W) = -\frac{u'''(W)}{u''(W)}$ can be interpreted as the measure of absolute prudence (Kimball, 1990). Therefore, a utility function can demonstrate downside RA without adhering to the characteristics of CRRA[7].

Cost of Risk Bearing Let u(W) denote the CRRA utility function for a worker, where $u' > 0$, $u'' < 0$, and u''' exists. For simplicity, consider a lottery L that yields wealth level W_l and W_h ($W_l < W_h$) with equal probability. This can be envisioned as a worker facing the uncertainty of the future with only two potential outcomes in the next time period: a

[7]For instance, the Constant Absolute Risk Aversion (CARA) utility demonstrates $u''' > 0$ while $\rho(W) = r(W)$.

higher level of human capital wealth and a relatively lower human capital wealth. Assume that the risk $\tilde{y}$ is sufficiently small to allow adequate approximation of expected utility using a higher-order Taylor expansions.

Definition of the Utility Premium If the individual faces downside RA (e.g., Individual with CRRA utility), by definition, he exhibits $u''' > 0$. His expected utility is given by $Eu(L) = \frac{1}{2}u(W_l) + \frac{1}{2}u(W_h)$. If he adds the risk $\tilde{y}$ to the outcome W, his expected utility changes by $\theta(W) = u(W) - Eu(W + \tilde{y})$. $\theta(W)$ is defined as the **utility premium** for the risk $\tilde{y}$ when added to W (Friedman and Savage, 1948). In the original paper, a second-order Taylor series approximation is applied, where:

$$\theta(W) \approx -\frac{\sigma^2}{2}u''(W) \tag{6}$$

where σ^2 is the variance of $\tilde{y}$. Note that in this equation there must have $\theta(W) > 0$, because $u''(W) < 0$ and $\sigma^2 > 0$. This intuition underlies the view that greater return volatility should curb demand for risky assets: as volatility rises, so does the cost of bearing risk.

However, I extend the analysis by using the third-order Taylor series approximation[8]:

$$\theta(W) \approx -\frac{\sigma^2}{2}u''(W) - \frac{E[\tilde{y}^3]}{6}u'''(W) \tag{7}$$

In contrast to the original paper, the determination of $\theta(W)$ as positive or negative in this study depends on the magnitude of the third moment of risk, represented by $E[\tilde{y}^3]$. Importantly, this approximation may not perform well in certain scenarios, particularly when the shocks ($\tilde{y}$) are substantial or the utility function is highly nonlinear.

Definition of the Risk Premium On the other hand, the **risk premium** for $\tilde{y}$ is a monetary measure of the harm from bearing risk. It is defined as the difference between the

[8] A detailed proof of this approximation is presented in the Appendix A3.

expected value and the certain equivalent, such that $\pi(W) = W - \hat{W} > 0$, where the certain equivalent is defined by $u(\hat{W}) = Eu(W + \tilde{y})$. Similarly, using the third-order Taylor series approximation:

$$\pi(W) \approx -\frac{\sigma^2}{2}\frac{u''(W)}{u'(W)} - \frac{E[\tilde{y}^3]}{6}\frac{u'''(W)}{u'(W)} \tag{8}$$

Within a Portfolio Choice Framework Again, for simplicity, I use the model of Campbell and Viceira (2001) for demonstration. Recall that being CRRA implies downside RA. Thus, the expressions for $\theta(C)$ and $\pi(C)$ are as follows:

$$\theta(C) = \frac{\sigma^2}{2}\frac{\gamma}{C^{\gamma+1}} - \frac{E[\tilde{y}^3]}{6}\frac{\gamma^2+\gamma}{C^{\gamma+2}}$$

$$\pi(C) = \frac{\sigma^2}{2}\frac{\gamma}{C} - \frac{E[\tilde{y}^3]}{6}\frac{\gamma^2+\gamma}{C^2}$$

$$\theta(C) = \frac{\pi(C)}{C^{\gamma}} \tag{9}$$

Using the utility premium as a measure of risk bearing magnifies the wealth effect as risk aversion heightened. This implies that individuals with higher levels of wealth will experience a much lower magnitude of utility premium compared to those with lower wealth levels. This aspect better explains investors' behavior as depicted in this paper. For households with higher levels of wealth, the portfolio effect of background risk is significantly lower because their cost of risk bearing is much reduced.

2.3 Implication from Simulation

I employ a basic CRRA utility function to demonstrate how skewness impacts an agent's utility. Figure 1(a) presents three distributions that share the same mean (10) and variance

(2), yet vary in skewness (-2, 0, 2). The utility function is written as:

$$U(C) = \begin{cases} \frac{C^{1-\gamma}-1}{1-\gamma}, & \text{for } \gamma \neq 1, \\ \ln(C), & \text{for } \gamma = 1. \end{cases} \tag{10}$$

Thus, the utility premium of such utility function can be written as:

$$\theta(C) = u(C) - Eu(C + \tilde{y}) = \frac{\gamma}{C^{\gamma+1}}(\frac{\sigma^2}{2} - \frac{E[\tilde{y}^3]}{6}\frac{\gamma+1}{C}) \tag{11}$$

Given that γ, C, and σ^2 are always non-negative, the sign and magnitude of skewness, $E[\tilde{y}^3]$, will determine the sign of the utility premium. Figure 1(b) illustrates the concept of the utility premium in relation to skewness levels. When individuals exhibit moderate risk aversion, they experience increased utility when dealing with risks with distributions skewed to the right. Conversely, the utility premium becomes negative for left-skewed risks, with the magnitude exceeding that of right-skewed risks. In situations marked by heightened risk aversion, the utility premium from risks with right-skewed distributions disappears, and the disutility (i.e., cost of bearing risk) for left-skewed risks significantly escalates. This phenomenon, known as downside risk aversion, is a characteristic shared by all CRRA utility functions, as demonstrated previously.

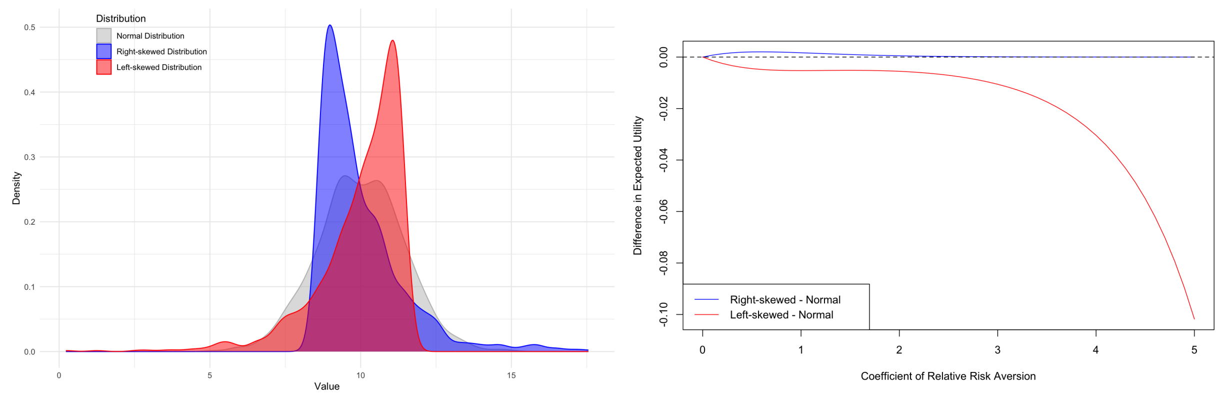
2.4 Relation to Portfolio Choices

From Campbell and Viceira (2001), an agent with constant relative risk aversion (CRRA) will choose his optimal risky allocation following[9]:

$$\pi W = \frac{\mu - r}{\gamma \sigma_s^2} W + \left(\frac{\mu - r}{\gamma \sigma_s^2} - \beta_H\right) H \tag{12}$$

[9] A detailed proof of this specification is presented in the Appendix A2.

Figure 1: Utility difference between distributions with same first and second moment



(a) Distribution

(b) Evolution of utility premium

Notes. Figure (b) illustrates the variation in utility premium when introducing a skewed shock versus a Gaussian shock, that is, the difference between $\tilde{y}_{skewed}$ and $\tilde{y}_{normal}$.

where W is financial wealth, H the certainty equivalent of future earnings, that is, the value each worker places on the claim to labor income given optimal behavior. Hence, the optimal share allocated to risky assets is positively correlated with the certainty equivalent of human capital. Relating back to equation 9, Catherine, Sodini and Zhang (2022) use a very similar approach and show that:

$$H_{t-1,it} \approx \bar{H}_{it} - \frac{\gamma}{2}\frac{\text{Var}_{t-1}(H_{it})}{W_{it}} + \frac{\gamma^2+\gamma}{6}\frac{\text{Skew}_{t-1}(H_{it})}{W_{it}^2} \tag{13}$$

where $H_{t-1,it}$ represents the certainty equivalent of human capital H_{it} at period $t-1$, and W_{it} is the total financial wealth possessed by the worker, which can be considered as an endowed financial wealth not subject to any uncertainty. The intuition is that the household faces human capital uncertainty at $t-1$ and adjusts their certainty equivalent of their human capital H_{it} accordingly, and then this will further drive them to adjust their portfolio holdings.

2.5 Testable Predictions

This theoretical setup yields several testable predictions closely linked to my empirical strategy:

H1. Variance channel.

- **H1.(a)** $\upsilon_g < 0$ **(left–skewed groups).** A larger idiosyncratic variance ($\sigma_i^2 \uparrow$) *reduces* the desired share in risky assets.
- **H1.(b)** $\upsilon_g > 0$ **(right–skewed groups).** When skewness is positive, an increase in σ_i^2 can *raise* the optimal risky share—provided the investor's risk-aversion coefficient γ is sufficiently low.

H2. Skewness channel. Holding variance fixed, a shift toward more negative skewness ($\upsilon_g \downarrow$) always lowers the optimal risky share; conversely, more positive skewness increases it.

H3. Wealth channel. Both variance and skewness corrections shrink with wealth: the variance term scales with $1/W$ (after dividing by W once more in α it becomes $1/W^2$), while the skewness term scales with $1/W^2$ (and thus appears as $1/W^3$ in α). Hence, as $W \to \infty$ the portfolio rule converges to the myopic Merton share α^*.

3 Data and Methodology

I use a high frequency, publicly available, large scale panel of labor earnings microdata collected by the U.S. Census Bureau. The baseline sample consists of households that report direct stock holdings and spans the 2013-2023 period.

3.1 Earning Instability in the U.S.

Given that this paper uses monthly labor income to study how people perceive income risk, it is important to highlight that workers in the U.S. face substantial fluctuations in earnings even on a monthly basis. The observed earnings instability among the U.S. labor force is much higher than one might expect. Since I do not have access to paycheck data, I reference Ganong et al. (2024), who also study earnings instability in the U.S. using payroll company data spanning the years 2010 to 2023 (while my study spans the years 2013 to 2022). They estimate the monthly change in labor income and show that although base wages exhibit some downward rigidity and are quite stable, total earnings are not. Furthermore, considering total earnings is important because, in the U.S. workforce, 60% are hourly workers and 40% are salaried[10]. For hourly employees, earnings volatility chiefly reflects changes in hours worked. By contrast, fluctuations in salaried earnings stem from variable components-performance pay, bonuses, and other items such as reimbursements—that cause month-to-month variation.

Figure 2, derived from the Survey of Income and Program Participation (SIPP), demonstrates that workers experience significant earnings fluctuations at the monthly level (note that I use month-on-month changes to reduce seasonality, while Ganong et al. (2024) use monthly differences). As I do not have base wage data, I simulate a similar cumulative distribution function (CDF) as in Ganong et al. (2024) to compare with the CDF I estimated from SIPP. It is obvious that unlike base wage (or hourly wage), total earnings can be very volatile even at monthly level, both upward and downward. Therefore, it is reasonable to study how monthly labor income risk affects people's portfolio decisions, especially regarding the most liquid assets like direct holdings of stocks and mutual funds.

[10]For a full exposition, see Ganong et al. (2024).

Predictability of Earnings Changes. Another important consideration is how predictable these changes in earnings are. For instance, if people intentionally choose to reduce their working hours—during the summer, for example—and consequently earn less in that month, they would have anticipated this risk well in advance and should not react unexpectedly. To address this issue, I use month-on-month changes in earnings instead of simple monthly changes to eliminate potential seasonality effects. Regarding the extent to which workers can control their weekly working hours, the General Social Survey (GSS), a nationally representative survey of U.S. residents, includes several questions about this topic. According to the analysis from Lambert, Henly and Kim (2019), 52% of hourly employees report having little to no control over their work schedules, 31% have some input, and 17% can decide freely or within certain limits. This suggests that employers largely determine schedules, contributing to at least half of the volatility in working hours.

