Countercyclical Income Risk and Portfolio Choices: Evidence from Sweden

Sylvain Catherine
Wharton

Paolo Sodini
Stockholm School of Economics

Yapei Zhang*
ShanghaiTech University

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Abstract

Using Swedish administrative panel data, we document 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, the relationship between cyclical skewness and equity shares is stronger among households with high human capital-to-wealth ratio and is driven by permanent income shocks.

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JEL codes: G11, G50, D14

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How does human capital risk affect households' portfolios? Early life-cycle models suggest that human capital increases demand for equity because labor income shocks and stock returns are largely uncorrelated (Viceira, 2001; Cocco et al., 2005). This prediction is at odds with the reluctance of young workers to invest in stocks and, more generally, makes it more difficult to explain the equity premium. By contrast, models in which the variance (Storesletten et al., 2007; Lynch and Tan, 2011) or skewness (Catherine, 2019) of income shocks varies over the business cycle explain the cross-section of equity holdings better. Furthermore, recent studies argue that general equilibrium models with countercyclical income risk can explain the level, volatility and cross-section of asset prices (Constantinides and Ghosh, 2017; Schmidt, 2016; Ai and Bhandari, 2020; Ebrahimian and Wachter, 2020). Overall, quantitative models show that countercyclical income risk can play an important role in solving key empirical puzzles in finance. Even though this idea dates back to Mankiw (1986), there is, to the best of our knowledge, 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 countercyclical variance and cyclical skewness of labor income shocks by education level and industry of employment. Second, we document that workers facing higher cyclical skewness are less likely to participate in the stock market and, when they do, invest a lower share of their financial wealth in stocks. Quantitatively, a one-standard-deviation increase in cyclical skewness is associated with a 2 to 6 percentage point decline in equity shares, a 7% to 23% drop relative to the sample average. This effect is largely driven by the decision not to participate. Furthermore, in line with theory, the relationship between cyclical skewness and equity shares decreases with the share of human capital in total wealth and is driven by permanent income shocks. As its effect declines smoothly over the last 25 years before retirement, cyclical skewness changes the life-cycle profile of equity holdings. However, its effect also declines with financial wealth and converges to zero in the top three deciles of the wealth distribution. Therefore, countercyclical labor income risk is unlikely to explain asset pricing puzzles.

Our methodology is the following. In a first step, we build measures of countercyclical risk for 327 groups of male workers between 25 and 55 years old, sorted by industry of employment and level of education. For each of these groups, and each year from 1984 to 2012, we compute the cross-sectional mean, variance, and skewness of growth rates in non-financial disposable income.

Then, we regress the time-series of these three moments on stock market returns. The coefficients of these regressions measure the level of covariance, countercyclical variance and cyclical skewness risk for each group. For example, a positive relationship between returns and skewness indicates that the latter is pro-cyclical: workers face higher left-tail income risk when the stock market performs poorly. These measures indicate the extent to which workers can hedge against increases in human capital risk by short-selling the market portfolio.

In a second step, we attribute these measures of risk to workers based on their education level and current industry of employment. Then, we regress the share of their 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.

Endogeneity are likely to bias our results because workers are not randomly assigned to different industries or education levels. Workers with higher risk aversion choose occupations with lower income risk and invest less in risky securities. Overall, the endogeneity of labor income risk is difficult to address but studies that mitigate this problem conclude that it biases estimates towards zero (Betermier et al., 2012; Fagereng et al., 2018). Nevertheless, we try to address endogeneity concerns in several ways.

First, most traditional control variables do not change our point estimate. One exception is education: our results remain statistically significant when we introduce education group fixed effects but our point estimate gets smaller. One possible explanation is that endogeneity becomes more severe within education groups because risk aversion is a key determinant of the industry of employment, the only remaining source of variation in income risk. In fact, when we introduce education fixed effects, the relationship between equity shares and covariance risk even becomes positive and statistically significant. This change is difficult to explain unless workers with higher risk aversion choose occupations with lower income risk (Bonin et al., 2007; Fouarge et al., 2014) and invest less in stocks.

Second, we test whether the interpretation of our findings is consistent with restrictions imposed by portfolio choice theory. The first restriction is that the effect of income risk should increase with the weight of human capital in the agent's overall endowment. The effect of cyclical skewness should be negligible among workers whose human capital risk is diversified by other forms of wealth.

