Countercyclical Income Risk and Portfolio Choices: Evidence from Sweden

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Abstract

Using Swedish administrative panel data, we show that workers facing higher left-tail income risk when equity markets perform poorly are less likely to participate in the stock market and, conditional on participation, have lower equity shares. We call this measure of income risk "cyclical skewness" and show that it is a better predictor of equity holdings than other income risk measures such as variance, covariance, and countercyclical volatility. In line with theory, our findings are stronger at the beginning of the life-cycle, are not significant for individuals with substantial financial wealth, and are stronger when we focus on permanent income shocks. Finally, within their risky portfolio, workers put less weight on securities generating negative returns when their own income risk increases.

Keywords: Household finance, Labor income risk, Portfolio choices

JEL codes:

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1 Introduction

How does human capital risk affect households' portfolio choices? Standard portfolio choice models suggest that human capital increases the optimal demand for equity because labor income shocks and stock returns are mostly uncorrelated (Viceira, 2001; Cocco et al., 2005). This prediction is at odds with the apparent reluctance of young workers to invest in stocks and, more generally, makes it more difficult to explain the equity premium. On the other hand, models that allow the variance (Storesletten et al., 2004; Lynch and Tan, 2011) or skewness (Catherine, 2019) of labor income risk to vary over the business cycle explain the cross-section of equity holdings better. Furthermore, several recent studies argue that countercyclical labor income shocks also matters to explain the level, volatility and cross-section of asset prices (Constantinides and Ghosh, 2017; Schmidt, 2016; Ai and Bhandari, 2018). Nonetheless, to the best of our knowledge, there is no direct evidence that households facing higher countercyclical income risk invest less in equity markets.

In this paper, we use administrative Swedish panel data to fill this gap in the literature. First, we measure the level of countercyclical variance and cyclical skewness of income shocks for different groups of workers conditional on their education and industry of employment. Then, we show that workers facing higher cyclical skewness are less likely to participate in the stock market and, conditional on participation, have lower equity shares. Quantitatively, a one-standard-deviation increase in cyclical skewness is associated with a 2 to 6 percentage point decline in equity shares. This effect is largely driven by the decision not to participate in the stock market. Furthermore, in line with theoretical predictions, the effect of cyclical skewness smoothly vanishes when workers get closer to retirement, which shows its importance to explain the evolution of equity holdings over the life-cycle. The effect of cyclical skewness also declines with financial wealth and is not statistically significant for households in the three wealthiest deciles. This last finding suggests that countercyclical income risk alone is unlikely to explain asset pricing puzzles.

Our methodology works as follows. In a first step, we restrict our sample to male workers between 25 and 55 years old and sort them by industry of employment and level of education. For each of these 309 groups, and each year from 1984 to 2012, we compute the cross-sectional mean, variance, and skewness of unexpected changes in non-financial disposable income. Then, we regress the time-series of these three moments on stock market returns. The resulting coefficients of these regressions give us measures of covariance, countercyclical variance and cyclical skewness for each group. These measures indicate the extent to which each group can hedge against changes in the distribution of shocks by short-selling the stock market.

In a second step, we attribute these measures of risk to workers based on their current group. Then, we regress the share financial wealth invested in equity on these measures of risk. Whether we look at participation, conditional or unconditional equity shares, we find that cyclical skewness is the only statistically significant predictor of equity holdings in univariate regressions. Including traditional controls do not change our findings, though the effect of cyclical skewness becomes somewhat smaller when we control for education.

Endogeneity issues are likely to bias our results because workers are not randomly assigned to different industries or education levels. For example, we expect workers with higher risk aversion to have lower equity share and make safer career choices. Moreover, education may reduce exposure to labor market risk and at the same time correlate with financial literacy. Overall, the endogeneity of labor income risk is difficult to address but studies that mitigate this problem conclude that endogeneity biases estimates *downward* (Betermier et al. (2012), Fagereng et al. (2018)). Nevertheless, we try to address endogeneity concerns in several ways.

First, we find that most traditional control variables do not change our point estimate. One exception is education, which when included as a control, reduces the effect of cyclical skewness by a third. However, this would be expected if education provides some protection against left-tail income risk. In particular, education increases the re-employment rates of unemployed workers (Riddell and Song (2011)) and therefore contains information about persistence that our measure of skewness overlooks.

More importantly, we test whether the interpretation of our findings is consistent with restrictions imposed by portfolio choice models. The first restriction is that the effect of labor income risk should decline with age, reflecting the lower importance of human capital relative to financial wealth for older workers. We find that the effect of cyclical skewness declines smoothly over the life-cycle and becomes statistically insignificant after 60 years old. We also find that the effect of education on the equity share is twice as large among young workers as among those close to retirement, which is consistent with education acting partially through the income risk channel. These findings are valid both at the intensive and extensive margins.

The second restriction is that the effect of cyclical skewness should be negligible among workers with substantial financial wealth. The economic intuition is that households who are less dependent on future wages do not need to cut consumption drastically when they receive large labor income shocks. And indeed, we find that the effect of cyclical skewness declines with financial wealth and is statistically insignificant in the top three deciles. Because the top three deciles hold 88% of the nation's financial wealth, these results suggest that cyclical skewness can only have limited consequences for asset prices, which is consistent with Catherine (2019) but not Constantinides and Ghosh (2017) nor Schmidt (2016).

The third restriction is that moments of the distribution of permanent income shocks should have larger effects on portfolio. This prediction directly follows from the greater impact of permanent income shocks on the present value of human capital. Following Kopczuk et al. (2010) and Bonaparte et al. (2014), we built an empirical proxy for permanent income by taking the average of log disposable income in years $t-1$, t and $t+1$, with the goal of smoothing away transitory variations. We then replicate our analysis by constructing moments of the unexpected changes in this measure of permanent income. Our new point estimate for the effect of cyclical skewness on equity share rises from -.23 to -3.29. However, when interpreting this larger coefficient, one must keep in mind that permanent shocks only represent a fifth of the total variance of income shocks.

Finally, we study whether workers put more or less weight on securities that deliver negative returns when their group receive negative aggregate shocks to their non financial income, face larger variance or higher left skewness. Consistent with Massa and Simonov (2006), we find that households tilt their portfolios towards stocks that are more correlated with their income but also find that they avoid securities that deliver lower returns on their labor market tail risk worsens. This piece of evidence shows that, despite their familiarity bias, workers have asset picking ability and can tilt their portfolio away from the market portfolio to hedge against the most salient income risk.

Related literature Our goal is to bridge a gap between two branches of the portfolio choice literature. The first strand of papers tries to rationalize the cross-section of equity holdings using calibrated extensions of Merton (1969)'s and Samuelson (1969)'s life-cycle models. Overall, this literature suggests that human capital can only reduce optimal equity shares when earnings and stock market returns are not independently distributed. In particular, labor income risk reduces optimal equity shares when earnings correlate with returns (Viceira (2001), Cocco et al. (2005), Benzoni et al. (2007)), or when lower returns predict higher wage volatility (Storesletten et al. (2004), Lynch and Tan (2011)) or higher left tail income risk (Catherine (2019)).

We seek to connect this literature to a second strand of empirical papers measuring labor income risk and using it to predict equity holdings. Several of these papers largely focus on variance (Betermier et al. (2012), Fagereng et al. (2018)) and most of the studies looking at covariance find no evidence of hedging (Vissing-Jorgensen (2002), Massa and Simonov (2006), Calvet and Sodini (2014)). One notable exception is Bonaparte et al. (2014)'s study which documents that workers with low income-return correlations are more likely to participate in the stock market and have higher equity shares. These authors estimate the covariance between income shocks and returns for each individual. When we follow this strategy, we also find that covariance reduces equity holdings but we show that this relationship is entirely driven by shocks that preceded the portfolio choice. When covariance is computed on the basis of *future* shocks (including the 2008 financial crisis), its ability to predict equity holdings vanishes. This result raises endogeneity concerns because past income shocks can affect portfolio decisions through other mechanisms than hedging, a problem to which our methodology is immune.