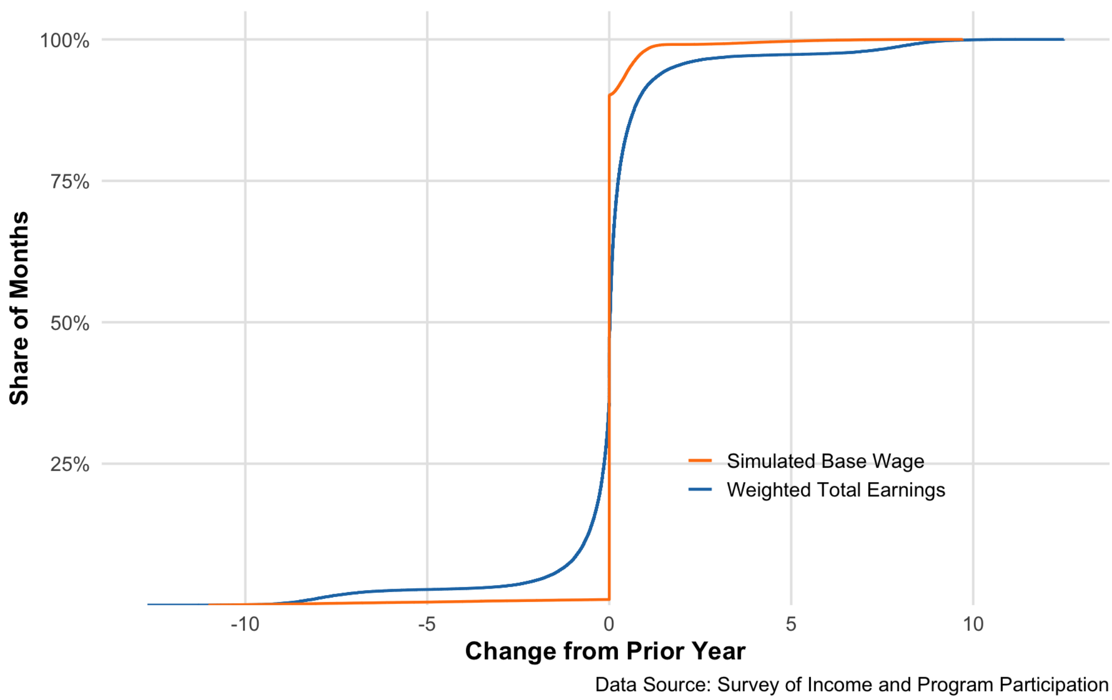
The final issue to consider is whether it matters if these earnings shocks are transitory or persistent. To address this, I refine my sample by creating a sub-sample that includes only workers who have never changed their job during the sample period. This is important because one of the biggest sources of persistent shocks is job transitions and within-job promotions or demotions. To achieve this, I select workers in the panel who:

- Have only one distinct observation of EJB1_JOBID

EJB1_JOBID is a unique identifier for a job that is consistent across waves. Only workers who satisfy this constraints are included in the subsample.

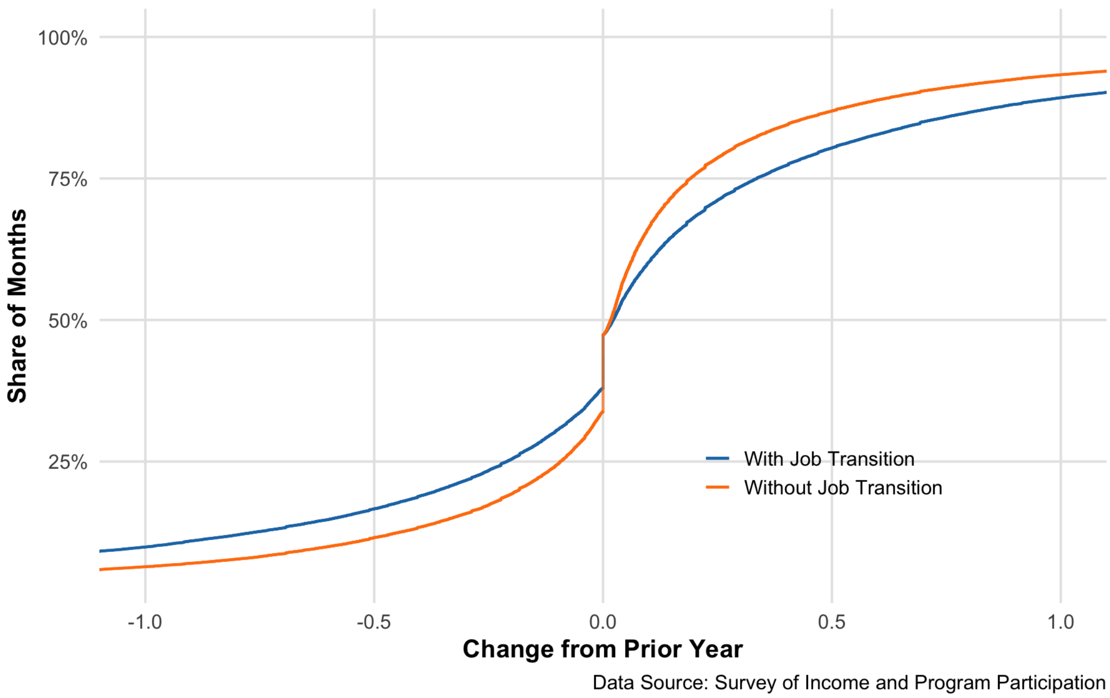
As shown in Figure 3, workers without job transition shocks have significantly more rigid earnings processes, as they are more resistant to downward movements. However, they also experience fewer upward movements because a large share of upward income adjustments comes from job hopping. In the robustness test section, I will examine to what extent my main empirical results are affected by persistent shocks.

Figure 2: Earning Instability



Notes. This figure shows the cumulative distribution function (CDF) of labor income growth (earnings change) estimated from my sample. The blue line represents the weighted total earnings, and the orange line is a simulated base wage designed to replicate the results from Ganong et al. (2024).

Figure 3: Persistent Shocks on Earnings



Notes. This figure presents the cumulative distribution function (CDF) of labor income growth (earnings changes) estimated from my sample. The blue line represents the weighted total earnings for workers who have changed their job at least once, while the orange line represents the same for workers who have never changed their job.

3.2 SIPP

I use the Survey of Income and Program Participation (SIPP), which is a nationally representative longitudinal survey conducted by the Census Bureau containing comprehensive information on the dynamics of income, employment, household composition, and government program participation.[1] It allows researchers[2] to examine the interaction between labor income risk, risk preferences, government or private policies, and demographic characteristics. For this study, I specifically selected households from the panel aged between 25 and 65 who also invested in the stock market for at least one month. This criteria reduced the total number of individuals in the panel from 118,591 to 20,767. The rationale behind such selection criteria lies in the consideration that households not investing in the stock market might have various unobservable reasons preventing them from participating, such as low financial literacy, high entry costs, or access to other sources of higher-return investments. Regarding the age range, I chose to start from 25 years old to include all education groups, under the assumption that by this age, most individuals, including those with post-graduate degrees, have entered the workforce. Additionally, I excluded retirees from the study because they are presumably not exposed to labor income risk. This exclusion further narrows the focus to those actively participating in the labor market and potentially influenced by labor income volatility in their investment decisions.

SIPP, as panels of national level continuous series of household-based survey, a large amount of households are interviewd multiple times over a four-year period. Starting 2014, the interviews are conducted once a year, where before 2014 it was conducted every 4 months. The selected sample should be a nationally representative sample of U.S. households that participate in the stock market. Table 1 presents a comparison of summary statistics between the sub-sample of investors in the SIPP and the overall population. Based on statistics

[1] See https://www.census.gov/programs-surveys/sipp/about.html

[2] Chetty, Sándor and Szeidl (2017) and Choukhmane and de Silva (2022) represent recent examples of the use of SIPP in the field of household finance

provided by the Bureau of Labor Statistics[1], typical weekly earnings for full-time workers fluctuated between \$795 and \$1,009 from 2014 to 2021. When extrapolated to a monthly scale, this translates to roughly \$3,180 to \$4,036. In my analysis, the figure stands at \$3,281.

Table 1: Descriptive statistics (households from age 25 to 65)

	All		Participants	
	Mean	Standard Deviation	Mean	Standard Deviation
Income				
Monthly labor income (\$)	4,852	6,311	7,430	9,744
Variance (short term)	0.69	2.80	0.72	3.01
Variance (long term)	2.35	7.58	2.63	8.30
Skewness	−0.04	1.44	0.01	1.52
Kelly skewness	−0.01	0.22	−0.01	0.22
Wealth				
Stock and mutual fund (\$)	21,278	154,454	96,798	333,493
Deposit in bank (\$)	16,346	58,196	43,037	105,801
Retirement account (\$)	72,533	277,066	202,407	504,738
Secured debt (\$)	63,049	361,784	126,401	734,422
Unsecured debt (\$)	9,980	35,909	10,109	36,805
Total net worth (\$)	258,969	1,825,956	722,779	3,108,161
Equity share (direct holding)	0.05	0.16	0.19	0.27
Demographic characteristics				
Age	44.78	11.95	47.14	11.57
Male	0.49	0.50	0.54	0.50
High school dummy	0.90	0.31	0.99	0.09
Post-high school dummy	0.37	0.47	0.64	0.48
U.S. citizen dummy	0.92	0.27	0.96	0.18
Individuals	118,591	–	20,767	–
Observations	2,939,746	–	567,920	–

Notes. The table summarises the moments of income, wealth, and demographic variables for the full U.S. sample (cols. 1-2) and for the subsample of equity-market participants (cols. 3-4) over the 2013-2022 period.

This comprehensive dataset presents significant benefits for my research. Firstly, it enables the observation of detailed labor market information and precise financial asset holdings on a monthly basis, maintaining consistency over the years—a rare feature in survey data. This capability allows for the estimation of clustered higher moments of labor income growth

[1]See https://www.bls.gov/news.release/pdf/wkyeng.pdf

at the monthly level, a novel approach given that most applied macro research relies on annual and aggregated measures of labor income skewness, and the calculation of individual labor income growth volatility on an annual scale. In comparison, similar datasets like the Panel Study of Income Dynamics (PSID), though frequently utilized, are only available biennially, making them unsuitable for the purposes of my study. Additionally, the Survey of Consumer Finances (SCF), despite its broader time frame, lacks detailed labor market information for households due to confidentiality issues, further underscoring the unique advantages of the dataset I employed.

3.3 Industry-Education Cluster

The construction of education dummies from SIPP raw data is as follows: for $EEDUC < 39$, $EDU == 100$; $EEDUC == 39$, $EDU == 200$; $39 < EEDUC < 43$, $EDU == 300$; $EEDUC == 43$, $EDU == 400$; $EEDUC > 43$, $EDU == 500$. These five levels represent "High school dropout", "With high school degree", "Below Bachelor's degree", "Bachelor's degree", "Post-graduate degree or equivalent (MD, JD)", respectively[1].

The industry classification follows the CPS standard, which includes 52 detailed groups and 14 major groups. To facilitate further separation of these groups based on education levels, I have chosen to use the 14 major groups, and end up with 90 groups. Detailed classification and summary statistics can be found in Table 2. Examining the data presented, it becomes evident that not all industries demonstrate a distribution of income growth that is approximately symmetric. This implies that in instances of heightened labor market volatility on a macroeconomic scale, the probabilities of achieving returns above and below the average are not equivalent. For example, the Public administration industry exhibits nearly identical dispersion in both its upper and lower tails, suggesting roughly equal probabilities of achieving upward or downward returns. This implies a distribution that approaches nor-

[1] cite some paper here indicating the connection between education and labor market outcomes

mality. However, despite also nearing a normal distribution, the Agriculture and Information industries display significantly greater dispersion on both sides. Regarding job risks as measured by wage volatility, the Financial activities and Construction sectors are identified as the most risky industries, whereas the Armed Forces and Public administration sectors are considered the safest.

Table 2: Ranking of Industries by wage volatility

IND	Volatility	Skewness	L9050	L5010	Individual
Agriculture, forestry and hunting	0.611	0.011	2.208	2.565	1,675
Mining	0.520	−0.036	1.196	1.704	748
Construction	0.874	−0.052	1.267	1.249	7,518
Manufacturing	0.448	0.026	0.594	0.560	12,835
Wholesale and retail trade	0.574	−0.016	0.850	0.858	14,002
Transportation and utilities	0.647	−0.007	0.842	0.887	6,515
Information	0.666	−0.004	1.142	1.101	2,372
Financial activities	0.839	−0.022	0.963	1.150	6,935
Professional and business services	0.668	−0.031	0.943	1.023	14,733
Education and health services	0.805	0.009	0.727	0.709	25,093
Leisure and hospitality	0.812	−0.077	1.141	1.417	8,679
Other services	0.574	−0.086	1.729	2.016	5,810
Public administration	0.359	0.013	0.552	0.553	6,016
Armed Forces	0.312	−0.048	1.148	1.595	442
EDU	Volatility	Skewness	L9050	L5010	Individual
W/O HS degree	0.717	−0.008	1.341	1.277	13,868
HS degree	0.670	−0.018	0.946	0.961	35,665
W/O Bachelor degree	0.687	−0.045	0.872	1.000	34,257
Bachelor degree	0.680	0.019	0.830	0.864	26,315
Post Bachelor degree	0.735	−0.017	0.845	0.942	15,024

Notes. This table ranks two cross-sectional partitions—14 major NAICS industries (upper panel) and five education groups (lower panel)–by the volatility of log wage growth over 2013-2022. *Volatility* is the within-cell variance of log wage changes; *Skewness* is the Kelly Skewness; $L9050 \equiv P90 - P50$ and $L5010 \equiv P50 - P10$ measure upper- and lower-tail spreads of the growth distribution, respectively. All statistics are calculated at the worker-month level. *Individual* denotes the number of distinct workers observed in each cell. Industries (IND) follow the SIPP three-digit classification; education (EDU) categories indicate highest completed credential.

3.4 Moments of Labor Income Growth

Using SIPP allows me to exploit a large sample size with detailed labor market micro data in monthly frequency. The labor income growth is measured as the unpredictable part of the year-on-year log monthly labor income changes. In order to capture the predictable part of income growth, I regress the demographic factors on log monthly labor income growth following:

$$\Delta w_{i,t} = d_t + x_{i,t}^{'}\eta + \varepsilon_{i,t} \tag{14}$$

Where $x_{i,t}^{'}$ contains 7 variables: non-native speaker, gender, hispanic origin, age, age-squared, race, nativity and citizenship. The estimated value of the stochastic part of labor income growth at the micro level can be obtained by extracting the residuals, such that $\hat{\varepsilon}_{i,t} = \Delta e_{i,t}$, and then matching them back to the panel used for the regression.