Indeed, households who are less dependent on future wages do not need to cut consumption drastically when they receive large labor income shocks. Consistent with theory, the negative relationship between cyclical skewness and equity shares increases with the human capital-to-wealth ratio, and is inexistent among workers whose human capital represents less than 20% of their total wealth.

The second restriction is that moments of the distribution of permanent income shocks should have larger effects on portfolios, which directly follows from their greater impact on future consumption. To test this prediction, we disentangle the permanent and transitory components of our risk measures and show that the relationship between cyclical skewness and equity holdings is driven by permanent shocks.

We also explore the implications of our findings for asset pricing and portfolio choice models. Because the effect of cyclical skewness declines with the human capital-to-wealth ratio, it also declines as workers get closer to retirement. Therefore, cyclical skewness helps explain why the equity share is not increasing with age as many life-cycle models predict. Regarding asset prices, we find that the relationship between cyclical skewness and equity shares decline with financial wealth, and is equal to zero in the top three deciles. As most of the financial wealth is concentrated in the top deciles, cyclical skewness is unlikely to have a strong effect on the aggregate demand for equity and asset prices.

The economic magnitude of our findings must be interpreted with caution. An important literature infers from asset prices the existence of consumption disaster risk, what Campbell (2018) refers to as "dark matter for economists." Tail risk, by nature, is hard to measure. In this paper, we measure the likelihood of income disaster shocks at the worker level based on the experience of comparable employees in past recessions and we document that this measure correlates with risk attitudes. However, as the recent pandemic illustrates, each recession is unique in the way it affects different industries and in the timing of the stock and labor markets' reactions.[1] Our measurement of countercyclical tail-risk rely on panel data from 1983 to 2012, which covers only four recessions. Unless these recessions are representative of future economic downturns –which is unlikely– our estimates may be strongly biased towards zero because of measurement error.

[1] The stock market fell by more than 30% in March 2020 but had fully recovered by the end of August. The labor market remained depressed much longer, in particular for the most affected industries.

Some studies document a negative relationship between variance or covariance and equity holdings when these moments are computed using individual income paths. This discrepancy with our findings can be explained by differences in methodologies. In our data, these moments also predict lower equity shares when they are estimated using each individual's own earnings history. However, we show that this relationship is driven by past experiences: we find no correlation between portfolios and the *future* variance or covariance of income shocks. These findings are not consistent with a rational hedging motive. Though it is plausible that workers use past shocks to assess covariance/variance risk before they decide how much to invest in stocks, the absence of relationship between future covariance/variance and current equity shares calls the efficiency of this method into question. An alternative explanation is that workers "scarred" by hard times remain pessimistic and cautious even though their past experiences do not predict future risk. These scars would increase precautionary savings (Malmendier and Shen, 2021) and reduce equity holdings.

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.[2] 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 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

[2] Krueger and Lustig (2010) show that this intuition extends to asset prices.

higher equity shares.[3] This second strand of papers is somewhat disconnected from quantitative studies: the effect of idiosyncratic variance on optimal equity shares is ambiguous[4] and covariance seems too small to have first-order effects. Hence, we contribute to this literature by studying measures of income risk that have been shown to matter in calibrated life-cycle models.

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). 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 there is no correlation between cyclical skewness and equity shares in the highest deciles of financial wealth. Importantly, our study focuses on income but many rich households hold most of their wealth in a single private business whose fate is also exposed cyclical skewness (Salgado et al., 2020).

Finally, our paper also contributes the growing literature on higher order moments of the income shock distribution (Guvenen et al., 2014, 2021). Indeed, our findings constitute evidence that workers are aware of these moments and their evolution over the business cycle because they would not adjust their portfolios otherwise.

[3] These authors estimate the covariance between income shocks and returns for each individual. When we follow this strategy, we also find that higher covariance is associated with lower equity shares but this relationship is entirely driven by *past* shocks. When covariance is computed on the basis of *future* shocks, its ability to predict equity holdings vanishes.