Our paper also relates to recent studies arguing that cyclical skewness in labor income risk can explain the equity premium (Constantinides and Ghosh (2017), Schmidt (2016) and Ai and Bhandari (2018)). Our findings suggest that cyclical skewness is unlikely to have large asset pricing implications as the magnitude of our results is much smaller for households close to retirement and in the highest deciles of financial wealth, which is consistent with Fagereng et al. (2018). On the other hand, our finding that workers are less likely to hold securities that generate negative returns when their income risk is more negatively skewed is consistent with Constantinides and Ghosh (2017)'s finding that cyclical skewness explains the cross section of excess returns.

The rest paper proceeds as follows: Section 2 provides a theoretical discussion to guide our empirical analysis. Section 3 describes. Section 4 discusses our empirical measures for labor income risk. Section 5 presents our main findings regarding the effect of income risk on portfolios. Section 6 provides robustness checks and Section 7 concludes.

2 Theoretical discussion

2.1 Income process

We assume that the log disposable income y of worker i is the sum of three components: a deterministic component (f), a permanent (z) and a transitory (ξ) component. Specifically, we assume that:

$$y_{it} = f(a_{it}, g_{it}) + z_{it} + \xi_{it}, \tag{1}$$

where ξ are transitory shocks that fully mean-revert within a year. The deterministic component f is a function of the agent's age a and group g. We think of these groups as workers with similar skills and same industry of employment. The permanent component follows a random walk with innovation η:

$$z_{it} = z_{it-1} + \eta_{it}. \tag{2}$$

We do not assume any parametric distribution for ξ or η. However, we assume that, in any given year, workers of the same group draw ξ or η from the same distributions. We denote ε_{it} the unexpected shock to workers' log disposable income:

$$\varepsilon_{it} = \eta_{it} + \xi_{it}. \tag{3}$$

2.2 Moments of the income shock distribution

We focus our analysis on the first three moments of the distribution of income shocks. For each year and group of workers, we define the mean, variance and skewness of income shocks as:

$$\text{Mean}(\varepsilon)_{gt} = \frac{1}{N_{gt}} \sum_{i \in g} \varepsilon_{it} \tag{4}$$

$$\text{Var}(\varepsilon)_{gt} = \frac{1}{N_{gt}} \sum_{i \in g} \varepsilon_{it}^2 \tag{5}$$

$$\text{Skew}(\varepsilon)_{gt} = \frac{1}{N_{gt}} \sum_{i \in g} \varepsilon_{it}^3 \tag{6}$$

where N_{gt} is the number of workers in group g in year t. We do not center the second and third moments because, from the worker's point of view, it does not matter if a large shock affects the entire group or only himself. Moreover, for the sake of clarity, we do not standardize the third moment. Indeed, standardized skewness is not a meaningful measure of risk: a large negative standardized skewness is not worrisome if variance is small.

In the data, these moments may covary with stock market returns. To capture these correlations, we construct three additional measures: covariance, countercyclical variance and cyclical skewness risks. We defined these moments as follows:

$$\text{Covariance risk}(\varepsilon)_g = \frac{\text{cov}(\text{Mean}(\varepsilon)_g, r_s)}{\text{Var}(r_s)} \tag{7}$$

$$\text{Countercyclical Variance risk}(\varepsilon)_g = -\frac{\text{cov}(\text{Var}(\varepsilon)_g, r_s)}{\text{Var}(r_s)} \tag{8}$$

$$\text{Cyclical Skewness risk}(\varepsilon)_g = \frac{\text{cov}(\text{Skew}(\varepsilon)_g, r_s)}{\text{Var}(r_s)} \tag{9}$$

where r_s denotes stock market log returns. The covariance risk captures the correlation between stock returns and income shocks. Variance is countercyclical if it increases when the stock market underperforms. Finally, skewness is cyclical if left-tail income risk is higher when stock market returns are low.

2.3 Relation to portfolio choices

Viceira (2001) provides a useful formula to understand how these moments should affect portfolio choices. Specfically, this formula tells us that the optimal share of wealth (W) invested in the stock market portfolio is:

$$\pi = \frac{\mu - r}{\gamma\sigma_s^2} + \left(\frac{\mu - r}{\gamma\sigma_s^2} - \beta_{HC}\right)\frac{HC}{W} \tag{10}$$

$$\beta_{HC} = \frac{\text{Cov}(r_{\text{HC}}, r_s)}{\text{Var}(r_s)} \tag{11}$$

where HC the certainty equivalent of future earnings, r_{HC} human capital returns, β_{HC} the market beta of human capital, γ relative risk aversion, $\mu - r$ the equity premium, and σ_s^2 the variance of stock market returns. The first term of equation (10) is the optimal equity share in Merton (1969)'s portfolio problem in the absence of human capital. The second term tells us that human capital increases the equity share if its market beta is greater than Merton's solution. Intuitively, workers can offset the exposure of their human capital to the stock market by adjusting the share of stocks in their financial portfolio. From this formula, we derive four predictions to guide our empirical analysis.

Prediction 1: Higher covariance, countercyclical variance and cyclical skewness risks reduce equity shares. Indeed a negative shock to earnings, an increase in the variance of income shocks or a decrease in its skewness all reduce the certainty equivalent of human capital: they imply negative human capital returns ($\frac{\partial HC}{\partial \text{Var}} < 0$ and $\frac{\partial HC}{\partial \text{Skew}} > 0$). Hence, Higher covariance, countercyclical variance and cyclical skewness risks increase the covariance between human capital and stock market returns, increasing β_{HC}. Hence, our three measures of cyclicality should unambiguously be associated with lower equity shares.

Prediction 2: The effect of unconditional variance and skewness depends on relative risk aversion and the beta of human capital. Neither variance nor skewness directly enters equation (10). However, they affect the human capital-to-financial wealth ratio ($\frac{HC}{W}$). Indeed, higher unconditional variance reduces the certainty equivalent of future earnings. Hence, if $\frac{\mu-r}{\gamma\sigma_s^2} > \beta_{HC}$, higher variance should be associated with a lower equity share because it reduces the weight of "bond-like" human capital in the worker's overall portfolio. On the other hand, if $\frac{\mu-r}{\gamma\sigma_s^2} < \beta_{HC}$, workers facing greater variance would have higher equity shares because variance reduces the weight of "stock-like" human capital in their overall portfolio. Similarly, because unconditional skewness increases the value of human capital, higher skewness increases the optimal equity share if human capital is "bond-like" ($\frac{\mu-r}{\gamma\sigma_s^2} > \beta_{HC}$). Overall, we do not have unambiguous predictions regarding the effects of unconditional variance and skewness on equity shares. Cocco et al. (2005) provide an example in which human capital has a market beta of zero and in which higher idiosyncratic volatility reduces the optimal equity share. By contrast, in Benzoni et al. (2007)'s model, because cointegration between the stock and labor markets implies a larger beta for human capital, the optimal equity share increases with idiosyncratic volatility.

Prediction 3: The portfolio effects of covariance, countercyclical variance and cyclical skewness risks should decline with age and financial wealth. This directly follows from the fact that $\frac{HC}{W}$ declines over the life-cycle and with financial wealth.

Prediction 4: The portfolio effects of all income risk measures should be greater for permanent income shocks than for transitory shocks. This prediction comes from the fact that the effect of a shock to earnings on the certainty equivalent of human capital is more important if this shock affect all future earnings.

3 Data

3.1 Swedish Wealth and Income Registry

The Swedish Wealth and Income Registry is an administrative panel of Swedish households. Swedish households pay taxes on both income and wealth. For this reason, the national Statistics Central Bureau (SCB) has a parliamentary mandate to collect highly detailed information on every resident in the country.[1] Sweden has 9 million inhabitants. For each of them, we observe disaggregated wealth, such as equity holdings, fund holdings, savings, debt and real estate holdings at the level of each security or property. The disaggregate wealth panel is available from 1999 to 2007 whereas the disaggregate income panel starts in 1983.

Individual-level information is observed annually as a snapshot at the end of the year and can be grouped into three categories: demographic characteristics, income, and disaggregated wealth. Demographic information includes age, gender, marital status, nationality, birthplace, place of residence and education level. For labor income, the database reports gross labor income, business sector, unemployment benefits and pensions. The disaggregated wealth data contains the assets owned worldwide by each resident on December 31 of each year, including bank accounts[2], mutual

[1]See, for instance, Calvet and Sodini (2007), Calvet et al. (2009a), Calvet et al. (2009b), Calvet and Sodini (2014), and Betermier et al. (2017).