To be specific, I have defined different moments of labor income growth as:

$$Mean(\varepsilon)_{it} = \mu_{i,Y} = \frac{1}{N_{i,M}} \sum \varepsilon_{i,M} \tag{15}$$

$$Mean(\varepsilon)_{gt} = \mu_{g(i,M)} = \frac{1}{N_{g(i,M)}} \sum \varepsilon_{g(i,M)} \tag{16}$$

$$Variance(\varepsilon)_{it} = \sigma_{i,Y}^2 = E[(\varepsilon_{i,M} - \mu_{i,Y})^2] \tag{17}$$

$$Skewness(\varepsilon)_{gt} = \upsilon_{g(i,M)} = \frac{\overbrace{(P90 - P50)}^{L9050} - \overbrace{(P50 - P10)}^{L5010}}{(P90 - P10)} \tag{18}$$

Where I further defined:

$$\text{Opportunity} = L9050 \tag{19}$$

$$\text{Disaster} = L5010 \tag{20}$$

It's important to note that all group-level estimations are conducted on a monthly basis, whereas individual-level estimations are carried out annually, due to limitations in the available data.

I assume that in any given month of any year, workers within the same education $\times$ industry cluster experience independent shocks, $\varepsilon_{l,t}$, drawn from an identical distribution. Hence:

$$Labor\ Income\ Risk_{it} = \overbrace{Skewness_{gt}}^{aggregate} \times \overbrace{Variance_{it}}^{idiosyncratic}$$

Consistent with the decomposition laid out in subsection 2.2, individual labor-income risk can be partitioned into two distinct elements: an aggregate component and an idiosyncratic component. The aggregate term captures the macro-level *shape* of earnings risk, whereas the idiosyncratic term reflects its individual-level *scale*. Formally,

$$Labor\ Income\ Risks_{i,M} = \upsilon_{g(i,M)} \times \sigma^2_{i,Y} \tag{21}$$

To better capture the effects of the upper and lower tails of the distribution, I further defined:

$$\text{Opportunity Risk} = L9050 \times \sigma^2_{i,Y} \tag{22}$$

$$\text{Disaster Risk} = L5010 \times \sigma^2_{i,Y} \tag{23}$$

This intersection term effectively quantifies labor income risks by encompassing, on a macro scale, the risks associated with specific industry-education groupings while also acknowledging the micro-level variances within each industry and educational tier. The term $\upsilon_{g(i,M)}$ gauges the skewness of the income growth distribution within the industry-education clusters. A larger magnitude of $\upsilon_{g(i,M)}$ indicates a greater disparity within a group, meaning individuals within the group will have different opportunities for achieving returns above or below the average. Increased skewness suggests that workers in a specific group are more likely to encounter either an upside surprise (**opportunity**) or downside risk (**disaster**). At the individual level, $\sigma^2_{i,Y}$ represents the labor income risk faced by an individual, specifically capturing the volatility of their labor earnings process, which is independent of the macro environment. Thus, this interaction term deduces human capital risks by evaluating the interplay between aggregate risk, group-level skewness, and idiosyncratic risk, which refers to the volatility of labor income growth at the individual level.

Practical Relevance of the Estimated Moments Figure 4 documents that aggregate skewness–calculated across the entire U.S. workforce without industry-education clustering–behaves pro-cyclically, rising in expansions and falling during contractions alongside quarterly GDP growth. Because it captures broad shifts in labor-income risk, this aggregate skewness also covaries with equity market performance. To gauge the macro financial link, Figure 5 plots month-over-month S&P 500 returns (red bars) against monthly labor-income skewness (black line). Periods in which the black line trends upward typically coincide with positive equity returns, implying a systematic, positive association between labor-market skewness and stock-market performance. The contemporaneous correlation is about 0.40; even with a two-month lag of skewness relative to returns, the correlation remains at roughly 0.30.

Table 3 reports the result of a simple OLS regression, following the specification:

$$S\&P\ 500_M = \alpha + \beta * Skewness_M + \varepsilon \tag{24}$$

Statistically, a decrease of 0.1 units in aggregate skewness level correlates with an approximate 453 points drop in the S&P 500 index.

While aggregate labor-income skewness comoves positively with broad equity returns, the covariation between *individual* labor-income risk and stock-market performance is far weaker and highly heterogeneous. At the micro level, exposure to market fluctuations is largely determined by industry and job type, so the link between personal earnings risk and equity returns varies substantially across occupations. In Figure 6, I present the time series

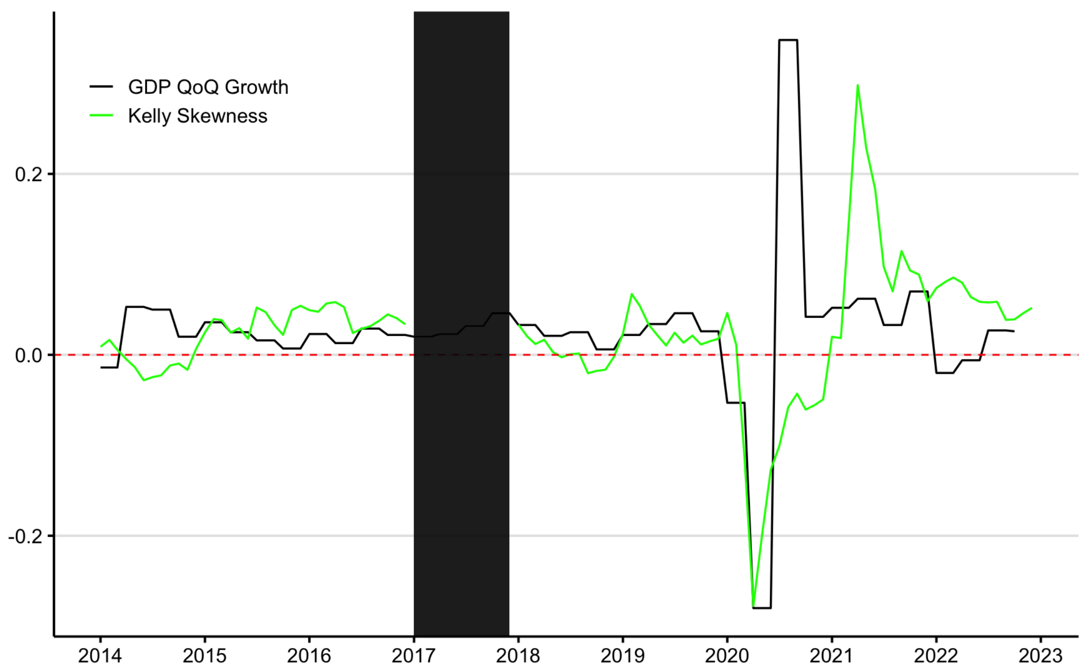


Figure 4: Procyclical Skewness of Labor Income

Notes. The figure plots aggregate skewness–estimated for the full SIPP sample—against quarter-over-quarter U.S. GDP growth. The shaded band marks 2017, the year for which SIPP data are unavailable.

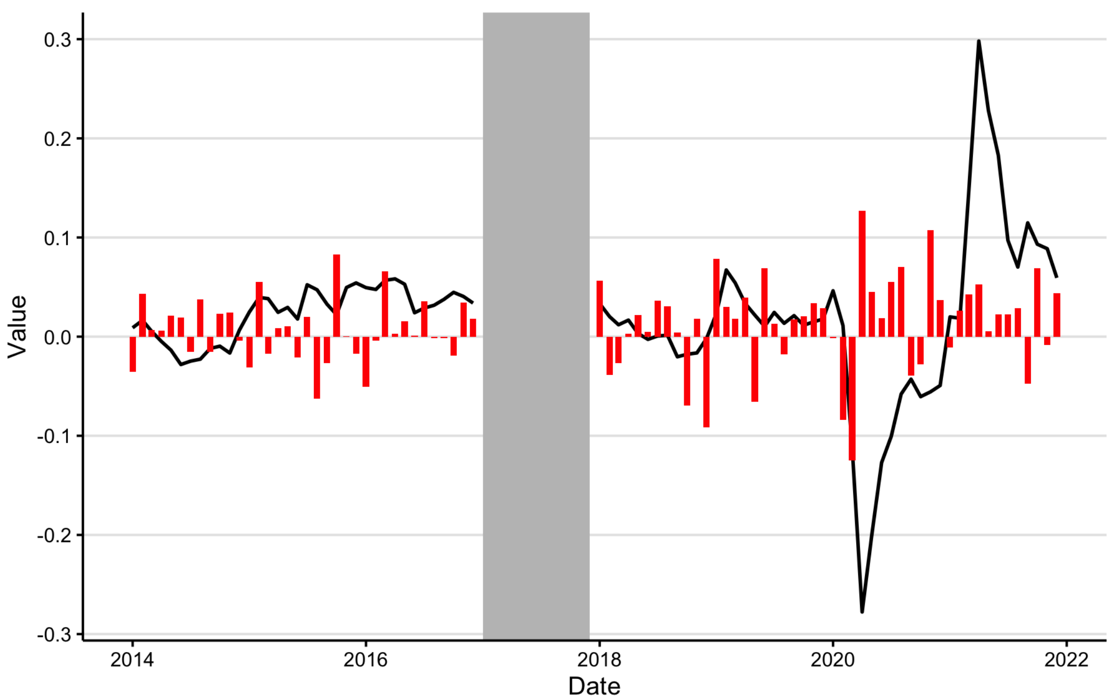


Figure 5: Market Performance and Labor Income Skewness

Notes. The figure juxtaposes aggregate labor-income skewness (black solid line) with month-over-month S&P 500 total-return performance (red bars) over 2014-2022. Labor income skewness is the Kelley measure computed each month from the SIPP panel for the full working-age population; larger values indicate a longer right tail of the earnings-growth distribution. Equity returns are calculated from the S&P 500 index. The two series are standardised to facilitate visual comparison. 2017 is omitted because SIPP was redesigned and monthly earnings microdata are unavailable.

Table 3: Labor Income Skewness and Stock Index

	S&P 500		
Skewness	4,531.983***		
	(1,201.405)		
Skewness_L1		4,219.379***	
		(1,213.829)	
Skewness_L2			3,877.396***
			(1,233.136)
Constant	2,665.403***	2,685.503***	2,706.260***
	(84.011)	(84.946)	(85.996)
Observations	84	83	82
Adjusted R^2	0.137	0.119	0.099

Notes. The table reports OLS estimates of monthly S&P 500 levels on current and lagged aggregate labour-income skewness, Skewness_{t-L} for $L = 0, 1, 2$. Each column adds one further lag. Robust (Eicker-White) standard errors are in parentheses. The sample spans 2013:M1-2020:M12; the number of observations therefore falls by one in each additional-lag specification. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

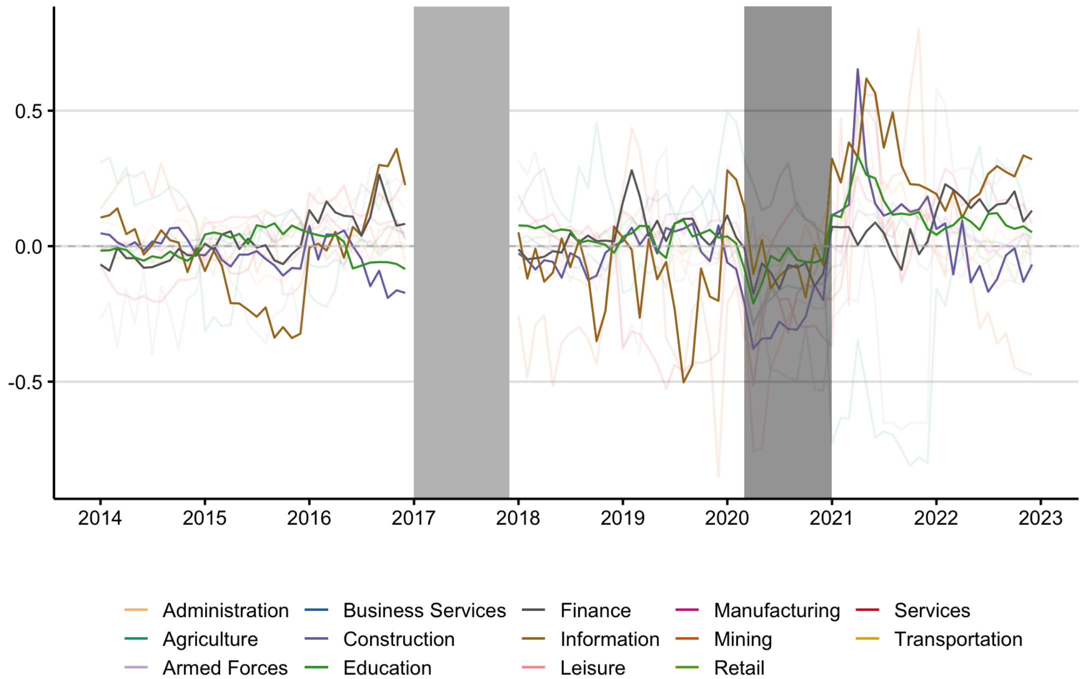


Figure 6: Skewness Heterogeneity of Labor Income

Notes. The figure shows skewness in labor-income growth, estimated separately for each industry cluster. The light-grey band marks 2017, when no SIPP data are available, and the darker shaded region highlights the onset of the COVID-19 pandemic.

evolution of skewness levels for all major industries, capturing the varying levels of labor income risks faced by workers across different sectors. The most recent recession, triggered by the COVID-19 pandemic in 2020, had a profound impact on the economy, with varying effects across industries. For instance, the construction industry was heavily impacted due to widespread anti-contagion measures and lockdowns, whereas the information industry was less affected. Post-2019, skewness levels for the Leisure and Hospitality industry reached an extreme, while for the Education and Health Services industry, despite having negative skewness levels, they remained moderate. This indicates that the majority of workers in the Education and Health Services industry experienced relatively better labor income growth in 2020.

3.5 Risky Share and Financial Assets

I categorize the asset types surveyed in SIPP into three groups: (1) financial assets; (2) non-financial assets; (3) human capital. In this section, I am presenting the financial and non-financial assets from a household balance sheet, and human capital will be discussed in the following section. Figure 7 illustrates the changes in the share of financial assets between rich and poor households from 2013 to 2022, clearly showing that over the last decade, the savings rate of the wealthy has decreased, while that of the poorer households has increased gradually. Table 4 juxtaposes household asset compositions in SIPP and PSID, enabling a cross-validation of the wealth measures reported by the two surveys[11]. A comparison of both tables shows that SIPP and PSID are consistent in terms of participation rates for various types of financial and non-financial assets. Although SIPP generally reports lower mean values compared to PSID, the differences can be attributed to variations in survey design and asset type definitions between the two surveys. Despite these differences, the cleaned version of SIPP is considered nationally representative.