[4] We discuss this ambiguity in Section 1.3. We refer to Chapter 6 of Campbell and Viceira (2002) for a formal discussion. Benzoni et al. (2007) provide an example in which idiosyncratic variance *increases* the optimal equity share.

1 Theoretical framework

In this section, we introduce three measures of human capital exposure to stock market returns: covariance risk, countercyclical variance risk and cyclical skewness risk. We then discuss why workers exposed to these risks should invest less in the stock market.

1.1 Income process

For the rest of the paper, 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, log disposable income is:

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

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 the same level of education 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, which is the sum of ξ and η:

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

1.2 Moments of the income shock distribution

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, we do not standardize the third moment because 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. For example, negative stock returns might be associated with lower earnings growth for an entire group, higher volatility of individual earnings in that group, or higher left tail risk. To capture these correlations, we construct three additional measures: covariance, countercyclical variance and cyclical skewness. We defined these co-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 returns. Covariance risk captures the relationship 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 market returns are low.

1.3 Relation to portfolio choices

Campbell and Viceira (2002) provide a useful formula to discuss how these moments affect portfolio choices. Specifically, the optimal share of wealth invested in the stock market portfolio by an agent with constant relative risk aversion (CRRA) is:

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

$$\beta_H = \frac{\mathrm{Cov}(r_\mathrm{H}, r_s)}{\sigma_s^2} \tag{11}$$

where W is financial wealth, H the certainty equivalent of future earnings, $\mathrm{Cov}(r_\mathrm{H}, r_s)$ is the covariance between stock market and human capital returns, β_H the market beta of human capital, γ the coefficient of relative risk aversion, $\mu - r$ the equity premium, and σ_s^2 the variance of stock market returns.

In dollar terms, Equation (10) can be rearranged as:

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

The first term of Equation (12) is the optimal equity investment in Merton (1969)'s portfolio problem when the agent's only endowment is financial wealth. The second term represents the effect of risk-less human capital. As Merton (1971) explains: "in computing the optimal decision rules, the individual capitalizes the lifetime flow of wage income at the market (risk-free) rate of interest and then treats the capitalized value as an addition to the current stock of wealth." Essentially, the agent optimal equity holdings represents a share $\frac{\mu - r}{\gamma \sigma_s^2}$ of his total wealth $H + W$, inclusive of the present value of bond-like human capital.

If human capital is risky, two things change. First, risk reduces the certainty equivalent value of human capital H. Second, equity holdings must be adjusted to offset the share of stocks in the replicating portfolio of human capital, measured by β_H: the slope of the regression of human capital returns onto stock returns. Hence, the third term of the equation represents how many dollars of "stocks" are embedded in human capital. If a 10% return on the stock market portfolio translates into a 1% increase in the value of human capital ($\beta_H = .1$), then each dollar of human capital already incorporates ten cents of the stock market portfolio. The higher the linear relationship between human capital returns and market returns, the lower the optimal equity share.

Empirically, β_H is difficult to estimate because returns on human capital are not observable. Indeed, the return on human capital is:

$$r_{\mathrm{H},it} = \frac{H_{it+1} - H_{it} + Y_{it}}{H_{it}}, \tag{13}$$

which cannot easily be computed as H is not directly observable either. In the early literature, human capital returns are interpreted as permanent income shocks. If earnings permanently drop by x%, so does the present value of human capital. Therefore, the parameter controlling β_H is the covariance between stock market returns and income shocks (Viceira, 2001; Cocco et al., 2005), which we empirically measure using Equation (7). However, if the income process is not stationary, the market beta of human capital is not exclusively determined by this covariance. For example, increased labor income volatility (Storesletten et al., 2004; Lynch and Tan, 2011) or higher left-tail risk (Catherine, 2019) also register as negative human capital returns and therefore contribute to a greater β_H if they coincide or follow low stock market returns. Empirically, we measure these two others contributors – countercyclical variance and cyclical skewness – using Equations (8) and (9).

Theoretical predictions Based on this discussion, we derive three theoretical 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 ($\frac{\partial H}{\partial \mathrm{Var}} < 0$ and $\frac{\partial H}{\partial \mathrm{Skew}} > 0$). Hence, higher covariance, countercyclical variance and cyclical skewness risks increase the linear relationship between human capital and stock market returns β_H. Hence, our three measures of cyclicality should unambiguously be associated with lower equity shares.
- **Prediction 2: The portfolio effects of covariance, countercyclical variance and cyclical skewness risks should decline with age or the share of human capital in**

the worker's total wealth. This directly follows from the fact that, in Equation (10), the $\frac{H}{W}$ term declines over the life-cycle and with financial wealth.