[2]The information on bank accounts is only available if the interest during the year exceeded 100 kroner. Missing bank account data can distort the estimate of the share held by a household in risky assets but does not affect our estimates of a portfolio's standardized skewness, which only depends on the composition of the risky portfolio. We follow methods developed in Calvet and Sodini (2007) to impute bank account balances. Details can be found in Calvet and Sodini (2007)'s appendix.

funds, and holdings of stocks, bonds, and derivatives. The database also records contributions made during the year to private pension savings as well as the outstanding debt at year's end and interest paid during that year.

This comprehensive dataset offers significant advantages for our study. The main advantage is to observe labor income trajectories for millions of workers over a couple of decades, which allows us to compute the cross-sectional skewness of income shocks for many sub-groups of the population. The size of our dataset is a critical advantage because higher moments can be highly sensitive to outliers. Similar datasets such as the US Social Security Master Earning File exist in other countries but, in general, do not include important demographic variable such as education and are restricted to wage income. Our ability to observe government transfers allow us to take into account the social safety net when measuring income tail risk. More importantly, other administrative panel data such as the MEF are not matched with portfolio data. The Swedish portfolio data is also significantly better than surveys used in other studies. For example, the US Survey of Consumer Finances does not provide detailed holdings on each asset and many empty answers are imputed from observed ones. Compared to the SCF data, the Swedish data covers accurate individual asset holdings, such as stocks and funds.

3.2 Portfolios and returns

Returns The risk-free rate is represented by the monthly average yield on the one-month Swedish Treasury bill. We use the All Country World Index (henceforth 'world index') compiled by Morgan Stanley Capital International (MSCI) in US dollars as our proxy for the stock market portfolio. As Sweden is a small and open economy, many funds specialize in investing in the global market. The local market index is closely correlated with the global one.

Portfolios We focus on holdings of cash and risky assets, excluding defined contribution pension accounts. Cash consists of bank account balances and Swedish money market funds. The risky portfolio contains risky financial assets that are directly held stocks and risky mutual funds.[3]

[3]Swedish investors rarely hold bonds and derivatives. They hold bonds through balanced funds that are part of the risky portfolio considered in the study. Direct holdings on these two assets categories are small enough to be left out of the analysis.

Within the financial portfolio, the average participant has a risky share of 40%, owns 4 different mutual funds, and directly invests in 2 or 3 firms. These estimates are similar to the average number of stocks in U.S. household portfolios (Barber and Odean 2000, Blume and Friend 1975). The vast majority of risky asset participants (90%) hold mutual funds, while 60% of them own stocks directly. For every individual, the complete portfolio consists of the risky portfolio and cash. The risky share is the weight of the risky portfolio in the complete portfolio. Market participants have strictly positive risky shares. Financial wealth is defined as the sum of cash, stocks, funds, bonds, derivatives, capital insurance, and other financial wealth. All values are expressed in Swedish Kronor.

3.3 Summary Statistics on Households

Table 1 reports summary statistics on all households (first two columns) and risky asset market participants (last two columns) at the end of 2003. The market participants are not different from non-participants in terms of age, sex and family size. Participants have slightly higher education level compared to non-participants and are relatively wealthier.

[Table 1]

4 Measuring income risk

In this section, we study the empirical properties of the distribution of income shocks conditional on workers' highest education achievement and industry of employment.

4.1 Sub-sample

To estimate labor income risk, we further restrict our data in several ways. First, we exclude students, retirees, and individuals for which the sector of employment is unavailable. We remove observations for which annual disposable income is below 1,000 kronas and, following Guvenen et al. (2014), only keep male workers between 25 and 55 years old. The goal of these restrictions is to filter out income changes that could reflect voluntarily life choices, such as maternity leaves or voluntary part-time employment.

4.2 Education-industry groups

We assume that workers with the same level of education and industry of employment face the same labor income shock process. Hence, we sort our sample by groups of workers sharing the same level of education and working in the same industry. Specifically, we use 71 industry codes and categorize individuals based on five levels of academic achievements: high school dropouts, high school, college (Bachelor) and graduate studies (Master, Doctorate). Because measuring higher moments in small samples is challenging, we ignore groups in years for which we have less than 100 observations. We end up with 309 groups. We allow workers to move from one group to another, which mostly happens when they switch employment.

4.3 Time series of cross-sectional moments

In a second step, we compute the mean, variance, and skewness of log disposable income growth rates for each year from 1984 to 2012 and each group of workers. Disposable income is the sum of all non-financial sources of income (including social transfers). We deflate this variable using the CPI index of 2009.

Specifically, we assume that workers correctly predicts the evolution of their log disposable income conditional on their group and their age. Therefore, We start by regressing yearly changes in log disposable income on a series of age dummies. We estimate an OLS regression for each of our 309 industry×education groups, which allows us to capture heterogeneity in life-cycle profiles of earnings across groups. Specifically, we estimate:

$$y_{it} - y_{it-1} = \dot{f}(a_{it-1}, g_{it-1}) + \hat{\varepsilon}_{it} \tag{12}$$

where $\dot{f}(a, g)$ are group×age fixed-effects which capture expected growth rate of earnings conditional on age and group. We use the residuals of these regressions $\hat{\varepsilon}_{it}$ as our empirical measure of ε_{it}: the unexpected change in log disposable income.

Finally, for each year and each industry-education group, we compute the mean, variance, and skewness of the distribution of observed shocks $\hat{\varepsilon}_{it}$ using equations (4) to (6). Overall, our methodology largely follows Guvenen et al. (2014) with two differences. First, we compute cross-sectional moments within industry and educational groups whereas these authors pool all prime age male workers. Second, we use disposable income rather than labor income, which is a better measure of what households can use for consumption. When we compute these moments using pre-tax earnings, we find skewness to vary over the business cycle like in the United States. However, magnitudes are smaller for disposable income because of redistribution, unemployment insurance and progressive taxation.

4.4 Cyclicality of moments

In a third step, we estimate the cyclicality of each moment by regressing its time-series on contemporaneous and lagged yearly stock market returns. Specifically, for each moment and group of workers g, we estimate:

$$\text{Moment}_{gt} = \beta_{1,g} \times \text{Market Return}_t + \beta_{2,g} \times \text{Market Return}_{t-1} + u_{gt} \tag{13}$$

.

We define the cyclicality of each moment as $\beta_{1,g} + \beta_{2,g}$. We call Covariance the cyclicality of the first moment, Countercyclical variance the negative of the cyclicality of the second moment, and Cyclical Skewness the cyclicality of the third central moment.

Including lag returns on the left handside takes into account that the stock market may react faster to economic news than the labor market. Indeed, we find that, in contrast to the US, the labor market tends to follow trends in the world stock market with a one year lag. For example, our economy-wide measure of skewness drops from .06 in 2007 to -.08 in 2008 and -.34 in 2009. So left-tail income risk peaked one year after the stock market crash of 2008. From an economic point of view, it would make sense that asset prices react to a change in economic risk before that risk materializes. From the point of view of an investor, the fact that negative stock market returns precede higher labor income risk is sufficient to increase the covariance between stock and human capital returns. Indeed, news that affect the distribution of income shock next year immediately change the present value of human capital.

4.5 Permanent shock moments

Because we cannot observe the permanent and transitory components of earnings in the data, we build an approximate measure of log permanent income by computing the average log disposable income over a three-year window, as in Bonaparte et al. (2014) and Kopczuk et al. (2010). Specifically, we compute:

$$\hat{y}_{P,it} = \frac{y_{it-1} + y_{it} + y_{it+1}}{3}. \tag{14}$$

We then follow the methodology exposed in Sections 4.3 and 4.4 to compute our six measures of risk for the permanent component of earnings. We just use $\hat{y}_{it}^{P}$ instead of y_{it}. Assuming the income process of Section 2.1, our empirical measure of permanent income shocks is therefore:

$$\hat{\eta}_{it} = \frac{\eta_{it+1} + \eta_{it} + \eta_{it-1} + \epsilon_{it+1} - \epsilon_{it-2}}{3} \tag{15}$$

While this proxy is not ideal, it has one convenient property for our analysis. Because $\hat{\eta}_{it}$ is not correlated with ϵ_{it} or ϵ_{it-1}, we should not capture changes in the distribution of transitory shocks when we regress the moments of the distribution of $\hat{\eta}$ on stock returns and lag stock returns. Hence, our measure covariance, countercyclical variance and cyclical skewness for the permanent component of income risk should not be overly contaminated by cyclical variations in transitory income risk.