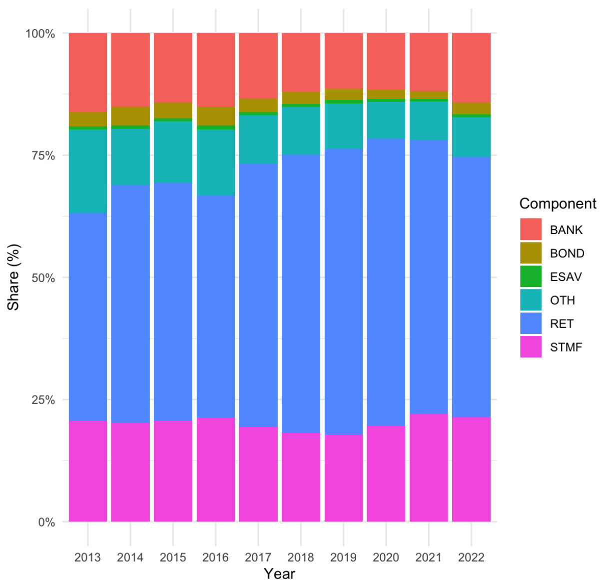
And the risky share is defined as:

$$RS_{i,t} = \frac{TVAL\_STMF_{i,t}}{TVAL\_FAST_{i,t}} \times 100 \tag{25}$$

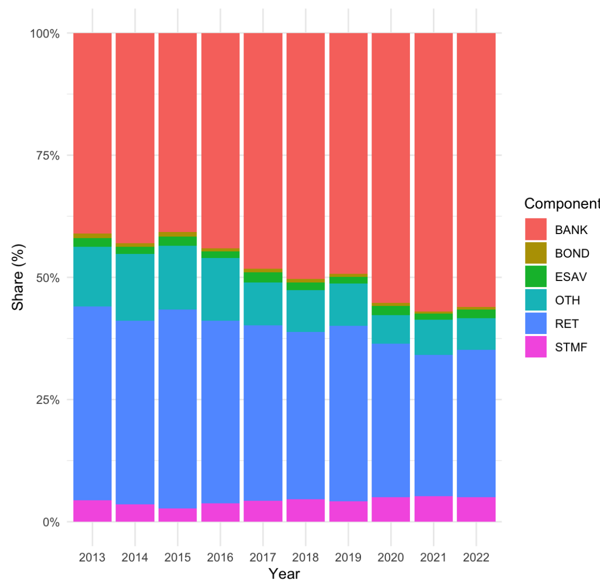
Where $TVAL\_FAST_{i,t}$ represents the total value of financial assets owned per household. It's worth noting that when I mention risky assets, I am specifically referring to stocks and mutual funds that are directly owned and recognized by the household, denoted as the variable $TVAL\_STMF_{i,t}$ in the equation. I have chosen this specific setting because it represents the most liquid form of a risky asset on a household's balance sheet. Additionally, I have set $RS_{i,t}$ to be within the range of [0, 100] for better visibility in the empirical section.

For stock market participation rates, I use two measures: (1) the proportion of people who have invested in the market at least once, and (2) the proportion of people currently

[11] For more information, see: https://psidonline.isr.umich.edu/Guide/Quality/DataComparisons.aspx



(a) Rich



(b) Poor

Figure 7: Asset Allocation: Whole Population

Notes. The figure traces average portfolio composition by asset class over 2013–2022. Asset codes are: BANK (bank deposits), BOND (bonds and other fixed-income securities), ESAV (education and health savings accounts), OTH (other financial assets), RET (tax-advantaged retirement accounts), and STMF (directly held stocks and mutual funds). Panel (a) reports households whose total net worth exceeds the sample median (Rich), while Panel (b) covers those below the median (Poor). Consistent with standard portfolio-choice theory, high-net-worth households allocate a substantially larger share of their financial wealth to risky assets.

Table 4: **Household Balance–Sheet Snapshot: SIPP & PSID, 2013–2019**

Panel A. Survey of Income and Program Participation (SIPP)

	2019			2015			2013		
	Mean	Median	%> 0	Mean	Median	%> 0	Mean	Median	%> 0
Total net worth	326 353	29 929	80	335 347	22 585	75	185 491	17 400	73
Business equity	87 548	0	8	85 077	0	7	36 013	0	7
Bank savings	19 602	2 000	84	13 962	1 000	76	15 344	725	73
Direct stock holdings	28 613	0	15	18 779	0	11	18 589	0	12
IRA / 401(k)	94 729	0	40	45 260	0	34	38 758	0	33
Vehicles (net)	7 844	2 680	61	7 138	2 795	61	7 194	2 863	62
Primary–home equity	98 185	0	50	84 047	0	49	77 141	0	47
Other real estate	12 631	0	6	8 718	0	5	9 390	0	5
Other assets	15 098	0	9	11 609	0	17	15 487	0	16

Panel B. Panel Study of Income Dynamics (PSID)

	2019			2015			2013		
	Mean	Median	%> 0	Mean	Median	%> 0	Mean	Median	%> 0
Total net worth	382 026	76 000	76	364 323	60 500	74	316 258	54 000	73
Business equity	48 479	0	5	61 556	0	6	48 372	0	7
Checking / savings	35 887	5 000	76	29 120	3 000	66	29 637	3 000	67
Stock holdings	59 267	0	10	66 937	0	11	56 759	0	12
IRA / annuities	67 578	0	19	61 462	0	19	52 452	0	20
Vehicles (net)	17 200	9 000	78	14 607	8 000	79	14 301	8 000	80
Primary–home equity	118 070	35 000	49	96 686	25 000	48	86 427	15 000	47
Other real estate	34 826	0	9	35 824	0	9	28 561	0	9
Other assets	13 186	0	9	9 821	0	11	10 335	0	10

Notes. %> 0 denotes the share of households holding a positive balance in the corresponding asset category. SIPP values derive from the the same sample used in this study; PSID values come from the official website. Apparent cross-survey differences–especially in business equity and liquid savings–reflect coverage, question wording, and survey frequency rather than sampling error.

holding a positive amount of stock.

3.6 Human Capital

Since human capital plays an important role in this research, it is crucial to have a measure of human capital for each worker. For simplicity, I impute human capital for working-age individuals as:

$$E[L_i] = \frac{1}{N_{i,t}} \sum TJB1\_MSUM_{i,t}$$

$$E[g_{IND\_EDU}] = \frac{1}{N_{i,t|g}} \sum g_{i,t|g}$$

$$H_{i,Y} = \frac{E[L_i]}{r - E[g_{IND\_EDU}]} \cdot (1 - (\frac{1 + E[g_{IND\_EDU}]}{1 + r})^{70-y}) \tag{26}$$

Where $E[L_i]$ represents the expected monthly labor income for each worker, estimated using all observations when they exist in the panel, and $E[g_{IND\_EDU}]$ is the labor income growth rate at the industry-education group level, estimated using all observations in the same group during the period they exist in the panel. r denotes the future earning discount rate, which is set at 4.1%, following the study by Calvet et al. (2021). The intuition behind this approach is to treat human capital as the present value of an investment that yields a growing stream of cash flows to workers throughout their working years. This investment can be interpreted as the time and money individuals invest in their early age for education or training.

In such a setting, human capital exhibits the following features: (1) Human capital decreases with age. (2) Workers within the same industry-education group share the same growth rate concerning labor income. (3) Workers retire at age 70, resulting in no human capital component beyond this age.

4 Empirical Results

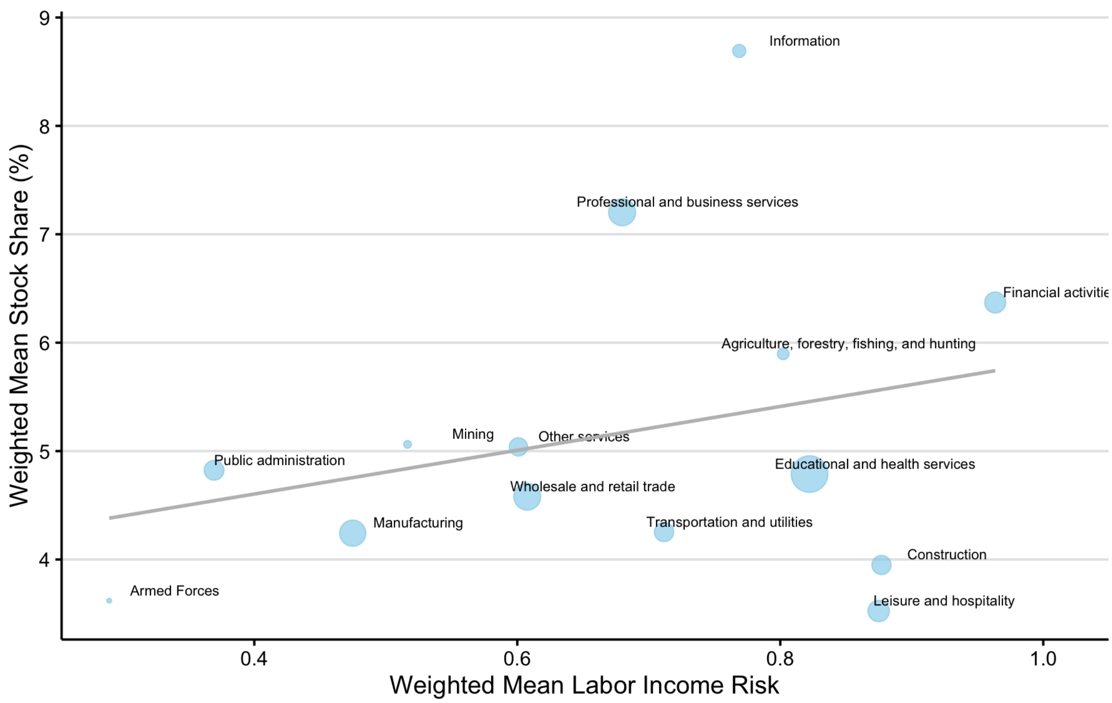
4.1 Group-level Analysis

Figure 8 provides an overview of the relationship between labor income variance, which are estimated for each industry group, and their corresponding risky asset holdings at the group level. The regression lines indicate that groups of workers with more volatile labor income also tend to hold a larger proportion of their portfolio in equities. This phenomenon has been analyzed by Ranish (2013), who utilized the Survey of Consumer Finances (SCF) dataset to identify a similar pattern, where households with higher labor income variance tend to hold a larger share of stock. Ranish (2013) concludes that this pattern is attributable to selection, whereby households with a higher tolerance for risk tend to choose jobs or occupations that come with higher levels of risk. While this finding is intriguing, in the subsequent section I propose an additional mechanism. The crucial margin is not higher *variance* per se, but the prospect of large upside *opportunity* risks embedded in right-skewed pay distributions. Groups whose earnings risk combines high volatility *and* a thick upper tail find equity-market risk relatively more attractive, generating the observed positive correlation even in the absence of pure risk-preference sorting.

4.2 Individual-level Analysis

The preceding subsection documented a positive cross-group correlation between labor income variance and equity shares. I now turn to the household level, asking whether–and how–individual-level labor income risk shapes the fraction of financial wealth invested in risky assets. This investigation is directly relevant to the central research question: Do households recognize and respond to higher moments of their labor income process, as anticipated by the canonical models and theory-driven simulations discussed in Section 2? The methodology for estimating the impact of labor income risk on portfolio choices is outlined

Figure 8: Labor income moments and risky asset holdings



Notes. This figure illustrates the relationship between labor income variance and risky asset holdings at the industry level. Circles represent group size, and the grey lines represent OLS regressions weighted by group size.

below, analogous to the approach of Catherine, Sodini and Zhang (2022):

$$RS_{i,M} = \alpha + \beta_1 \cdot var_{i,Y} + \beta_2 \cdot sk_{g(i,M)} + \beta_3 \cdot \overbrace{sk_{g(i,M)} \times var_{i,Y}}^{\text{Labor income risk}} + Control_{i,M} + \varepsilon_{i,M}, \tag{27}$$

where $RS_{i,M}$ represents the proportion of household i's financial assets directly invested in the equity market, measured on a monthly basis M. Financial assets include assets held at financial institutions, other interest-earning assets, educational savings accounts, the value of retirement accounts, and the value of stocks and mutual funds. $var_{i,Y}$ is the annual volatility of labor monthly income. $sk_{g(i,M)}$ is the skewness of labor income by industry-education clusters $g(i,M)$. $Control_{i,M}$ comprises the logarithms of income and wealth, age and age squared, education, gender, unemployment status, and home-ownership status. $sk_{g(i,M)} \times var_{i,Y}$ are estimated following equation 17 and 18, thus:

$$\upsilon_{g(i,M)} \times \sigma^2_{i,Y} = sk_{g(i,M)} \times var_{i,Y} = \frac{(P90 - P50) - (P50 - P10)}{(P90 - P10)} \cdot E[(\varepsilon_{i,M} - \mu_{i,Y})^2] \tag{28}$$

State-dependent individual labor income risk In Equation (28), the interaction term serves as a theoretically grounded metric for a worker's effective exposure to human-capital risk. The group-level skewness, $\upsilon_{g(i,M)}$, functions as a macro wage index that captures the *shape* of the earnings-growth distribution within an industry-education cell–indicating the probability of extreme upside (opportunity) or downside (disaster) outcomes. The individual variance, $\sigma^2_{i,Y}$, reflects the *scale* of idiosyncratic wage fluctuations around that group distribution. Hence, a worker with very stable earnings (low $\sigma^2_{i,Y}$) is only weakly affected by the aggregate skewness, whereas a worker whose earnings are highly volatile amplifies the macro tail risk embodied in $\upsilon_{g(i,M)}$. The product $\upsilon_{g(i,M)} \times \sigma^2_{i,Y}$ therefore aligns with the theoretical framework in Section 2.2: it combines the state-dependent *shape* and individual-specific *scale* of labor income risk into a single, economically meaningful measure that enters household portfolio decisions.