- **Prediction 3: The portfolio effects of income risk should be greater for permanent than for transitory income 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. Prediction 3: 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.

On the other hand, there is no clear theoretical prediction regarding the effect of idiosyncratic variance and skewness. Neither variance nor skewness directly enters Equation (10). However, they affect the human capital-to-wealth ratio $\frac{H}{W}$. Indeed, all else equal, future income streams are less valuable if they are more volatile. But the relationship between the optimal equity share and $\frac{H}{W}$ is ambiguous. If $\frac{\mu-r}{\gamma\sigma_s^2} > \beta_H$, 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 $\frac{\mu-r}{\gamma\sigma_s^2} < \beta_H$, 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" ($\frac{\mu-r}{\gamma\sigma_s^2} > \beta_H$). 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), because cointegration between the stock and labor markets implies a larger beta for human capital, the optimal equity share increases with idiosyncratic volatility.[5]

[5]Their Figure 9 shows that a higher variance of permanent idiosyncratic shocks increases the demand for equity for workers below age 50. In their model, cointegration between the labor and stock markets makes human capital stock-like for workers who are more than a decade away from retirement. For them, $\beta_H > \frac{\mu-r}{\gamma\sigma_s^2}$, and therefore higher volatility reduces the optimal equity share by reducing H. Older workers have shorter horizons on the labor market and are not that exposed to cointegration. For them, $\beta_H < \frac{\mu-r}{\gamma\sigma_s^2}$ and a reduction of H caused by higher idiosyncratic variance reduces their equity share. As the Panel B of their Figure 5 illustrates, the correlation between stock returns and returns to human capital drops rapidly after age 50.

2 Data

2.1 Swedish Wealth and Income Registry

The Swedish Wealth and Income Registry is an administrative panel of Swedish households. Because Swedes paid taxes on wealth, the national Statistics Central Bureau (SCB) had a parliamentary mandate to collect highly detailed information on every resident's income and wealth.[6] 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 disaggregated wealth panel is available from 1999 to 2007. We also the disaggregated 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, including bank accounts[7], mutual 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 variables such as education

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

[7] 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.

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.

2.2 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.[8] 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). 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.

[8] 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.

2.3 Income risk

Our measures of countercyclical income risk are built in three steps. First, we sort workers by education$\times$industry group. Second, we compute the first three moments of the distribution of income shocks for each group and year. Third, for each group, we regress these moments on stock market returns.

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 327 groups. We allow workers to move from one group to another, which mostly happens when they switch employment.

To measure labor income risk, we further restrict our data in several ways. We exclude students, retirees, and individuals for which industry of employment is missing. 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 early retirement.

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.

We assume that workers correctly anticipate the expected growth 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 327 industry$\times$education groups, which captures the heterogeneity in life-cycle profiles of earnings across groups. Specifically, we estimate:

$$y_{it} - y_{it-1} = \dot{f}(a_{it-1}, g_{it-1}) + \hat{\varepsilon}_{it} \tag{14}$$

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)-(6). Overall, our methodology largely follows Guvenen et al. (2014)'s study of US workers 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 in ways quantitatively similar to the United States. However, magnitudes are smaller for disposable income because of redistribution, unemployment insurance and progressive taxation.

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. Denoting μ_n the n-th moment of income shock, for each group of workers g, we estimate:

$$\mu_{n,gt} = \beta_{n,1,g} \cdot r_{s,t} + \beta_{n,2,g} \cdot r_{s,t-1} + u_{n,gt}. \tag{15}$$

We define the cyclicality of the n-th moment as $\beta_{n,1,g} + \beta_{n,2,g}$. 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 moment.

We include lag returns on the left handside because stock market may react faster to economic news than the labor market. Indeed, we find that, in contrast to the US, the Swedish 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. During that recession, left-tail income risk peaked one year after the stock market crash. From an economic point of view, it makes sense that asset prices react to a change in economic risk before that risk actually materializes. From the point of view of investors, 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 the distribution of income shocks will worsen in the coming year immediately reduces the present value of human capital.