4.6 Summary statistics on income risk

In Table 2, we report report the summary statistics regarding our income shock moments and co-moments. Income shock moments include the total and idiosyncratic permanent and transitory income shock moments. Income shock co-moments include the cyclicality of income shock mean, variance and unscaled skewness.

Total income shock moments are largely driven by idiosyncratic shock moments, and group-level shock has relatively very small variation. Income shock skewness, regardless the measure, is negative for more than 90% of the group-year pairs, suggesting that income shock distributions have negative skewness for most workers, i.e. they face labor income downside risk in general. Also, a large fraction of the risk comes from transitory income shock that doesn't have persistent effect on long-run humain capital.

As total income shock moments are mainly driven by idiosyncratic part, in Panel C, D and E, we only report the co-moments of idiosyncratic income shock moments with the market returns. Coskewness tends to be negative and cokurtosis tends to be positive, which correspond to the contercyclical variance risk and cyclical skewness risk. Though, the contercyclical variance is close to zero, suggesting that the cross-sectional income shock variance is relative persistent over time, confirming Guvenen et al. (2014).

5 Results

This section presents the main regression results. We start by showing that cyclical skewness is our only measure of labor income risk that robustly predicts lower equity shares. More specifically, workers with higher cyclical skewness are less likely to participate in the stock market, and, conditional on participation, have lower equity shares. Moreover, the effect of cyclical skewness slowly decays with age and the accumulation of financial wealth.

Figure 1 offers a rapid preview of our main finding by plotting the relationship between our measure of cyclical skewness and the average equity share, participation rate and conditional equity share of each group of workers.

[Figure 1]

Clearly, there is a strong relationship between cyclical skewness and the propensity to invest in stocks and moving from highest levels of cyclicality to the lowest one is associated with nearly a 40% increase in participation and a 10% increase in the average equity share of participants.

In the rest of this section, we run regressions where the left-hand-side variable are the equity share, a stock market participation dummy or the risky share conditional on participation. The right-hand-side variables are our measures of income risk co-moments as well as year fixed effects and demographic and economic control variables.

$$\begin{aligned}\text{Risky Share}_{it} = \; & \beta_1 \cdot \text{Covariance}_{it} + \beta_2 \cdot \text{Countercyclical variance}_{it} \\ & + \beta_3 \cdot \text{Cyclical skewness}_{it} + \text{controls}_{it} + v_t + \varepsilon_{it}\end{aligned} \tag{16}$$

5.1 Unconditional equity share

Table 3 reports the results of Tobit regressions where the dependent variable is the unconditional equity share.

[Table 3]

Specifically, we start by regressing the unconditional equity share against each co-moment separately. As reported in columns (1)-(3), only cyclical skewness is significantly correlated with portfolio choices. In column (4), we include all labor income risk moments in the regression as well as controls that have been traditionally used the literature, except for education. Neither the point estimate nor the significance of cyclical skewness falls. However, adding education dummies in column (5) causes our main coefficient of interest to fall from -.37 to -.23. This result is consistent with education mitigating labor market risk, and in particular left tail risk, which is the assumption that guided our methodology in the first place. Riddell and Song (2011) find that education significantly increases re-employment rates of the unemployed. Because our measure of cyclical skewness does not take into account persistence, education dummies could contain additional information on left tail risk.

In terms of economic magnitudes, a one-standard-deviation change in cyclical skewness reduces equity shares by 2 to 6 percentage points. Strangely, when we control for cyclical skewness, the coefficient associated with covariance becomes positive and is sometimes statistically significant, which is difficult to reconcile with portfolio theory. Most papers that looked at the effect of covariance on the propensity to invest in stock do not report any significant result (Vissing-Jorgensen (2002), Massa and Simonov (2006), Calvet and Sodini (2014)). Bonaparte et al. (2014) is an exception which we discuss in section 6.2.

5.2 Participation and conditional equity share

We now distinguish the intensive and extensive margins by regressing a participation dummy and the equity share of participants on the same independent variables. As reported in Table 4, the effect of cyclical skewness on conditional equity shares is three times smaller than on the unconditional equity shares. This suggests that the results of Table 3 are mostly driven by the extensive margin. This result is not surprising if, as suggested by theory, cyclical skewness mostly reduces the optimal equity shares of workers with low financial wealth. Indeed, in the presence of a fixed participation costs, only households with significant financial wealth participate, but those do not need to hedge against cyclical skewness as much as their poorer counterparts.

[Table 4]

Table 5 reports the results of OLS regressions where the dependent variable is a participation dummy. Catherine (2019) shows that countercyclical income risk is a substitute for large fixed costs when it comes to matching low participation rates among young households with modest financial. Interestingly, variance becomes statistically significant in some specifications, though, unlike variance this significance depends on the set of control variables included in the regression.

[Table 5]

5.3 Results by age group

Life-cycle models suggest that countercyclical income risk can change the relationship between age and the equity share because its effect is more severe at the beginning of a worker's career when his human-to-financial wealth ratio is high (Lynch and Tan (2011) and Catherine (2019)). To test this prediction, we split our sample into age groups and rerun our main Tobit regression. Results are reported in Table 6.

[Table 6]

In line with theory, we find that the effect of cyclical income risk declines with age, which is consistent with labor income representing a smaller fraction of future consumption. This decline also suggests that our results are not driven by an age-invariant omitted variables. To explain our findings, an omitted variable would need to cause individuals to choose occupations with high left tail risk during the recession and safer portfolios, and more so when they are younger.

Interestingly, the relationship between education and the equity share also declines with age: the dummy coefficients for high school and post high schools are both twice smaller at retirement age than among young households. This finding is consistent with education acting at least through the labor income risk channel.

As reported in appendix Tables A.1 and A.2, we also run our analysis on participation and conditional shares and similarly find that the effect of cyclical skewness on participation and conditional equity shares are respectively three times and twice larger in the late twenties than in the earlies sixties.

5.4 Results by decile of financial wealth

Another prediction of Catherine (2019) is that the effect of countercyclical risk is small for individuals with higher financial wealth. Table 7 shows that consistent with theory, cyclical skewness has no statistically significant effect on the equity share of households in the three highest deciles of financial wealth. Besides being statistically insignificant, our point estimate is also close to zero, and 25 times lower than in the first decile.

[Table 7]

As the top three deciles concentrate 88.2% of total financial wealth, it therefore doubtful that cyclical skewness could have large implications for asset prices. Fagereng et al. (2018) find that the portfolio response to their measure of uninsurable wage risk also vanishes as financial wealth is accumulated and also argue that income risk is therefore unlikely to impact stock prices. Our findings complement theirs in the sense that their measure of income risk is orthogonal to stock market returns, which makes our measure a priori more likely to generate a hedging motive.

Just as we did for our analysis by age group, we show in appendix Tables A.4 and A.3 that these findings hold both at the intensive and extensive margins.

5.5 Permanent income shocks

Economic theory tells us that the effect of permanent income shocks should be much larger because, by contrast to transitory shocks, permanent shocks reduce earnings for many years. To test this prediction, we rerun our main analysis by running a Tobit regression in which the left-handside variable is the equity share and using our measures of risk for permanent income on the right handside. Table 8 reports our findings. We find results that are qualitatively comparable to Table 3 but the effects are of a magnitude larger quantitatively. This is expected because the effect of shock of a given size on the value of human capital is of a magnitude greater if this shock is permanent.

[Table 8]

5.6 Portfolio weights

In this section, we turn our attention to the composition of households' risky portfolios. To do so, we start by evaluating the relationship between returns on individual securities and cross-sectional moments of income shocks at the group level. Essentially, we repeat the procedure outlined in Section 4.4. For each pair of education-industry group g and security s, we regress the cross-sectional mean, variance and skewness of shocks to disposable income on asset yearly returns and lag returns using data from 1985 to 2009. This gives us a first dataset including measures of covariance, coskewness and cokurtosis for each education×industry×security triplets. Coskewness and cokurtosis corresponds to what we previously called cyclical variance and cyclical skewness when we conducted these regressions with aggregate stock market returns.