Table 5 presents the key findings [1]. Columns (1), (2) and (3) isolate the independent effects of $Skewness$ and $Variance$. Columns (4) and (5) display the partial effects when both variables are included simultaneously, while columns (6) introduces interaction terms. Column (6) suggests that households with more volatile labor income (higher $Variance$) are inclined to allocate a smaller portion of their financial assets to the stock market when the skewness is negative, and the opposite when the skewness is positive. Therefore, whether volatility is considered a disutility or not depends on the level of skewness.

Table 5: Risky Asset Share and State-Dependent Labor Income Risk

	Dependent variable: % of direct stock holdings								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Kelly skewness	1.342^{***}			1.337^{***}		1.184^{***}			
	(5.44)			(5.42)		(4.64)			
Opportunity risk ($P90-P50$)		0.341^{***}			0.336^{***}		0.132		0.161^{*}
		(3.91)			(3.85)		(1.49)		(1.80)
Disaster risk ($P50-P10$)		-0.243^{***}			-0.246^{***}			-0.203^{***}	-0.211^{***}
		(-3.31)			(-3.36)			(-2.74)	(-2.81)
Idiosyncratic variance			0.057^{***}	0.057^{***}	0.057^{***}	0.060^{***}	-0.084^{***}	0.055^{**}	-0.059^{**}
			(3.51)	(3.48)	(3.49)	(3.68)	(-3.36)	(2.44)	(-2.22)
Kelly × variance						0.279^{***}			
						(4.14)			
Opportunity × variance							0.146^{***}		0.173^{***}
							(7.36)		(8.04)
Disaster × variance								0.003	-0.047^{***}
								(0.19)	(-3.00)
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year–month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.028
Observations	259,485	259,485	259,485	259,485	259,485	259,485	259,485	259,485	259,485

Notes. Weighted OLS estimates. The dependent variable is the household share of directly held stocks (bounded in $[0, 100]$). Robust t-statistics are in square brackets. All specifications include the full set of household controls (log income, log wealth, age, age^2, education, gender, unemployment and housing dummies), industry fixed effects, and year–month fixed effects. ***/**/* denote significance at the 1%, 5%, and 10% levels.

Nevertheless, even in column (6), after incorporating interaction terms and all control variables, the coefficient for $Variance$ remains positive and significant, contradicting traditional portfolio choice theory. To address this puzzling result, I replicated the OLS regression from column (6), altering the measure of skewness. Columns (7), (8), and (9) present the

[1] Due to concerns about the potential impact of the COVID period on the results, a robustness test using data from before February 2020 is presented in Table 12 in the appendix.

findings, where L9050 indicates the dispersion in the upper tail, and L5010 denotes the dispersion in the lower tail. It becomes evident that the significant and positive effect of $Variance$ is largely captured by the dispersion from the upper tail, suggesting that the positive influence of $Variance$ on risky asset holding primarily stems from upward surprises.

Column (9) serves as my preferred (full) specification in the remainder of the analysis. Relying solely on Kelley skewness can mask situations in which the right and left tails of the earnings growth distribution are simultaneously fat–offsetting one another and yielding a near-Gaussian net skewness. By including both L9050 and L5010 I separately identify the influence of the upper and lower tails, respectively. Moreover, every coefficient in column (9) aligns with the comparative-static predictions derived in the theoretical section.

4.3 Participation Rate and Labor Income Skewness

In the previous section, I primarily focused on the intensive margin. I will now explore the impact of labor income risk on the extensive margin using a probit model, as outlined below:

$$\begin{aligned} P\Big(\text{PART\_STMF}_{i,M} = 1 \mid \mathbf{X}_{i,M}\Big) = \Phi\Big(&\beta_0 + \beta_1\,\text{vol}_{i,Y} + \beta_2\,L5010_{g(i,M)} + \beta_3\,L9050_{g(i,M)} \\ &+ \beta_4\,L9050_{g(i,M)} \times \text{vol}_{i,Y} + \beta_5\,L5010_{g(i,M)} \times \text{vol}_{i,Y} \\ &+ \underbrace{\text{Controls}_{i,M}}_{\text{income, wealth, education, gender, age, etc.}} \Big) \end{aligned}$$

Where $\text{PART\_STMF}_{i,M}$ is a binary variable indicating whether investor i has any direct investment in the equity market during month M. It is important to note that in this setting, I still only consider workers who participate in the market at least once, as there are numerous unobservable factors that may prevent individuals from investing directly in the equity market.

Table 6 reports the probit results. In Column (1) labor income volatility is positively associated with stock market participation. After adding higher-order risk in Column (5), the volatility coefficient turns significantly negative: households with more volatile wage growth are less likely to hold equities, in line with prior work. The control variables perform as expected. Greater financial wealth and higher educational attainment both increase the likelihood of participation; men are more inclined to invest than women; and the negative linear age effect–offset by a positive age-squared term–indicates that the probability of entering the equity market first falls and then rises as households approach retirement.

Table 6: Determinants of Stock Market Participation

	Dependent variable: Stock Market Direct Participation (Binary: 1/0)				
	(1)	(2)	(3)	(4)	(5)
Labor income risk					
Individual Risk (Variance)	0.002**	0.001	−0.004**	−0.003*	−0.004***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Opportunity (L9050)			−0.001	0.008	−0.001
			(0.005)	(0.005)	(0.005)
Disaster (L5010)			−0.002	0.007*	0.008**
			(0.004)	(0.004)	(0.004)
L9050×Var			0.07***	0.006***	0.006***
			(0.01)	(0.001)	(0.001)
L5010×Var			−0.001	−0.001	−0.001
			(0.01)	(0.001)	(0.001)
Demographics & Controls					
Log labor income	0.005*	−0.003	0.005*	0.003	−0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Log total assets	0.267***	0.261***	0.267***	0.268***	0.261***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Education	0.0004***	0.0004***	0.0004***	0.0003***	0.0004***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Age	−0.039***	−0.036***	−0.039***	−0.039***	−0.036***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age squared	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Male (1=Yes)	0.059***	0.064***	0.059***	0.060***	0.064***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)
Unemployed (1=Yes)	0.014	−0.052*	0.016	−0.003	−0.050*
	(0.028)	(0.029)	(0.028)	(0.029)	(0.029)
Fixed effects					
Industry FE		✓		✓	✓
Year–Month FE		✓			✓
Observations	259,485	259,485	259,485	259,485	259,485

Notes. This table presents the results of Probit regressions, where the dependent variable is the a binary variable indicating direct stock market participation, and the independent variables include measures of income risk, and control variables such as income, wealth, age, age squared, gender, education level, and housing status. Columns (2) and (5) account for Industry and Year-Month fixed effects. Robust standard errors are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

To gauge whether the shape of labor income risk matters differently across the life-cycle, I re-estimate the specifications in Columns (3)-(5) of Table 6 using the subsample of households whose heads are younger than 36. The results, reported in Table 7, reveal a stark contrast with the full sample. For this younger cohort, the interaction with downside–or disaster risk is large and significantly negative, implying that a left-skewed income distribution sharply reduces their likelihood of holding stocks. By contrast, the interaction with upside–or opportunity risk is statistically insignificant, indicating that potential windfalls do not entice young households into the equity market. In short, younger investors are quick to retreat in the face of downside risk but do not respond to comparable upside prospects. This evidence helps explain the long-standing puzzle: standard life-cycle models predict far more equity participation by young households than we observe in practice (Haliassos and Bertaut, 1995).

Table 7: Age < 36 Subsample: Stock Market Participation

	Dependent var.: Stock Market Direct Participation (Binary: 1/0)		
	(1)	(2)	(3)
Labor-income risk			
L9050×Var	0.008**	0.007*	0.006
	(0.004)	(0.004)	(0.004)
L5010×Var	−0.017***	−0.018***	−0.017***
	(0.004)	(0.004)	(0.004)
Fixed effects			
Industry FE		✓	✓
Month–Year FE			✓
Observations	49,034	49,034	49,034

Notes. Each column reports estimates for the age < 36 subsample. Robust standard errors are shown in parentheses. Results correspond to columns (3)–(5) of Table 6 respectively. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.4 The Role of Risk Aversion and Human Capital Share

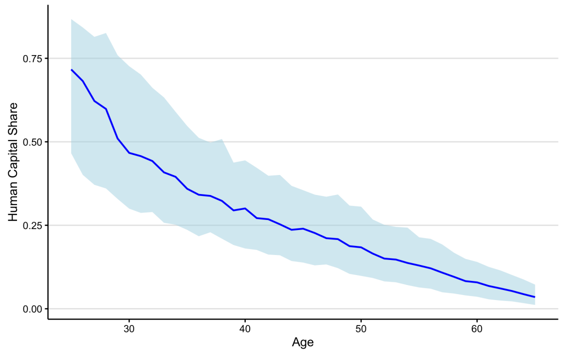
In the preceding subsection, I explored the overall impact of labor income skewness on portfolio decisions. However, theoretical predictions suggest that households with varying levels of risk aversion respond differently to skewness. Specifically, risk-neutral agents are indifferent to skewness, meaning they do not alter their behavior in response to changes in skewness levels. Agents with a higher level of risk tolerance experience a utility premium in right-skewed situations, yet they also endure utility losses in left-skewed scenarios. Conversely, risk-averse agents do not derive any benefit from positive skewness and suffer exclusively from negative skewness levels. This differentiation in behavior underscores the nuanced way in which skewness influences investment decisions, contingent upon an individual's risk tolerance.

However, the Survey of Income and Program Participation (SIPP) does not provide data regarding households' risk preferences. Consequently, I must infer their level of risk aversion using alternative variables. Given the focus on the relationship between labor income risk and the holding of financial risky assets, it seems reasonable to correlate households' risk tolerance levels with the proportion of human capital in their total asset portfolio. Specifically, the hypothesis is that households relying more heavily on their human capital for income are likely to exhibit greater risk aversion towards human capital risk. Thus, I calculate the share of human capital following:

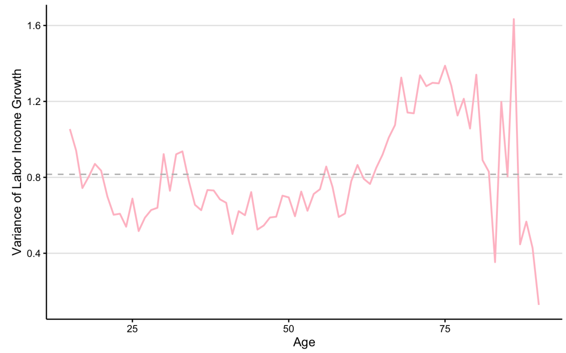
$$Human\,Capital\,Share_{i,M} = \frac{Human\,Capital_{i,M}}{TVAL\_AST_{i,M} + Human\,Capital_{i,M}} \tag{29}$$

Here, $TVAL\_AST_{i,M}$ represents the aggregate value of all assets at the individual level. Figure 9(a) illustrates the age distribution of human capital share within my sample, aligning closely with real-world observations. Specifically, it shows that younger households possess a higher proportion of human capital in their total assets, accompanied by greater variability. As individuals approach retirement age, the proportion of human capital in their asset portfolio tends to decrease, eventually approaching zero.

Effect by human capital share level. Building on this result, I partition the sample into five intervals of the human-capital share and re-estimate the full specification in equation



(a) Life-cycle Human capital share



(b) Life-cycle variance of labor income growth

Figure 9: The role of risk aversion and human capital share

(27) (Table 5, column 9) within each bin[12]. Skewness is captured by both the right-tail measure $L90-50$ and the left-tail measure $L50-10$. Figure 10 plots the coefficient on the interaction term $sk_{g(i,M)} \times \text{var}_{i,Y}$ for every human-capital bin.

The pattern is fully consistent with the theory. For households whose earnings constitute at most 20 percent of total wealth, opportunity risk (the right tail) raises equity holdings, whereas disaster risk (the left tail) is essentially irrelevant. Once the human-capital share reaches the 0.2-0.4 range, disaster risk starts to depress risky-asset demand. Beyond a share of 0.4, households no longer benefit from right-tail (positive) skewness and face progressively larger penalties from left-tail risk, as predicted when higher effective risk aversion dominates portfolio choice.

Effect by age. I divide the sample into three age cohorts that mirror the life-cycle pattern of wage volatility documented in Figure 9(b). Earnings risk is highest at career entry, settles to its lowest point in mid-career, and rises again as workers approach retirement. Figure 11 plots the estimated coefficients on the state-dependent skewness–variance interaction for each cohort.

[12]Bins above 0.6 are omitted from the figure: the number of observations in those cells is too small for reliable inference.