2.4 Human capital

Equation (10) tells us that the effect of countercyclical income risk depends on the relative importance of human capital relative to wealth. To test this prediction, we build a simple measure of human capital, defined as the present value of expected future earnings. We compute human capital as:

$$H_{it} = \sum_{k=0}^{T_i} s_{it} \frac{E[Y_{ik}]}{(1+r)^{k-t}} \tag{16}$$

where T_i denotes the number of years before worker i retires, which we assume to be at age 64, s_{it} is his survival probability up to year k. Survival probabilities are imputed from life tables computed by the Bureau of Statistics Sweden. Future expected earnings are determined by current earnings and age specific growth rates which we estimate by regressing log disposable income on a set of age dummies for each education group. Our definition of human capital does not include future pensions, which are not exposed to similar risk. Following Calvet et al. (2019), we discount future earnings at $r = 4.1\%$.

2.5 Summary statistics

Table 1 reports summary statistics for all workers (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. We also report summary statistics regarding our income shock moments and co-moments.

Table 1: Summary Statistics

	All		Participants	
	Mean	Std Deviation	Mean	Std Deviation
Income				
Non financial disposable income ($)	27,470	13,520	29,798	14,719
Entrepreneur (%)	9.36%		11%	
Variance	.094	.06	.095	.046
Skewness	-.009	.03	-.010	.013
Covariance	-.011	.028	-.011	.029
Countercyclical variance	.018	.025	.017	.025
Cyclical skewness	.012	.047	.010	.049
Wealth				
Financial wealth ($)	22,182	76,082	34,836	97,818
Real estate wealth ($)	79,118	162,060	102,495	192,547
Gross wealth ($)	101,571	207,617	137,776	252,394
Debt ($)	41,644	120,955	46,375	145,574
Demographic characteristics				
Age	44.17	11.05	45.32	11.12
Sex	.52	.50	.53	.50
High school dummy	.84	.37	.87	.34
Post-high school dummy	.38	.48	.44	.50
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

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.

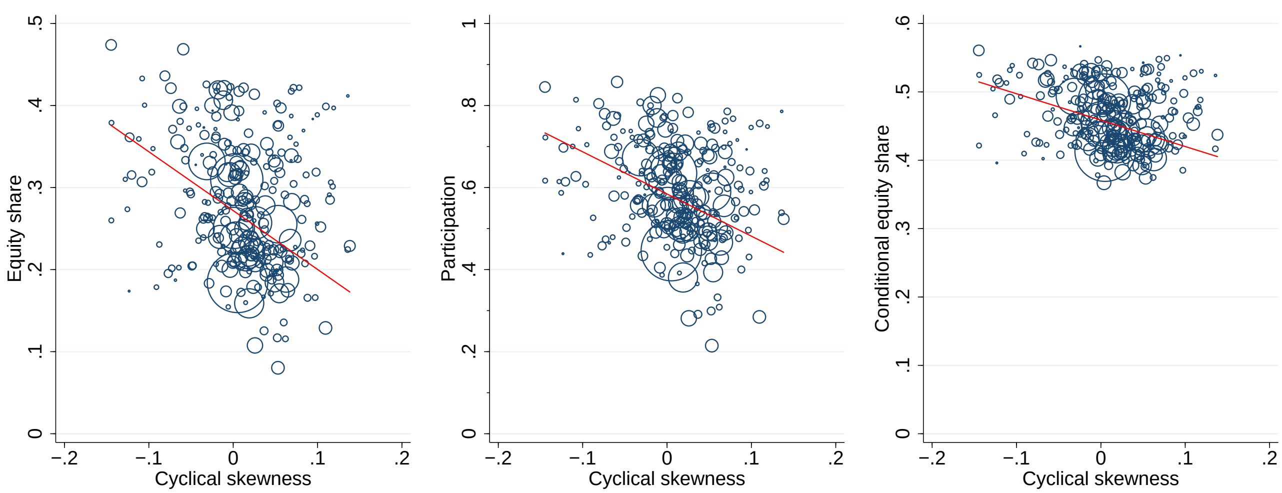
3 Main Results

This section presents our main findings. First, we show that cyclical skewness is our only measure of labor income risk that robustly predicts lower equity shares and lower stock market participation.