We then construct a second dataset by computing the weight of each risky security in the risky portfolio of each year and education×education group. Specifically, the weight of asset s in the risky portfolio of group g in year t is the sum of holdings of security s across all group members divided by the sum of their holdings of all risky assets. Overall, this procedure generates more than four millions education×industry×security observations from 1999 to 2007 which we merge with the first dataset.

Finally we regress group-wide portfolio weights on our measures of risk co-moments and report the results in Table 9. Specifically, we estimate the following equation

$$\text{Weight}_{sgt} = \beta_1 \cdot \text{Covariance}_{sg} + \beta_2 \cdot \text{Coskewness}_{sg} + \beta_3 \cdot \text{Cokurtosis}_{sg} + u_s + v_t + \varepsilon_{sgt} \qquad (17)$$

where u_s and v_t are security and year fixed effect. We cluster standard errors by group.

[Table 9]

In univariate regressions, all co-moments are associated with statistically significant coefficients but the covariance has a positive sign, which violates standard portfolio theory. This anomaly was already documented in Swedish data (Massa and Simonov (2006)) and is probably explained by familiarity bias, that is the tendency of households to invest in their own country or their own industry. On the other hand, household put less weight on securities with negative returns when they face higher variance or higher left skewness in their income risk.

The interpretation of these findings rely on the presence of security fixed effects and the fact that we measure weights within the risky share. The latter implies that the hedging behavior documented in Table 9 goes beyond our previous finding that workers facing more cyclical skewness hold less risky securities. They particularly avoid the securities whose returns predict lower labor income risk skewness. Therefore, we should expect cyclical skewness to affect the cross-section of returns, which is what Constantinides and Ghosh (2017) find in the US data.

Furthemore, the security fixed effect implies that assets are relatively less likely to be held by those workers for which they predict income risk skewness relatively more. This finding indicates the presence of risk-sharing within the economy.

6 Robustness

6.1 Collapsed regressions

As key variables, cyclical skewness, countercyclical variance, and Covariance are measured on the group level, we perform collapsed regression as a robustness test. We collapse all variables into the average at group level to obtain one cross-section of different groups. The dependent variables are group level average risky share and the rate of market participation of that group. The independent variables are three cyclical income risk, the group average across years of skewness and variance of labor income growth and control variables taking as the average of the group across years.

[Table 10]

[Table 11]

Table 10 and 11 report the collapsed regression for risky share and participation rate respectively. The cyclical skewness has a strong negative effect on both risky share and participation rate of the group, while the countercyclical variance and the Covariance have very little explanatory power. The R-square for univariate regression also shows that cyclical skewness, instead of countercyclical variance and Covariance, explains to a very large extent the average market participation in the group.

6.2 Measuring risk at the individual level

Previous papers have found statistically significant effects of volatility and covariance on the propensity to invest in risky securities. One important methodological difference between these papers and ours is the way moments of the income shock distribution are computed. Previous papers generally estimate income risk at the worker level using the entire time series of his income shocks whereas we use the cross-section of shocks within groups of workers facing similar income risk.

To verify whether this makes a difference, we replicated the former strategy using a randomly selected subsample of workers. Specifically, for each worker, we construct a time series of shocks using variations in income net of life-cycle effect and compute the variance of these shocks and their covariance with stock market returns for each individual's time series. Using this methodology, we were able to replicate the findings of former papers, in particular Bonaparte et al. (2014)'s results regarding covariance.

We conjectured that this discrepancy between the two methodologies came from the fact that income risk measures constructed using individuals' time series depends on shocks they actually experienced, by opposition to shocks that have could happened. To test this conjecture, we cut our sample into two periods: 1984 to 1999 and 2000 to 2012. We then reconstructed our measure of income risk at the individual level for each sub-period and use them to predict equity shares in 2000.

[Table 12]

As reported in table 12, variance and covariance only have negative and significant effects when they are estimated using shocks anterior to the portfolio choice. This finding is difficult to interpret but raises endogeneity concerns as the realization of income shocks could affect portfolio decisions for other reasons than hedging. In principle, workers should hedge their income risk on the basis of the distribution of future shocks only.

7 Conclusion

In this paper, we document that workers whose labor income left tail risk is predicted by stock market returns are less likely to participate in the stock market and, when they participate, invest less in risky assets. Moreover, the cyclical income growth skewness is the only source of income risk that consistently predicts lower propensity to invest in risky securities across our different specification. On the other hand, covariance and countercyclical variance are statistically insignificant in most specification, which is consistent with variance being relatively acyclical and covariance being small.

Cyclical skewness has been proposed as a solution to important puzzles regarding the cross-section of portfolio choices and the overall level and volatility of asset prices. With regards to the former, we find that the effect of cyclical skewness to be much stronger for younger workers and therefore contribute to the life-cycle profile of the equity share. Cyclical skewness also has a strong effect on workers with modest financial wealth can therefore deter them from holding any equity. By contrast, our findings suggest that countercyclical risk has no effect on the equity share of wealthy investors, and is therefore unlikely to explain the overall level of asset prices, or generate a large equity premium.

Finally, we found evidence that workers tild their risky portfolios away from securities that generate low returns when their own labor income risk increases, which is consistent with cyclical skewness explaining the cross-section of returns (Constantinides and Ghosh (2017)) and suggests a form of efficient risk-sharing within the economy.

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8 Tables and figures

Figure 1: Cyclical skewness and equity holdings

This figure reports the relationship between our measure of skewness cyclicality estimated for each education×industry group and the average equity share of these groups (left panel), their participation rate (center) and the average equity share of participants (right). Circles reflect group size and red lines represent OLS regressions weighted by group size. Cyclical skewness is winsorized (trimmed) at the bottom and top 1%.

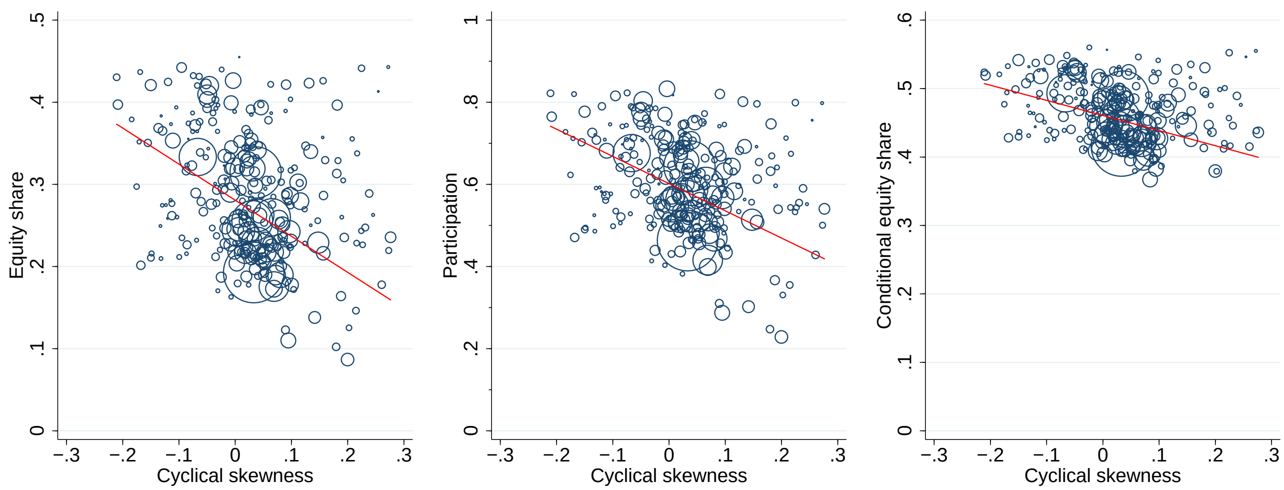

Table 1: Summary Statistics

This table reports the main income, financial and demographic characteristics of all Swedish population (colum 1 and 2) and market participants (colum 3 and 4) at the end of 2003. Financial wealth consists of cash, direct stock holding, fund holding, bond holding, derivatives, capital insurance and other financial wealth. Total wealth consists the sum of financial wealth and real estate wealth. Income is inflation adjusted, using CPI index of 2009.