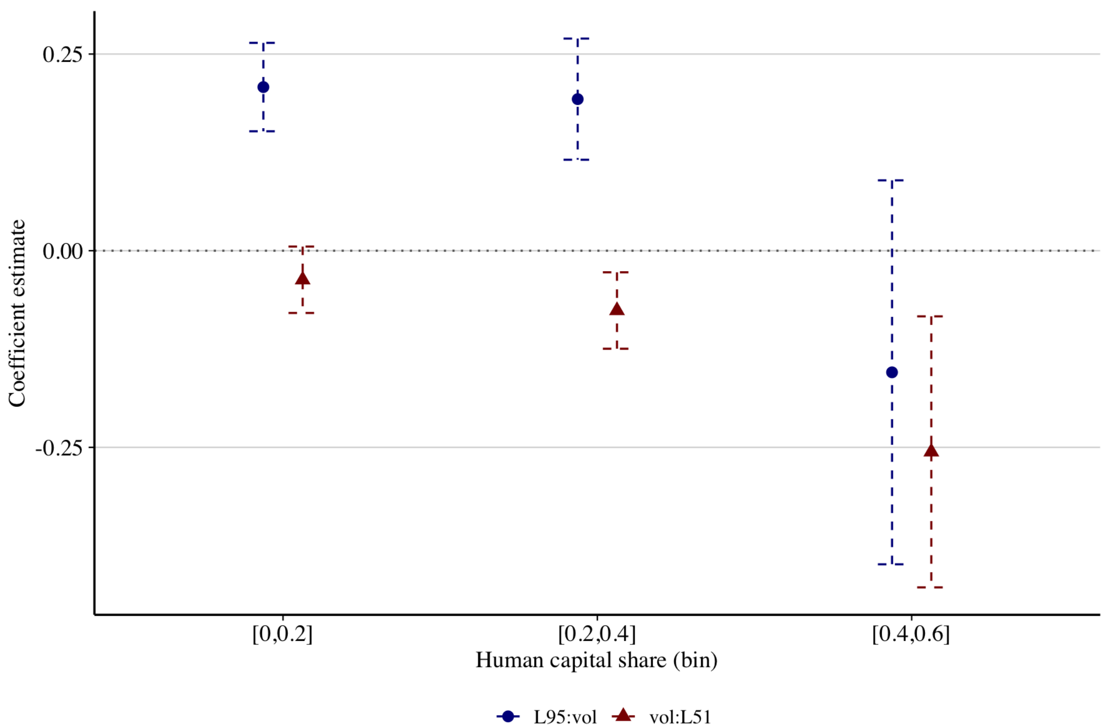


Figure 10: Effect of labor income risk by human capital share level

Notes. This figure displays the regression coefficients of the equity share on labor income risk when I run the same regressions as in column (9) of Table 5 in subsamples of workers with different levels of human capital-to-wealth ratio. Dashed lines represent 95% confidence intervals.

The estimates reveal a clear ranking of effective risk aversion. Households younger than 36 display the strongest precautionary response, those older than 54 occupy an intermediate position, and prime-age investors are the least risk-averse. The ordering is intuitive. In early adulthood, financial wealth is scant and income is dominated by human capital, so exposure to background risk sharply reduces equity demand. Near retirement, portfolios are larger, but labor income volatility rises again, pulling the coefficient toward greater caution. Prime-age households combine accumulated financial assets with the lowest earnings risk of the life cycle, and therefore tolerate the most exposure to risky assets. The findings from different age groups provide additional evidence supporting the puzzle of why younger cohorts are less likely to hold stocks than predicted by standard lifecycle models. Not only do they fail to benefit from opportunity risk, but they also suffer disproportionately from disaster risk compared to other age groups. This contributes to return heterogeneity that can widen inequality gaps–an issue I further explore in the appendix using a model.

Effect by wealth. Finally, I explore how households' overall financial resources shape their portfolio responses. I divide the sample into three net-worth tiers and re-estimate equation (27). Figure 12 reports the coefficients on the skewness-variance interactions for each wealth group.

The pattern is clear. Households in the bottom wealth tercile capture no benefit from upside (opportunity) risk and are already slightly exposed to downside (disaster) risk. As wealth increases, the opportunity risk coefficient turns positive and the sensitivity to disaster risk falls–but at a diminishing rate. The highest wealth group still gains from upside risk, yet their overall responsiveness is weaker than that of the middle tier. This is consistent with Prediction H3: greater wealth dampens the influence of labor income risk on equity demand.

These results provide additional evidence that using only volatility as the standard for labor income risk is insufficient because the effect of volatility varies with skewness levels.

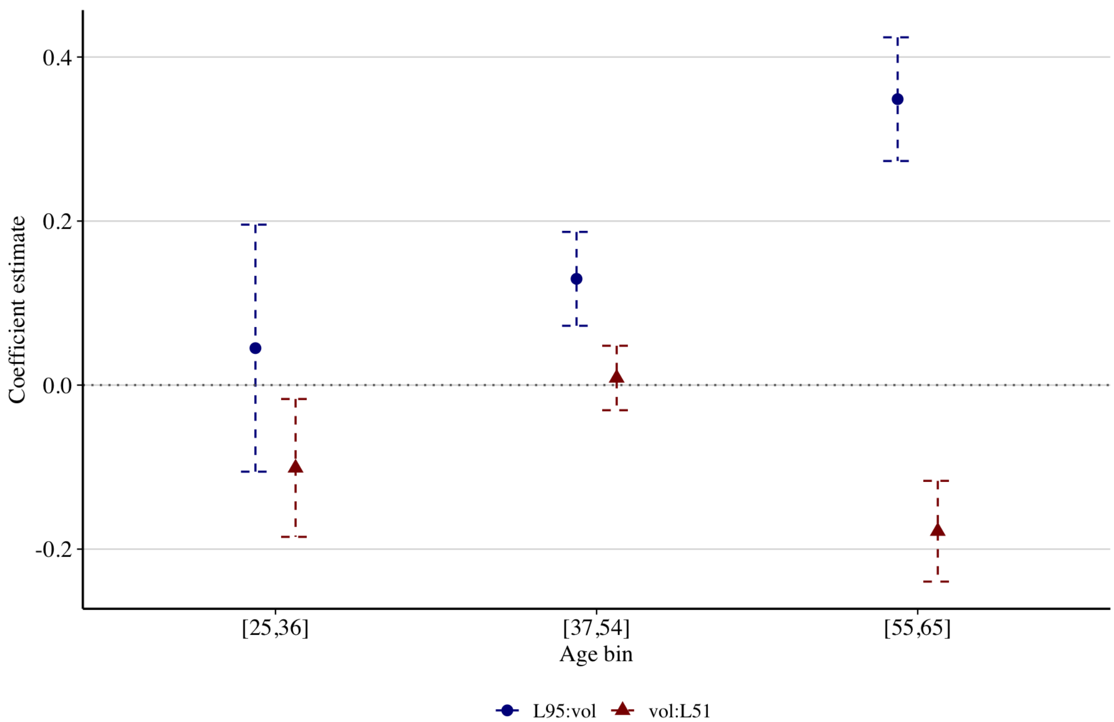
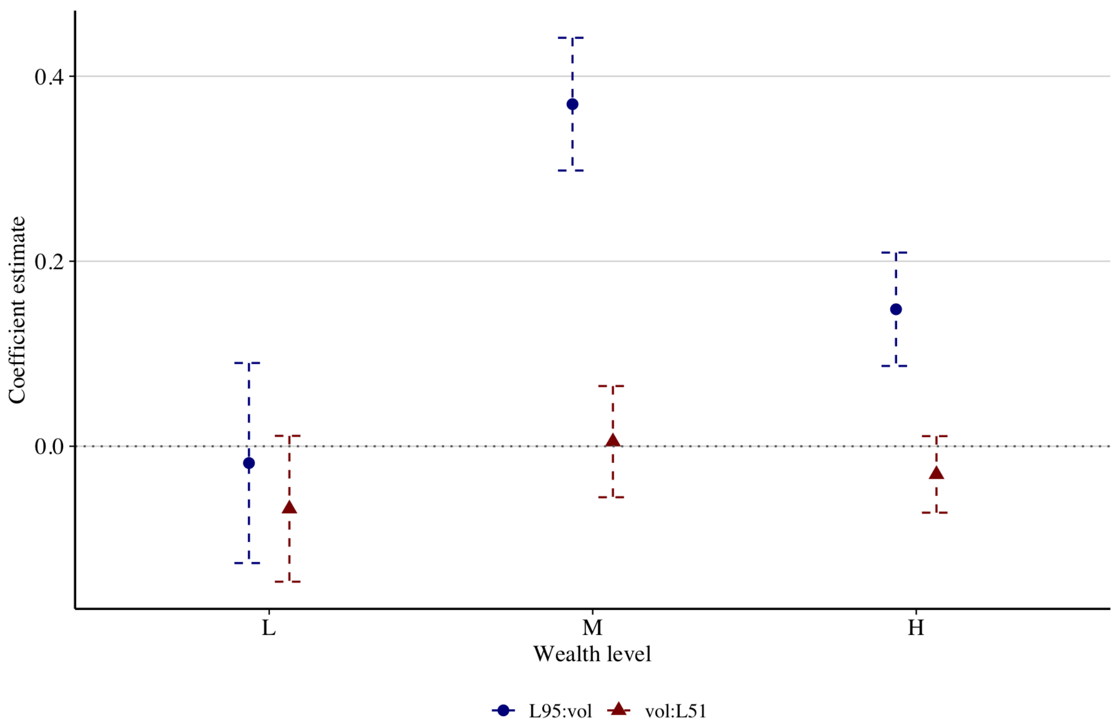


Figure 11: Effect of labor income risk by age group

Notes. This figure displays the regression coefficients of the equity share on labor income risk when I run the same regressions as in column (9) of Table 5 using different age groups of workers. Dashed lines represent 95% confidence intervals.

Figure 12: Effect of labor income risk by wealth level



Notes. This figure displays the regression coefficients of the equity share on labor income risk when I run the same regressions as in column (9) of Table 5 in subsamples of workers with different levels of total net worth. Dashed lines represent 95% confidence intervals.

4.5 Within-household level

Much of the prior empirical research has concentrated on the investment decisions of individuals. In this section, I will examine the within-household impact of labor income shocks. I refer to the primary earner in a household as the head, and the secondary earner as the spouse. I initially identify all households with two earners from the dataset, as they constitute the majority of households with multiple earners. Subsequently, I divide them into two subgroups based on whether the spouse is exposed to a lower or higher level of skewness. The spouse exposed to a lower skewness level is considered to be facing risk, while the one exposed to a higher skewness level is regarded as facing opportunity, consistent with the terminology used in earlier sections. I am interested in exploring how heads react to the labor income risks of their spouses, specifically whether they act to mitigate the risks faced by their spouse.

Figure 13 offers a revealing picture. The shaded red mass plots the distribution of head-of-household labor income skewness conditional on the spouse currently facing negative skewness–i.e., a disaster risk environment. Put differently, it traces the macro-level earnings risk borne by the head when the spouse is exposed either to downside or upside risk.

Some intra-household correlation is evident, though not pronounced. On the left tail ($x < 0$) the red density lies slightly above the blue density, indicating that when the spouse experiences disaster risk, the head is somewhat more likely to do so as well. A symmetric, though modest, pattern appears on the right tail for positive skewness (opportunity risk). Overall, spouses' labor income risks are positively but only weakly correlated within the household.

I utilize the following formula to examine the within-household impact of labor income

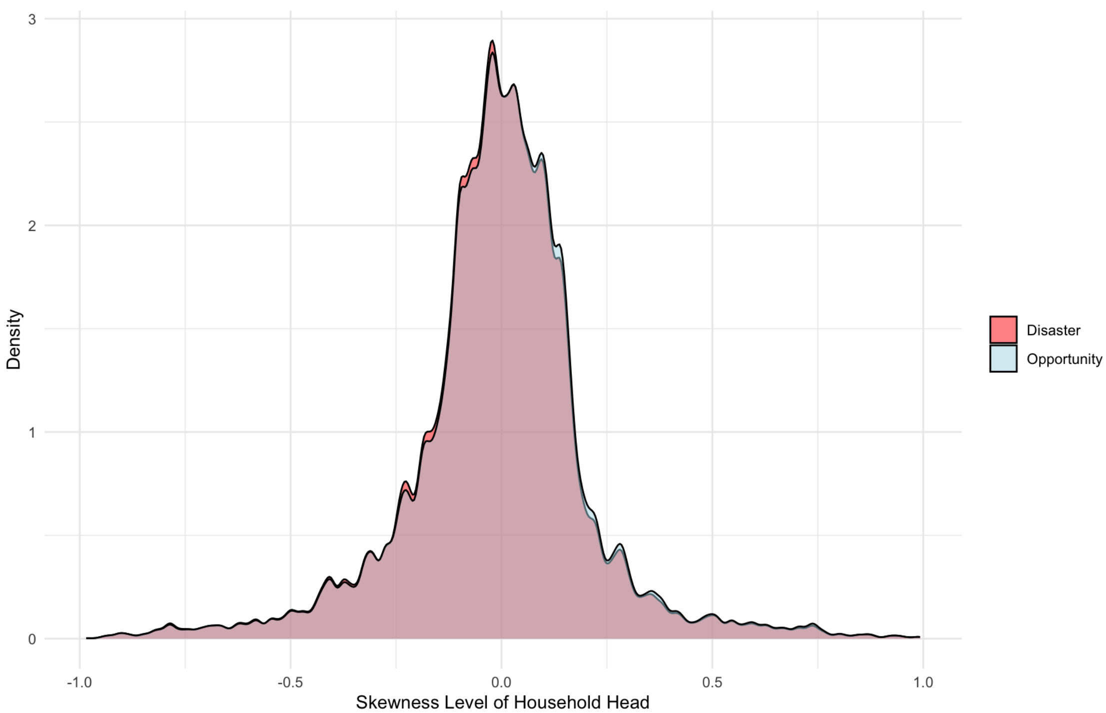


Figure 13: Labor income risks within households

Notes. This figure shows the distribution of household head skewness, conditional on whether the spouse is exposed to opportunity risk or disaster risk. The red distribution represents households where the spouse faces disaster risk, while the blue represents those with opportunity risk.

volatility, taking into account the skewness level of spouses:

$$RS_{i,M} = \alpha + \beta_1 \cdot vol_{i,Y} + \beta_2 \cdot SS_{i,M} + \beta_3 \cdot SS_{i,M} \times vol_{i,Y} + Control_{i,M} + \varepsilon_{i,M}, \tag{30}$$

where $SS_{i,M}$ denotes the skewness level of the spouse, with $SS_{i,M} = LSS_{i,M} = 1$ indicating that the spouse's skewness level is below 0, and $SS_{i,M} = RSS_{i,M} = 1$ signifying that the spouse's skewness level exceeds 0. The findings are presented in table 8.