3.1 Graphical overview

Figure 1 offers an overview of the relationship between cyclical skewness and the propensity of each group of workers to invest in stocks, measured by its average equity share (left panel), its participation rate (center) and the average equity share of stock market participants (right). Clearly, groups of workers facing higher cyclical skewness invest less in stocks. Moving from highest levels of cyclicality to the lowest ones is associated with a 30% increase in participation and a 10% increase in the average equity share of participants.

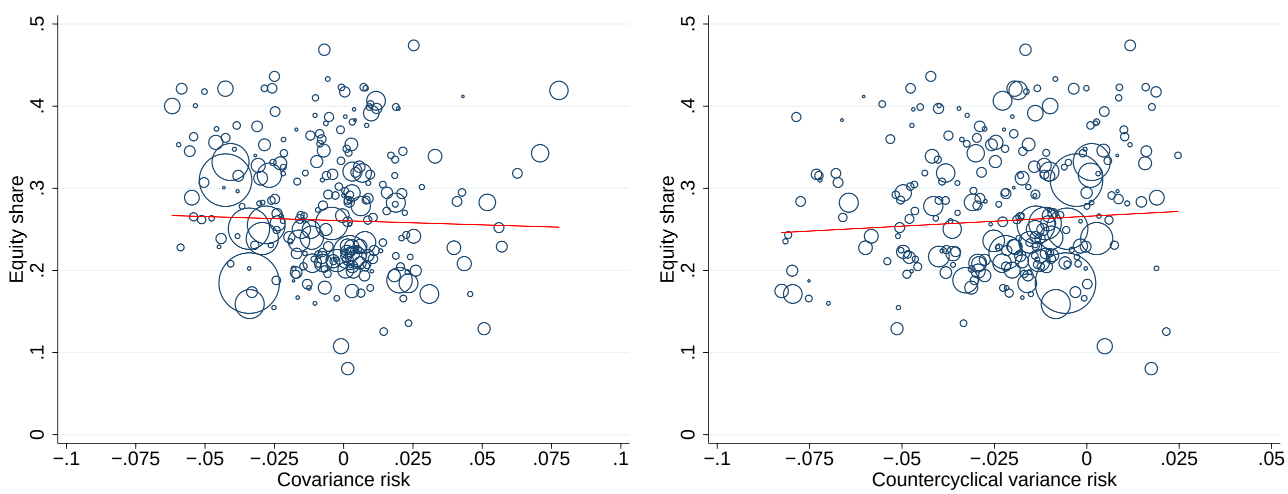
Figure 1: Cyclical skewness and equity holdings



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%.

Do we observe similar patterns for other co-moments? Figure 2 shows that our measures of covariance risk and countercyclical volatility are not correlated with equity shares. Theoretically, these moments are important for optimal portfolios but previous studies have already argued that, in the overall population, the correlation between individual income growth and stock market returns is close to zero (Cocco et al., 2005) and the variance of income shocks is not cyclical (Guvenen et al., 2014). Heterogeneity across different groups of workers does not seem to matter. After all, workers in groups with the highest covariance risk (≈ 0.075) expect their earnings to fall by only 3% when the stock market loses 40%.