	All		Participants	
	Mean	Std Deviation	Mean	Std Deviation
Income				
Non-real estate, non financial income ($)	27,470	13,520	29,798	14,719
Entrepreneur (%)	9.36%		11%	
Financial characteristics				
Financial wealth (kr)	22,182	76,082	34,836	97,818
Real estate wealth (kr)	79,118	162,060	102,495	192,547
Total wealth (kr)	101,571	207,617	137,776	252,394
Debt (kr)	41,644	120,955	46,375	145,574
Demographic characteristics				
Age	44.17	11.05	45.32	11.12
Sex	.52	.50	.53	.5
High school dummy	.84	.37	.87	.34
Post-high school dummy	.38	.48	.44	.5
Immigration dummy	.14	.34	.08	.27
Family size	2.59	1.41	2.56	1.35
Observations	3,840,468	3,840,468	2,169,152	2,169,152

Table 2: Summary Statistics: Income Shock Moments

This table reports summary statistics regarding our income shock moments and co-moments. Panel A reports the average historical undemeaned and demeaned standard deviation of our empirical proxy for permanent and unexpected income shocks. Panel B reports the third moment (non standardized skewness) of these shocks. Income shock moments are computed on the group-year level. Panel C reports the relationship between income shocks and stock market returns, obtained by regressing the time series of mean yearly income shocks on stock returns and lag returns for each group following equation (13). Similarly we use equation (13) to estimate the relationship between the variance of income shocks and stock returns (Panel D) and between the skewness of income shocks and stock returns (Panel E).

	mean	sd	p10	p25	p50	p75	p90
Panel A: Income shock volatility							
Total perm. income shock vol	12.62%	3.54%	8.24%	10.10%	12.39%	15.02%	17.35%
Idiosyncratic perm. income shock vol	12.41%	3.58%	8.03%	9.77%	12.14%	14.82%	17.20%
Panel B: Income shock skewness							
Total perm. income shock skewness	-0.0029	0.0031	-0.0056	-0.0040	-0.0022	-0.0012	-0.0006
Idiosyncratic perm. Income shock skewness	-0.0033	0.0029	-0.0060	-0.0042	-0.0027	-0.0016	-0.0010
Panel C: Covariance risk							
Idiosyncratic total shock mean	-0.0066	0.0292	-0.0374	-0.0263	-0.0097	0.0067	0.0246
Idiosyncratic perm. shock mean	-0.0129	0.0201	-0.0349	-0.0257	-0.0150	-0.0036	0.0053
Panel D: Countercyclical variance							
Idiosyncratic total shock variance	-0.0175	0.0311	-0.0533	-0.0314	-0.0128	-0.0018	0.0091
Idiosyncratic perm. shock variance	-0.0008	0.0048	-0.0043	-0.0024	-0.0010	0.0006	0.0032
Panel E: Cyclical skewness							
Idiosyncratic total shock skewness	0.0274	0.0790	-0.0351	-0.0027	0.0242	0.0578	0.0800
Idiosyncratic perm. shock skewness	0.0022	0.0057	-0.0012	0.0005	0.0022	0.0045	0.0067

Table 3: Effect of income risk on equity share

This table reports tobit regressions of the unconditional risky share on labor income risk measures and worker characteristics. Control variables include age, sex, an entrepreneurship dummy, log disposable income, household size, log real-estate wealth and log debt. t-stat clustered by industry×education groups are reported in parenthesis.

	(1)	(2)	(3)	(4)	(5)
Cyclical skewness	-0.414***			-0.245***	-0.163***
	(-4.19)			(-3.18)	(-3.49)
Contercyclical variance		-0.015		0.036	0.116
		(-0.05)		(0.19)	(0.99)
Covariance			-0.439	-0.278	0.303*
			(-0.98)	(-0.86)	(1.66)
Skewness				-1.785***	-0.667**
				(-4.75)	(-2.33)
Variance				0.233*	0.041
				(1.74)	(0.55)
High School					0.080***
					(6.94)
Post High School					0.116***
					(7.83)
Controls				Yes	Yes
Education dummies					Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	34,461,450	34,461,450	34,461,450	20,362,629	20,362,629
Pseudo R^2	0.006	0.004	0.004	0.059	0.071

Table 4: Effect of income risk on equity share among participants

This table reports OLS regressions of the risky share on labor income risk measures and worker characteristics conditional on participating in financial market. Control variables include age, sex, an entrepreneurship dummy, log disposable income, household size, log real-estate wealth and log debt. t-stat clustered by industry×education groups are reported in parenthesis.

	(1)	(2)	(3)	(4)	(5)
Cyclical skewness	-0.096***			-0.075**	-0.036*
	(-3.12)			(-2.12)	(-1.75)
Contercyclical variance		-0.005		-0.021	0.025
		(-0.06)		(-0.27)	(0.51)
Covariance			-0.098	-0.199	0.068
			(-0.72)	(-1.32)	(0.95)
Skewness				-0.756***	-0.229**
				(-4.89)	(-2.12)
Variance				0.169**	0.074
				(2.18)	(1.58)
High School					0.039***
					(6.80)
Post High School					0.058***
					(10.73)
Controls				Yes	Yes
Education dummies					Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	19,836,593	19,836,593	19,836,593	12,937,710	12,937,710
Adjusted R^2	0.025	0.024	0.024	0.049	0.059

Table 5: Effect of income risk on participation

This table reports OLS regressions of the participation dummy on labor income risk measures and worker characteristics. Control variables include age, sex, an entrepreneurship dummy, log disposable income, household size, log real-estate wealth and log debt. t-stat clustered by industry×education groups are reported in parenthesis.

	(1)	(2)	(3)	(4)	(5)
Cyclical skewness	-0.368***			-0.225***	-0.162***
	(-4.35)			(-3.58)	(-3.96)
Contercyclical variance		-0.011		0.056	0.112
		(-0.04)		(0.36)	(1.09)
Covariance			-0.390	-0.153	0.301*
			(-1.01)	(-0.59)	(1.87)
Skewness				-1.454***	-0.594**
				(-4.65)	(-2.37)
Variance				0.140	-0.005
				(1.30)	(-0.07)
High School					0.062***
					(5.54)
Post High School					0.088***
					(6.65)
Controls				Yes	Yes
Education dummies					Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	34,461,450	34,461,450	34,461,450	20,362,629	20,362,629
Adjusted R^2	0.005	0.002	0.002	0.068	0.078

Table 6: Effect of income risk on equity share by age

This table reports tobit regressions of the risky share on labor income risk measures and worker characteristics for different age groups. Control variables include age, sex, an entrepreneurship dummy, log disposable income, household size, log real-estate wealth and log debt. t-stat clustered by industry×education groups are reported in parenthesis.

	Age							
	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64
Cyclical skewness	-0.212***	-0.229***	-0.222***	-0.201***	-0.157***	-0.091**	-0.053	-0.023
	(-3.90)	(-4.35)	(-4.28)	(-4.09)	(-3.46)	(-2.02)	(-1.07)	(-0.57)
Contercyclical variance	0.187	0.190	0.205	0.167	0.109	0.111	0.093	0.073
	(1.39)	(1.35)	(1.51)	(1.33)	(0.91)	(0.95)	(0.82)	(0.80)
Covariance	0.175	0.348*	0.401**	0.385**	0.356**	0.201	0.045	-0.144
	(0.81)	(1.73)	(2.08)	(2.17)	(2.06)	(1.11)	(0.23)	(-0.83)
Skewness	-0.905***	-0.841**	-0.811**	-0.647**	-0.550**	-0.524*	-0.514*	-0.344
	(-2.71)	(-2.51)	(-2.46)	(-2.25)	(-1.99)	(-1.77)	(-1.74)	(-1.52)
Variance	0.047	0.069	0.051	0.053	-0.002	-0.006	0.012	0.069
	(0.46)	(0.71)	(0.56)	(0.66)	(-0.03)	(-0.08)	(0.16)	(1.03)
High School	0.157***	0.143***	0.122***	0.096***	0.080***	0.071***	0.069***	0.071***
	(13.32)	(10.60)	(9.13)	(6.93)	(5.69)	(5.31)	(5.50)	(7.07)
Post High School	0.165***	0.155***	0.138***	0.118***	0.100***	0.080***	0.071***	0.072***
	(13.26)	(10.84)	(9.10)	(7.57)	(6.45)	(5.20)	(4.94)	(5.94)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,327,055	2,394,720	2,989,865	3,020,059	2,921,758	2,925,158	2,716,469	1,819,019
Pseudo R^2	0.060	0.060	0.063	0.066	0.068	0.069	0.070	0.071

Table 7: Effect of income risk on equity share by decile of financial wealth

This table reports tobit regressions of the risky share on labor income risk measures and worker characteristics on subsample sorted by financial wealth. Control variables include age, sex, an entrepreneurship dummy, log disposable income, household size, log real-estate wealth and log debt. t-stat clustered by industry×education groups are reported in parenthesis.