Table 8: Regression Analysis of Household Heads' Portfolio Holdings

	% Share of Assets Directly Invested in Stocks (Head)
Disaster Risk (Spouse)	−0.884***
	(0.123)
Opportunity Risk (Spouse)	1.233***
	(0.124)
Variance (Head)	0.070***
	(0.012)
Disaster Risk (Spouse)×Variance (Head)	0.468***
	(0.059)
Opportunity Risk (Spouse)×Variance (Head)	−0.552***
	(0.059)
Observations	529,265
Adjusted R^2	0.031

Notes. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Interestingly, even when not accounting for the skewness of the head's income, if spouses exhibit a skewness level below 0, heads of households also tend to decrease their investment in risky assets. This behavior might stem from the correlation within the household regarding labor income skewness. However, this effect diminishes as the head's own labor income variance increases, suggesting a household-level strategy to smooth income fluctuations. Essentially, heads of households appear to adjust their risky asset allocations to compensate for the level of risk their spouses are unable to bear. On the flip side, when paired with a spouse whose skewness level is positive, heads of households are observed to increase their holdings in risky assets. Nevertheless, this inclination weakens as their personal labor income volatility rises, pointing to a household income smoothing mechanism. In these cases, the heads' choice to lower their investments in risky assets reflects an accommodation to their spouse's more stable labor income, effectively leveraging the spouse's greater capacity for risk tolerance.

5 Links to Previous Evidence

This section discusses how the paper's findings complement, refine, and in some cases challenge, existing evidence on the portfolio consequences of labor income risk.

5.1 Selection Bias as a Confounding Factor

A long-standing concern is that the positive correlation between earnings volatility and risky asset demand may simply reflect ex-ante sorting: individuals with greater risk tolerance choose occupations with volatile pay and, for the same reason, hold more equities. Recent studies address this by instrumenting labor income volatility. Ranish (2013), for instance, use survey-based risk preference measures, whereas d'Astous and Shore (2024) exploit quasi-random university admission cutoffs that assign students to programs with different earnings risk profiles. Both strategies recover a negative, statistically significant effect of volatility on stock-holding once the endogeneity of job choice is purged.

This paper tackles a different identification problem. Instead of instrumenting the variance of earnings shocks, I abstract from occupational choice and ask whether *higher-order* moments–specifically, skewness–shape households' appetite for market risk. Focusing on skewness offers two advantages:

(i) **Within-occupation variation.** Skewness fluctuates over time *within* industry cells because of firm-specific and macro shocks that are plausibly orthogonal to any worker's initial job choice, sharply limiting the scope for selection bias.

(ii) **Direct theoretical mapping.** Skewness enters portfolio choice models in a transparent way: downside (left-tail) risk lowers the certainty equivalent of labor income, while upside (right-tail) risk raises it. Estimating the effect of income growth *variance* ***conditioned on*** *the sign of skewness* offers a direct test of the theoretical claim that volatility's influence on equity demand hinges on the shape of the distribution. With CRRA preferences, volatility *conditioned on* negative skewness should reduce households' risky asset holdings–precisely the pattern uncovered here.

Taken together, the evidence shows that–even after accounting for potential selection into volatile jobs–*downside* labor income risk exerts an independent, economically meaningful drag on equity demand. Instrumental variables (IVs) studies and the present analysis are therefore complementary: the former illuminate *who* selects into risky occupations, whereas this paper reveals *how* the shape of labor income shocks feeds into portfolio choice once the occupation is given.

6 Conclusion

This paper provides the first direct, reduced-form evidence that non-Gaussian features of labor income risk–specifically, the interplay between skewness and variance–substantially influence household portfolio choice. Whereas earlier work has shown, within calibrated life-cycle models, that countercyclical earnings risk can reconcile macro-micro puzzles, it has not established a micro-level link between the shape of income shocks and equity demand.

Exploiting SIPP data, I construct a state-dependent risk measure by interacting each individual's wage growth volatility with the skewness of income shocks. This approach captures how households perceive their idiosyncratic uncertainty relative to the distributional tail risks faced by peers. Three key findings emerge:

1. **Opposing Tail Effects.** Conditional on the same volatility, right-skewed income

shocks encourage greater equity allocation, whereas left-skewed shocks induce households to withdraw from stocks. A variance-only metric would entirely obscure these countervailing forces.

2. **Distributional Drivers.** The upside potential from opportunity risk accrues almost entirely to high-wealth households, who benefit from right-skewed income shocks. In contrast, less wealthy households–those most vulnerable to large negative shocks–respond in exactly the opposite way.

3. **Downside Aversion and Life-Cycle Patterns.** Consistent with CRRA-derived models of downside risk aversion, households whose human capital constitutes a large share of total wealth (e.g., the young and financially constrained) are particularly penalized by left-skewed risks and therefore least likely to hold equities. This mechanism helps explain both low participation rates among the young and the hump-shaped life-cycle profile of equity holdings.

These results deliver three important implications. First, they lend micro-level validation to portfolio choice frameworks that incorporate higher-order background risk. Second, they underscore the limitations of variance-only measures when quantifying labor income uncertainty. Third, they reveal how labor income risk contributes to return heterogeneity and, over time, may widen the wealth gap between richer and poorer households.

A natural next step is to embed these reduced-form findings within a structural life-cycle model that nests skewness-variance interactions. Such an extension would permit quantitative assessment of how non-Gaussian income shocks shape long-run wealth accumulation and portfolio dynamics–and ultimately inform policy debates on retirement security and inequality.

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Appendix A. Proof

A1. Proof of Guvenen, Ozkan and Song (2014)

The original specification in Guvenen, Ozkan and Song (2014) is given by a log earnings process defined as follows:

$$y_{it} = z_{it} + \varepsilon_{it} \tag{31}$$

where y_{it} is the log earnings of individual i at time t, z_{it} is the persistent component, and $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$ is the purely transitory shock.

Step 1: Introducing the Persistent Component The persistent component z_{it} follows an AR(1) process:

$$z_{it} = \rho z_{i,t-1} + \eta_{it}, \quad \eta_{it} \sim \text{Mixture of Normals}, \tag{32}$$

where η_{it} is the persistent innovation to earnings. Guvenen, Ozkan and Song (2014) explicitly model η_{it} as a mixture of two normal distributions to capture asymmetric and non-Gaussian labor-income shocks.

Step 2: Differencing the Earnings Process Consider the year-on-year change in log earnings:

$$\Delta y_{it} = y_{it} - y_{i,t-1}. \tag{33}$$

Substitute equation (31) into (33) to obtain:

$$\Delta y_{it} = (z_{it} + \varepsilon_{it}) - (z_{i,t-1} + \varepsilon_{i,t-1}). \tag{34}$$

Step 3: Expanding the Persistent Component Using equation (32), rewrite z_{it}:

$$z_{it} = \rho z_{i,t-1} + \eta_{it}. \tag{35}$$

Substituting this into (34), we have:

$$\begin{aligned}\Delta y_{it} &= (\rho z_{i,t-1} + \eta_{it} + \varepsilon_{it}) - (z_{i,t-1} + \varepsilon_{i,t-1}) \\ &= (\rho - 1) z_{i,t-1} + \eta_{it} + \varepsilon_{it} - \varepsilon_{i,t-1}. \end{aligned} \tag{36}$$

Step 4: Steady-State Approximation and Simplification In empirical applications, it is common to approximate around a steady state or to assume the persistence parameter ρ is close to 1. Formally, assume for simplicity that:

$$\rho \approx 1. \tag{37}$$

Under this assumption, the term $(\rho - 1)z_{i,t-1}$ becomes negligible. Thus, equation (36) simplifies to:

$$\Delta y_{it} \approx \eta_{it} + \varepsilon_{it} - \varepsilon_{i,t-1}. \tag{38}$$

Step 5: Aggregation of Transitory Shocks Given that ε_{it} is purely transitory and i.i.d., the two consecutive transitory shocks ε_{it} and $\varepsilon_{i,t-1}$ combine into a single aggregate transitory shock term with variance $2\sigma_\varepsilon^2$. That is, define:

$$\tilde{\varepsilon}_{it} \equiv \varepsilon_{it} - \varepsilon_{i,t-1} \quad \Rightarrow \quad \tilde{\varepsilon}_{it} \sim N(0, 2\sigma_\varepsilon^2). \tag{39}$$

Thus:

$$\Delta y_{it} = \eta_{it} + \tilde{\varepsilon}_{it}. \tag{40}$$

Step 6: Explicit Mixture-of-Normals Structure Finally, explicitly state the mixture-of-normals structure for the persistent innovation h_{it}:

$$\eta_{it} = m_{s_{it}} + \sigma_{s_{it}} Z \quad Z \sim N(0, 1), \tag{41}$$

where s_{it} is an indicator variable denoting different labor-market regimes or states (e.g., normal vs. large shocks, expansions vs. recessions) with probability distribution:

$$s_{it} = \begin{cases} 1, & \text{with probability } \pi, \\ \\ 0, & \text{with probability } 1 - \pi. \end{cases} \tag{42}$$

Final Result: Combining equations (40) and (41), we arrive explicitly at your empirical specification:

$$\Delta y_{it} = \eta_{it} + \tilde{\varepsilon}_{it}, \quad \text{with} \quad \eta_{it} = m_{s_{it}} + \sigma_{s_{it}} Z. \tag{43}$$

Thus, I have shown step-by-step how the original process from Guvenen, Ozkan and Song (2014) translates precisely into a simplified empirical setting, clearly highlighting the assumptions required and their economic interpretation.

Q.E.D.

A2. Derivation of Campbell–Viceira (2001) Portfolio Rule

1. Setup. Let $R_s \equiv \mu + \sigma_s \varepsilon_s$ denote the gross return on the risky asset ($E[R_s] = \mu,\ Var(R_s) = \sigma_s^2$), and let the **gross return on human capital** be $R_H \equiv \mu_H + \sigma_H \varepsilon_H$ with $Cov(\varepsilon_s, \varepsilon_H) = \rho$.

The household begins period t with $W \equiv W_t$ in financial wealth and $H \equiv H_t$ in the (tradable) present value of future labor income. It allocates the **dollar amount** α ($= \pi W$) to the risky asset and $(W - \alpha)$ to the risk-free asset (R^f).

2. One-period portfolio return. Total end-of-period wealth (financial + human) is

$$W' = (W - \alpha) R^f + \alpha R_s, \qquad H' = H R_H,$$

so total **portfolio return** on “comprehensive” (financial + human) wealth $W_T \equiv W + H$ is

$$R_p \;=\; \frac{W'}{W_T} + \frac{H'}{W_T} \;=\; R^f + \frac{\alpha}{W_T}\,(R_s - R^f) + \frac{H}{W_T}\,(R_H - R^f).$$

3. Quadratic (mean–variance) objective. Using a second-order approximation to CRRA utility (Campbell–Viceira), the investor maximises

$$\max_{\alpha}\Big\{\,E[R_p] - \frac{\gamma}{2} Var(R_p)\Big\}.$$

4. Compute $E[R_p]$ and $Var(R_p)$ (conditional on current information).

$$E[R_p] = R^f + \frac{\alpha}{W_T}(\mu - R^f) + \frac{H}{W_T}(\mu_H - R^f), \tag{44}$$

$$Var(R_p) = \frac{\alpha^2}{W_T^2}\sigma_s^2 + \frac{H^2}{W_T^2}\sigma_H^2 + 2\frac{\alpha H}{W_T^2}\sigma_s\sigma_H\rho. \tag{45}$$

5. First-order condition (FOC). Differentiate the quadratic objective with respect to α:

$$0 = \frac{\partial}{\partial\alpha}\Big[E[R_p] - \frac{\gamma}{2}Var(R_p)\Big] = \frac{\mu - R^f}{W_T} - \gamma\Big(\frac{\alpha}{W_T^2}\sigma_s^2 + \frac{H}{W_T^2}\sigma_s\sigma_H\rho\Big).$$

Multiply through by W_T^2 and solve for α:

$$\alpha = \frac{\mu - R^f}{\gamma\sigma_s^2}\,W_T - \frac{H\sigma_H\rho}{\sigma_s}\;.$$

6. Express the covariance term via β_H. Define the regression (CAPM-style) beta of human-capital returns on stock returns

$$\beta_H \;\equiv\; \frac{Cov(R_H, R_s)}{Var(R_s)} \;=\; \rho\,\frac{\sigma_H}{\sigma_s}.$$

Hence $H\sigma_H\rho = \beta_H\, H\, \sigma_s^2$. Substitute back:

$$\alpha = \frac{\mu - R^f}{\gamma\sigma_s^2}\, W_T \;-\; \beta_H\, H.$$

7. Separate financial (W) and human (H) wealth. Since $W_T = W + H$,

$$\begin{aligned}\alpha &= \frac{\mu - R^f}{\gamma\sigma_s^2}\,(W + H) - \beta_H H \\ &= \frac{\mu - R^f}{\gamma\sigma_s^2}\, W \;+\; \Big(\frac{\mu - R^f}{\gamma\sigma_s^2} - \beta_H\Big) H.\end{aligned}$$

Set $R^f \equiv r$ for notational consistency. Finally, recalling $\alpha = \pi W$, we obtain

$$\boxed{\alpha = \frac{\mu - r}{\gamma\sigma_s^2}\, W \;+\; \Big(\tfrac{\mu - r}{\gamma\sigma_s^2} - \beta_H\Big)\, H}.$$

This is precisely equation (3.15) in Campbell & Viceira (2001) and (4.4) in their 2002 monograph, showing step-by-step how the portfolio demand decomposes into:

* **Myopic demand** $(\mu - r)/(\gamma\sigma_s^2) \times W$; * **Hedging (human-capital) demand** $\big[(\mu - r)/(\gamma\sigma_s^2) - \beta_H\big] \times H$.