Figure 2: Covariance, countercyclical variance risk and equity shares



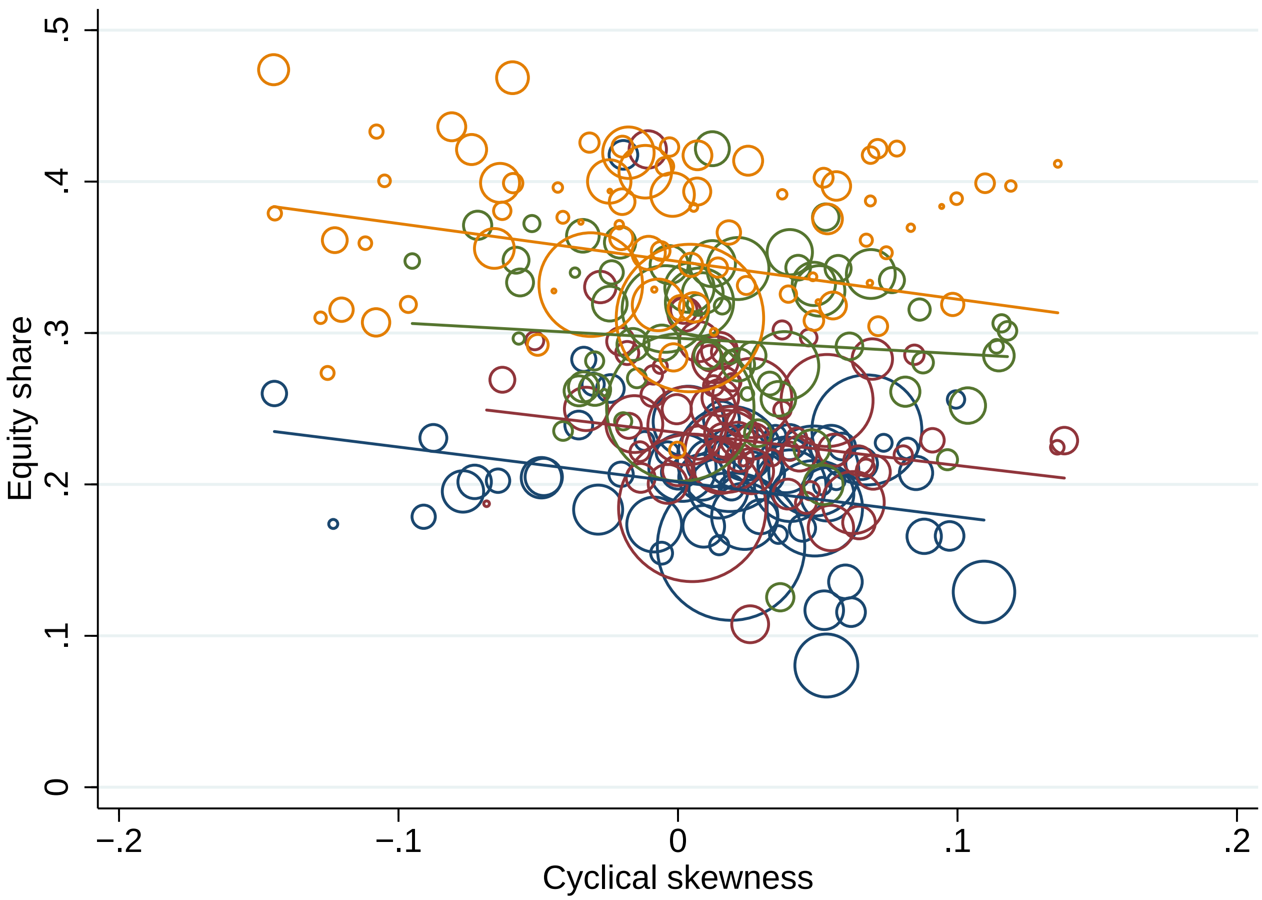
This figure reports the relationship between our measures of covariance and countercylical variance risks estimated for each education×industry group and the average equity share of these groups. Circles reflect group size and red lines represent OLS regressions weighted by group size. Covariance and countercyclical variance risk measures are winsorized (trimmed) at the bottom and top 1%.

The fact that more educated workers are less exposed to left-tail income risk during recessions and invest more in stocks accounts for an important part of the relationship between cyclical skewness and equity shares. One reason more educated workers invest more in stocks could be that they face less countercyclical income risk. However, we want to check that, of two workers with similar educational achievement, the one employed in the more cyclical industry invest less in stocks. To do so, in Figure 3, we decompose the left panel of Figure 1 into four education groups.[9] The graph shows that, for a given level of education, workers employed in industries with higher

[9]Here, because the population with doctoral degrees is fairly small, we pool workers with masters and doctorates together.

cyclical skewness invest less in the stock market, though this relationship is weak for those with Bachelor's degrees only.

Figure 3: Cyclical skewness and equity share by education group



This figure reports the relationship between our measure of cyclical skewness estimated for each education×industry group and the average equity share of these groups. Workers who did not complete high school are in blue, those who completed high school but did not receive any higher education in red, those who only completed a Bachelor's degree in green and those with at least a Master's degree in orange. 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%.