	Decile of Financial Wealth									
	Bottom	2	3	4	5	6	7	8	9	Top
Cyclical skewness	-0.283***	-0.202***	-0.181***	-0.103***	-0.063***	-0.045**	-0.034*	0.007	0.019	0.007
	(-3.78)	(-3.70)	(-3.94)	(-3.71)	(-3.78)	(-2.48)	(-1.82)	(0.38)	(0.96)	(0.33)
Contercycl. variance	0.282	0.261*	0.223**	0.047	0.024	0.027	0.014	0.020	0.043	0.036
	(1.35)	(1.87)	(2.09)	(0.70)	(0.55)	(0.56)	(0.30)	(0.41)	(0.83)	(0.66)
Covariance	1.134***	0.573***	0.452***	0.218***	0.160***	0.145**	0.081	-0.063	-0.112*	-0.109
	(3.98)	(3.14)	(3.32)	(2.68)	(2.77)	(2.27)	(1.24)	(-0.99)	(-1.72)	(-1.58)
Skewness	-1.022*	-0.564*	-0.452*	-0.314**	-0.236**	-0.163	-0.167	-0.058	0.035	0.009
	(-1.85)	(-1.74)	(-1.73)	(-1.96)	(-2.09)	(-1.44)	(-1.45)	(-0.54)	(0.32)	(0.07)
Variance	-0.126	-0.030	-0.030	-0.035	-0.042	-0.078**	-0.118***	-0.111**	-0.187***	-0.225***
	(-0.82)	(-0.26)	(-0.31)	(-0.61)	(-1.28)	(-2.26)	(-2.97)	(-2.39)	(-3.33)	(-3.39)
High School	0.087***	0.055***	0.066***	0.046***	0.032***	0.031***	0.036***	0.041***	0.041***	0.042***
	(5.09)	(3.76)	(5.53)	(6.18)	(6.92)	(7.54)	(7.63)	(8.06)	(6.55)	(5.08)
Post High School	0.123***	0.077***	0.069***	0.041***	0.034***	0.040***	0.043***	0.046***	0.048***	0.059***
	(7.03)	(5.70)	(7.64)	(7.41)	(8.39)	(8.56)	(8.70)	(9.79)	(9.45)	(10.07)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,261,132	1,553,748	1,608,467	2,045,714	2,318,978	2,419,540	2,414,023	2,376,628	2,278,896	2,085,503
Pseudo R^2	0.106	0.084	0.163	0.256	0.162	0.082	0.066	0.063	0.073	0.116

Table 8: Effect of permanent income risk on equity share

This table reports tobit regressions of the unconditional risky share on measures of permanent income risk and worker characteristics. Control variables include age, sex, high-school and post high school degree dummies, an entrepreneurship dummy, log disposable income, household size, log real-estate wealth and log debt. t-stat clustered by industry×education groups are reported in parenthesis.

	(1)	(2)	(3)	(4)	(5)
Cyclical skewness	-6.313***			-5.488***	-3.295***
	(-4.42)			(-4.42)	(-4.61)
Contercyclical variance		1.798		2.900*	0.725
		(0.87)		(1.75)	(0.86)
Beta			-0.314	-0.426	0.459*
			(-0.43)	(-0.81)	(1.78)
Skewness				-27.504***	-14.223***
				(-5.38)	(-4.23)
Variance				-0.237	-0.394
				(-0.26)	(-0.81)
Controls				Yes	Yes
Education dummies					Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	34,468,342	34,468,342	34,468,342	20,364,810	20,364,810
Pseudo R^2	0.007	0.004	0.004	0.061	0.072

Table 9: Effect of income risk on security weight within the risky portfolio

This table reports OLS regressions in which the dependent variable are asset weights in the risky portfolio of education×industry groups and the independent variables are the statistical relationship between an asset's returns and the mean ("covariance"), variance ("coskewness") and skewness ("cokurtosis") of income shocks of an education×industry group. One observation is a group×security pair. t-stat are reported in parenthesis.

	(1)	(2)	(3)	(4)
Cokurtosis	-.001***			-.001***
	(6.09)			(6.54)
Coskewness		-.001*		-.000
		(1.82)		(.54)
Covariance			.002***	.002**
			(3.04)	(1.96)
Asset FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,196,713	4,300,694	4,300,592	4,151,145
Adjusted R^2	.672	.664	.663	.673

Table 10: Risky Share - Group level regressions

This table reports collapsed OLS regressions of of the unconditional risky share collapsed by group on labor income risk measures and group average of worker characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)
Cyclical skewness	-.306***			-.333***	-.291***	-.033*
	(6.63)			(6.61)	(5.94)	(1.82)
Countercyclical variance		.057		-.036	-.031	-.029
		(.56)		(.35)	(.28)	(.70)
Covariance			-.161	.142	-.043	-.089
			(1.36)	(1.10)	(.32)	(1.48)
Skewness					-.998***	.025
					(5.24)	(.31)
Variance					.013	-.040
					(.17)	(.96)
Controls						Yes
Observations	306	306	306	306	306	306
Adjusted R^2	.124	-.002	.003	.123	.192	.906

Table 11: Participation - Group level regressions

This table reports collapsed OLS regressions of the participation rate of the group on labor income risk measures and group average of worker characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)
Cyclical skewness	-.466***			-.508***	-.450***	-.070**
	(6.56)			(6.55)	(5.92)	(2.49)
Countercyclical variance		.099		-.037	-.133	-.055
		(.64)		(.24)	(.77)	(.89)
Covariance			-.238	.233	.071	-.001
			(1.30)	(1.17)	(.33)	(.01)
Skewness					-1.399***	.020
					(4.74)	(.16)
Variance					-.138	-.234***
					(1.15)	(3.73)
Controls						Yes
Observations	306	306	306	306	306	306
Adjusted R^2	.121	-.002	.002	.121	.178	.907

Table 12: Effect of income risk (estimated with workers' own income path) on equity share

This table reports tobit regressions in which the dependent variable is the equity share in 2000 and the independent variables are the variance and covariance of income risk and stock market returns, estimated using the time series of his own disposable income path before or after 2000.

	(1)	(2)	(3)	(4)	(5)	(6)
Covariance (1984-1999)	-.019***		-.012**			
	(6.20)		(3.06)			
Covariance (2000-2012)		-.002	-.005			
		(.56)	(1.23)			
Variance (1984-1999)				-.047***		-.028
				(5.82)		(2.65)
Variance (2000-2012)					-.014	.024*
					(1.90)	(2.26)
Observations	43,778	45,771	29,355	43,778	45,771	29,355

APPENDIX

Table A.1: Effect of income risk on participation by age

This table reports OLS regressions of a participation dummy on labor income risk measures and worker characteristics for different age groups. t-stat clustered by industry×education groups are reported in parenthesis.