A3. Proof of Third-order Taylor series approximation

The proof of Equation 7 step by step is as follows:

$$u(W + \tilde{y}) \approx u(W) + u'(W)\tilde{y} + \frac{u''(W)}{2}\tilde{y}^2 + \frac{u'''(W)}{6}\tilde{y}^3$$

$$E[u(W + \tilde{y})] \approx u(W) + E[u'(W)\tilde{y}] + \frac{E[u''(W)\tilde{y}^2]}{2} + \frac{E[u'''(W)\tilde{y}^3]}{6}$$

Since $E[\tilde{y}^2] = \sigma^2$ when $E[\tilde{y}] = 0$:

$$E[u(W + \tilde{y})] \approx u(W) + E[u'(W)\tilde{y}] + \frac{\sigma^2 u''(W)}{2} + \frac{E[\tilde{y}^3]u'''(W)}{6}$$

$$\theta(W) = u(W) - Eu(W + \tilde{y}) \approx -E[u'(W)\tilde{y}] - \frac{\sigma^2 u''(W)}{2} - \frac{E[\tilde{y}^3]u'''(W)}{6}$$

Under the assumption that $\tilde{y}$ is independent of $u'(W)$, we have $E[u'(W)\tilde{y}] = u'(W)E[\tilde{y}]$. For the case when $E[\tilde{y}] = 0$, Equation 7 is proven (Q.E.D.). If $\tilde{y}$ represents an unfair risk, Equation 7 can be further extended as follows:

$$\theta(W) \approx -E[\tilde{y}]u'(W) - \frac{\sigma^2 u''(W)}{2} - \frac{E[\tilde{y}^3]u'''(W)}{6}$$

Appendix B. Statistics

Definitions of Key Variables

Table 9: Definitions of key variables

Variable	**Definition**
Monthly earnings from job (TJB1_MSUM)	The dollar value of the monthly earnings from job 1, varying with the number of days in the month.
Total asset value (TVAL_AST)	The total dollar value of an individual's assets, constructed as the sum of: assets held at financial institutions (checking and savings), direct stock and mutual-fund holdings, bond holdings, value of rental properties, value of other real estate, other financial assets, retirement account balances (e.g., 401(k) and IRAs), business equity, value of primary residence, vehicle net equity, and educational savings accounts in which the person is the owner.
Total financial asset value (TVAL_FAST)	The total dollar value of an individual's assets, constructed as the sum of: assets held at financial institutions (checking and savings), direct stock and mutual-fund holdings, bond holdings, other financial assets, retirement account balances (e.g., 401(k) and IRAs), and educational savings accounts in which the person is the owner.
Risky share (RS)	The share of directly held stocks and mutual-fund investments in total financial assets.

About Cluster

- Why Cluster? To correct standard errors when errors may be correlated within clusters, violating OLS assumptions.
- Why Not Cluster? A low ICC (0.008) shows minimal intra-cluster correlation, so clustering isn't necessary and may reduce statistical power.

Table 10: One-way Analysis of Variance for *RS100*

Source	SS	df	MS	F	Prob > F
Between IND_EDU	1,303,216.6	67	19,450.994	30.76	0.0000
Within IND_EDU	164,100,000	259,417	632.40653		
Total	165,400,000	259,484	637.26558		

Number of observations	= 259,485
R-squared	= 0.0079

Table 11: Intraclass Correlation and Related Statistics

	Intraclass Correlation	Asymptotic S.E.	95% Confidence Interval
Value	0.00796	0.00231	[0.00343, 0.01249]

Estimated SD of IND_EDU effect	= 2.252772
Estimated SD within IND_EDU	= 25.14769
Estimated reliability of an IND_EDU mean	= 0.96749
(evaluated at n)	= 3708.11

Consider a case where you have 2000 individuals that are assigned to 100 clusters. When the intracluster correlation is 0, individuals within clusters are no more similar than individuals in different clusters, and it is as if you effectively assigned 2000 individuals to treatment or control. When the intracluster correlation is 1, everyone within a cluster acts the same, and so you effectively only have 100 independent observations.

The code in STATA to generate the table is **loneway RS100 IND_EDU**. In my case, since the ICC is 0.008, which is neglectable, and given that my number of culster is relatively small, using cluster error might create a bias where lead to a type I error, that is I will reject null hypothesis more than necessary.

Pre-COVID sample test

This section re-estimates the baseline specification on a pre-pandemic subsample–observations through December 2019–thereby excluding the extraordinary market conditions triggered by

COVID-19, retail-trading surges, and large fiscal transfers (see Fedyk (2022)). Table 12 confirms that the core findings are intact. While a few coefficients shift in magnitude, the full specification (column 9) continues to show that households adjust their equity exposure to the state-dependent component of labor income variance exactly as the theory predicts.

Table 12: Robustness Test for Pre-COVID Sample

	(6)	(7)	(8)	(9)
Kelly skewness	−0.014			
	[−0.40]			
L9050 (opportunity risk)		−0.322**		−0.335**
		[−2.59]		[−2.64]
L5010 (disaster risk)			−0.045	0.012
			[−0.47]	[0.13]
Variance	0.015	−0.050	0.045	−0.017
	[0.74]	[−1.57]	[1.57]	[−0.50]
Kelly × Variance	0.176*			
	[1.76]			
L9050 × Variance		0.063*		0.092***
		[2.56]		[3.43]
L5010 × Variance			−0.030	−0.055**
			[−1.68]	[−2.81]
Household controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year–month FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.025	0.028	0.028	0.028
Observations	176,384	176,384	176,384	176,384

Notes. Weighted OLS estimates. The dependent variable is the household share of directly held stocks (bounded in $[0, 100]$). Robust t-statistics are in square brackets. All specifications include the full set of household controls (log income, log wealth, age, age^2, education, gender, unemployment and housing dummies), industry fixed effects, and year–month fixed effects. ***/**/* denote significance at the 1%, 5%, and 10% levels.

Appendix C. Model

A Simple GE model

This is a very simple general equilibrium model intended to illustrate how downside risk aversion can widen the gap between the rich and the poor. It is based on the model from Auclert, Rognlie and Straub (2023), where a stock market is not included in their setting.

Consider a continuous-time model featuring N types of households, where $i = 1, \cdots, N$. These households vary in their spending and investment behaviors based on their wealth levels. Drawing from empirical evidence indicating that wealthier individuals tend to exhibit a lower marginal propensity to spend (MPC) (Fagereng et al. (2019); Straub (2019); Mian, Straub and Sufi (2020)) while simultaneously allocating a larger proportion of their wealth to risky asset markets (Favilukis (2013); Bender et al. (2022)), resulting in significantly higher total return on assets compared to poorer households. To demonstrate this, I employ the following framework: (1) $m_1 > m_2 > \cdots > m_N$, indicating that wealthier households have lower MPCs; (2) $r_1 < r_2 < \cdots < r_N$ representing an increase in asset returns with wealth; (3) Agents commence work at the age of 25 and retire at 65, and their behavior is described by a utility function over consumption.

The model is linearized around the steady state where each household type owns a certain stock of assets:

$$c_{it} = m_i a_{it} \quad s_{it} = r_i a_{it} \quad Y_t = \sum_{i=1}^{N} (c_{it} - s_{it}) \tag{46}$$

Where a_{it} represents the value of the financial asset possessed by household i at time t, c_{it} denotes consumption, s_{it} signifies the net income from investment, r_i is the return on assets (ROA) for household i. Y_t stands for the aggregate demand and income. The interpretation is straightforward: each year, households spend a portion of their assets on consumption and earn returns on the assets they own. The total output of the economy is determined by the aggregate consumption of the entire population minus the amount paid to those who invested and required returns. This output is then redistributed among the population based on their assigned labor income shares. For simplicity, consider consumption and investment occurring simultaneously, meaning there's no need to subtract the portion they consumed before obtaining returns from assets. Thus, the law of motion for the value of financial assets can be expressed as follows:

$$\dot{a}_{it} = \theta_i Y_t + s_{it} - c_{it} \tag{47}$$

Here, θ satisfies $\sum_{i=1}^{N} \theta_i = 1$, denoting the labor income shares across types. An N-dimensional linear differential equation can be derived by stacking variables into length-N vectors, as follows:

$$\dot{\mathbf{a}}_t = (-M + R + \boldsymbol{\theta}\mathbf{m}' - \boldsymbol{\theta}\mathbf{r}')\mathbf{a}_t$$

Where $M = \text{diag}(m)$ and $R = \text{diag}(r)$. In table 13, I calibrate the initial assets, labor income shares, and return on assets from SIPP. Since there is no consumption data in SIPP, I utilize the annual MPC from other studies.

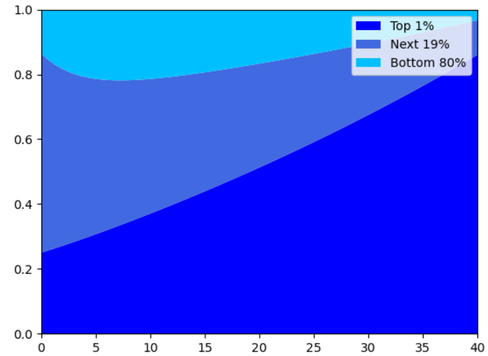
The results of simulation are shown in figure 14 and 15. During the early years, roughly from 25 to around 30, the bottom 80% group gains more shares due to the continued significance of human capital. However, after 40, the share of the top 1% rises sharply. This trend is a result of the compounding effect of the lower MPC and the higher return on assets. As the top 1% consume a smaller proportion of their wealth and invest more, the value of their financial assets grows increasingly faster as their wealth accumulates. By the time of retirement, the asset shares of the top 1% have risen from 25% to around 80%, while the sum of the next 99% of the population shares roughly 20% of the assets in the economy.

Furthermore, these figures illustrate the distinction between partial equilibrium and general equilibrium. In the partial equilibrium case, it demonstrates the scenario where output is made exogenous ($\theta = 0$), representing the absence of income feedback. As shown in the figure 15, in the partial equilibrium scenario, the aggregate return on investment initially decreases, then gradually increases after age 35. However, in the general equilibrium case, which better fits the real-life scenario, the return on investment consistently grows from the outset because households accumulate wealth as they age. Regarding aggregate consumption, the general equilibrium case better mirrors reality: it initially increases during early ages and then gradually decreases as people age.

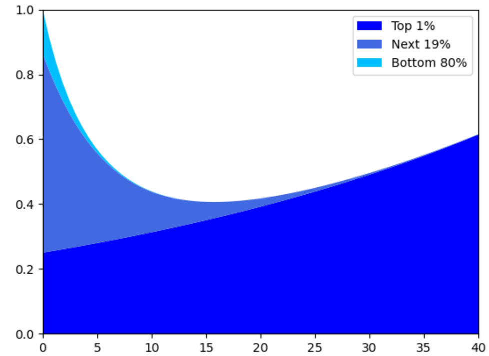
To present a counterfactual scenario, Figure 16 displays the case where all types of households have the same return on assets ($r = 0.1$). It is evident that under these circumstances, inequality is less pronounced compared to the previous case, and at aggregate level, consumption path over the life cycle will also be smoother. This simple model emphasizes the impact of return heterogeneity in addition to the existing heterogeneity in MPC when addressing wealth inequality. If the bottom 80% of households can fully utilize their financial assets and achieve a similar return on assets as wealthier groups, despite having a higher MPC, this group of people can still be better off in terms of financial wealth when they reach retirement.

Table 13: Basic Calibration

	Asset Value Percentile			
	80%	20%	1%	Source
Initial Assets (Age 25)	0.136	0.614	0.250	SIPP
Labor Income Shares	0.63	0.34	0.03	SIPP
MPC	0.4	0.2	0.1	Baseline
Return on Assets	0.015	0.062	0.12	SIPP

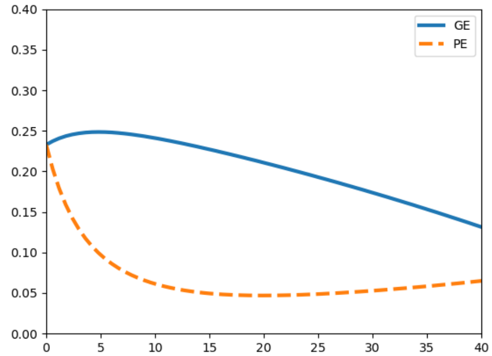


(a) General equilibrium

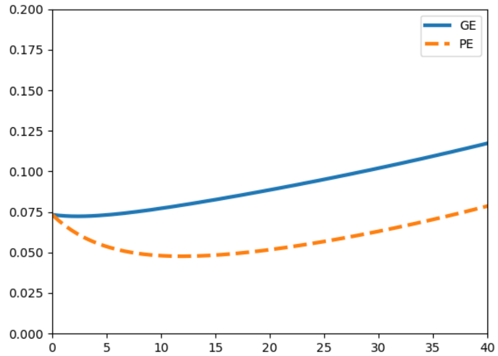


(b) Partial equilibrium

Figure 14: Life cycle evolution

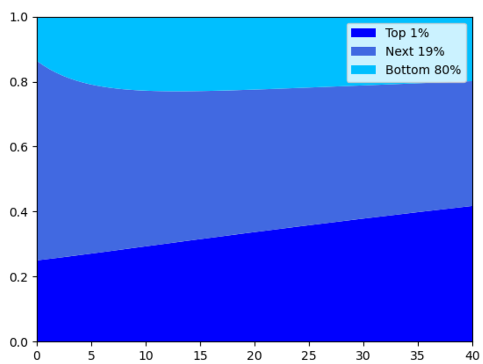


(a) Consumption

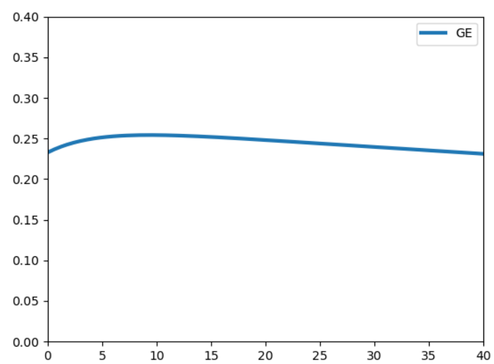


(b) Return on investment

Figure 15: Aggregate evolution



(a) Life cycle evolution



(b) Consumption

Figure 16: Counterfactual case