	Age							
	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64
Cyclical skewness	-.202***	-.205***	-.201***	-.182***	-.159***	-.127***	-.113***	-.070**
	(-4.17)	(-4.68)	(-4.66)	(-4.57)	(-4.27)	(-3.76)	(-3.42)	(-2.51)
Countercyclical variance	.081	.170	.238	.197	.138	.159	.166	.086
	(.68)	(1.20)	(1.52)	(1.36)	(1.01)	(1.18)	(1.39)	(.93)
Covariance	.216	.353**	.364***	.328***	.308***	.172	.073	-.014
	(1.49)	(2.55)	(2.74)	(2.73)	(2.61)	(1.40)	(.57)	(-.12)
Skewness	-.810***	-.867***	-.827***	-.727***	-.629***	-.541***	-.471***	-.367***
	(-4.66)	(-5.24)	(-5.39)	(-5.28)	(-5.16)	(-4.55)	(-3.98)	(-3.80)
Variance	-.030	-.048	-.069	-.070	-.109	-.094	-.077	-.004
	(-.41)	(-.63)	(-.87)	(-.90)	(-1.36)	(-1.17)	(-1.02)	(-.06)
High school	.128***	.119***	.103***	.081***	.064***	.054***	.051***	.052***
	(14.28)	(1.73)	(8.97)	(6.50)	(4.82)	(4.19)	(4.36)	(5.33)
Post high school	.124***	.121***	.105***	.088***	.071***	.054***	.043***	.042***
	(11.52)	(9.97)	(8.42)	(6.93)	(5.65)	(4.34)	(3.81)	(4.32)
	(12.70)	(18.61)	(23.35)	(23.28)	(25.78)	(36.28)	(38.79)	(35.11)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,308,313	2,368,943	2,952,004	2,979,424	2,879,854	2,877,314	2,657,686	1739277
Adjusted R^2	.067	.070	.073	.076	.075	.072	.069	.068

Table A.2: Effect of income risk on equity share of participants by age

This table reports OLS regressions of the risky share of participants on labor income risk measures and worker characteristics for different age groups. t-stat clustered by industry×education groups are reported in parenthesis.

	Age							
	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64
Cyclical skewness	-.080***	-.088***	-.094***	-.085***	-.077***	-.073***	-.062***	-.041**
	(4.35)	(4.75)	(4.65)	(4.04)	(4.02)	(3.82)	(3.26)	(2.36)
Countercyclical variance	-.042	-.061	-.074	-.095*	-.086*	-.030	-.021	-.047
	(.98)	(1.42)	(1.58)	(1.90)	(1.75)	(.60)	(.50)	(1.45)
Covariance	.113*	.106*	.143**	.168***	.152***	.168***	.132**	.022
	(1.84)	(1.89)	(2.56)	(3.28)	(2.92)	(2.79)	(2.01)	(.36)
Skewness	-.408***	-.419***	-.447***	-.414***	-.396***	-.379***	-.339***	-.344***
	(6.18)	(6.54)	(5.98)	(5.13)	(4.69)	(4.03)	(3.65)	(4.82)
Variance	.038	.044	.023	.021	.006	-.041	-.052	-.039
	(1.04)	(1.08)	(.53)	(.45)	(.13)	(.77)	(1.01)	(.87)
High school	.050***	.052***	.044***	.037***	.036***	.036***	.036***	.037***
	(11.58)	(9.69)	(7.31)	(5.95)	(5.92)	(6.04)	(6.39)	(7.54)
Post high school	.076***	.068***	.062***	.055***	.051***	.045***	.045***	.047***
	(18.47)	(15.82)	(13.77)	(11.58)	(1.38)	(8.86)	(8.47)	(9.06)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	740,639	1,403,829	1,769,853	1,811,650	1,820,070	1,923,472	1,883,953	1266802
Adjusted R^2	.061	.051	.054	.057	.061	.063	.060	.058

Table A.3: Effect of income risk on participation by decile of financial wealth

This table reports OLS regressions of a participation dummy on labor income risk measures and worker characteristics for different deciles of financial wealth. t-stat clustered by industry×education groups are reported in parenthesis.

	Decile of Financial Wealth									
	Bottom	2	3	4	5	6	7	8	9	Top
Cyclical skewness	-112***	-115***	-093***	-082***	-071***	-071***	-065***	-035**	-026**	-022**
	(-4.87)	(-4.12)	(-3.60)	(-3.73)	(-3.68)	(-3.59)	(-3.46)	(-2.21)	(-2.15)	(-2.38)
Counter. variance	083	141*	116*	055	057	090	068	075	074*	040
	(1.30)	(1.88)	(1.89)	(95)	(89)	(1.37)	(1.05)	(1.34)	(1.66)	(1.31)
Covariance	301***	277***	229***	160***	141**	150**	094*	035	008	002
	(4.41)	(4.07)	(3.96)	(2.87)	(2.29)	(2.40)	(1.69)	(79)	(22)	(08)
Skewness	-189***	-162**	-111*	-070	-126*	-180**	-178**	-136**	-127***	-125***
	(-2.62)	(-2.18)	(-1.66)	(-1.09)	(-1.93)	(-2.58)	(-2.57)	(-2.29)	(-2.60)	(-3.84)
Variance	-021	-050	-059	-102**	-142***	-141***	-151***	-134***	-125***	-071***
	(-57)	(-1.04)	(-1.32)	(-2.39)	(-3.16)	(-3.17)	(-3.57)	(-3.67)	(-4.14)	(-3.13)
High school	019***	021***	032***	029***	032***	027***	030***	029***	024***	018***
	(3.99)	(3.26)	(5.69)	(5.33)	(4.99)	(4.98)	(5.48)	(5.86)	(5.15)	(4.91)
Post high school	028***	028***	029***	019***	022***	032***	029***	026***	022***	016***
	(6.83)	(5.38)	(7.52)	(4.90)	(4.91)	(6.13)	(6.07)	(6.40)	(5.85)	(5.90)
	(12.10)	(5.11)	(1.05)	(8.57)	(11.89)	(1.32)	(1.61)	(5.86)	(6.05)	(8.93)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,272,971	1,525,425	1,590,998	1,977,575	2,263,421	2,351,889	2,339,393	2,289,204	2,176,017	1,972,972
Adjusted R^2	108	091	221	300	082	039	035	027	020	013

Table A.4: Effect of income risk on equity share of participants by decile of financial wealth

This table reports OLS regressions of the risky share of participants on labor income risk measures and worker characteristics for different deciles of financial wealth. t-stat clustered by industry×education groups are reported in parenthesis.

	Decile of Financial Wealth									
	Bottom	2	3	4	5	6	7	8	9	Top
Cyclical skewness	-.071***	-.091***	-.089***	-.078***	-.051***	-.022***	-.014*	.002	.007	-.014
	(3.10)	(4.54)	(4.91)	(5.03)	(4.96)	(2.84)	(1.68)	(.19)	(.54)	(.87)
Counter. variance	-.109	-.092**	-.017	-.024	-.018	-.026	-.023	.001	.023	.010
	(1.64)	(2.29)	(.51)	(.78)	(.84)	(1.44)	(1.01)	(.02)	(.56)	(.19)
Covariance	.179**	.224***	.211***	.195***	.134***	.059***	.008	-.086***	-.113***	-.118**
	(2.52)	(3.78)	(3.40)	(4.31)	(4.64)	(2.61)	(.29)	(2.65)	(2.72)	(2.12)
Skewness	-.336***	-.456***	-.372***	-.331***	-.292***	-.167***	-.143***	-.112**	-.127*	-.324***
	(3.30)	(6.26)	(5.84)	(5.37)	(6.99)	(5.25)	(3.70)	(2.11)	(1.85)	(3.76)
Variance	.060	.057	.000	.008	-.017	-.029*	-.041	-.049	-.127***	-.211***
	(.92)	(1.57)	(.01)	(.26)	(.81)	(1.73)	(1.65)	(1.41)	(2.60)	(3.76)
High school	.024***	.024***	.024***	.024***	.020***	.018***	.019***	.025***	.027***	.032***
	(2.91)	(4.74)	(6.46)	(7.97)	(8.00)	(8.13)	(6.06)	(5.11)	(3.99)	(3.47)
Post high school	.026***	.038***	.036***	.036***	.028***	.023***	.026***	.030***	.034***	.048***
	(5.70)	(11.45)	(9.01)	(1.09)	(12.99)	(14.46)	(11.90)	(11.21)	(9.47)	(9.85)
	(3.94)	(4.26)	(13.93)	(25.51)	(34.29)	(32.75)	(15.56)	(5.42)	(6.20)	(23.83)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	207,257	270,164	352,222	760,789	1,564,069	1,795,109	1,883,554	1,953,375	1,959,538	1,874,191
Adjusted R^2	.057	.229	.118	.055	.130	.114	.063	.061	.070	.095