3.2 Micro-level analysis

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

$$\begin{aligned}\text{Risky Share}_{it} = \quad & b_1 \cdot \text{Covariance}_{g(it)} + b_2 \cdot \text{Countercyclical variance}_{g(it)} \\ & + b_3 \cdot \text{Cyclical skewness}_{g(it)} + \text{controls}_{it} + \upsilon_t + \varepsilon_{it}\end{aligned} \tag{17}$$

Our control variables include the average variance and unscaled skewness of income growth (see Equations (5)-(6)), age, gender, household size and dummy variables identifying entrepreneurs and immigrants. We also control for the composition of workers' overall endowment by including the value of human capital, real-estate, financial assets and debt. Following most of the life-cycle literature, we assume that workers have constant relative risk aversion and therefore scale these variables by total wealth, inclusive of human capital. Indeed, most models predict the equity share to be a function of the wealth composition of the agent in relative terms, as in Equation (10). We examine the role of financial wealth, in absolute terms, in Section 5.2.

3.2.1 Equity share

Table 2 reports the results of Tobit regressions where the dependent variable is the unconditional equity share. First, we regress the unconditional equity share against each co-moment separately. As reported in columns (1)-(3), only cyclical skewness is significantly correlated with equity shares. In column (4), we include all labor income risk moments, including unconditional variance and skewness, in the regression as well as controls, except for education. Neither the point estimate nor the significance of cyclical skewness falls substantially. However, adding education dummies in column (5) causes our main coefficient of interest to drop from -.665 to -.237.

There are several possible explanations. First, education can reduce equity shares for reasons unrelated to countercyclical income risk, such as financial literacy. In that case, it is important to control for education to obtain the right estimate of the relationship between cyclical skewness and equity shares. Second, education can increase equity shares because it reduces countercyclical income risk. In principle, this should not be a concern because we control for measures of countercyclical income risk. But these variables are measured with error. They are based on a handful of recessions. Moreover, education significantly increases re-employment rates of the unemployed

(Riddell and Song, 2011) and therefore contains information on the persistence of income shocks not embedded in our risk variables. Finally, we would expect the correlation between cyclical skewness and equity shares to be lower within education groups if workers with higher risk aversion choose industries with lower income risk (Bonin et al., 2007; Fouarge et al., 2014). This would explain why the coefficients for each of our three co-moments move in the same direction.

Table 2: Equity share and countercyclical income risk

	(1)	(2)	(3)	(4)	(5)
Cyclical skewness	-0.790***			-0.665***	-0.237***
	(-5.10)			(-4.88)	(-3.37)
Countercyclical variance		-0.532		-0.815***	-0.020
		(-1.20)		(-2.73)	(-0.11)
Covariance			-0.022	-0.375	0.510***
			(-0.04)	(-0.92)	(2.40)
Demographics				Yes	Yes
Wealth composition				Yes	Yes
Education group FE					Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	34,957,935	34,957,935	34,957,935	34,957,935	34,957,935
Pseudo R^2	0.007	0.004	0.003	0.114	0.133

This table reports the result of tobit regressions of the equity share on measures of countercyclical income risk, controlling for worker and households characteristics. Demographic controls include age, sex, household size, and dummies identifying immigrants and entrepreneurs. Wealth composition variables control for the share of human capital, financial wealth, real-estate and debt in the household's overall endowment. Education fixed effects control for the five levels of educational attainment used to sort workers into industry×education groups. T-stats are clustered by industry×education groups and reported in parenthesis.

Strangely, when we control for education, the coefficient associated with covariance even becomes positive and statistically significant, which is difficult to reconcile with portfolio theory unless risk aversion is an important determinant of the industry of employment. 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.

In terms of economic magnitudes, a one-standard-deviation change in cyclical skewness reduces equity shares by 2 to 6 percentage points.

3.2.2 Participation and conditional equity share

In a second step, we distinguish the intensive and extensive margins by regressing a participation dummy and the equity share of participants on the same explanatory variables. As reported in Panel B of Table 3, the effect of cyclical skewness on conditional equity shares is three times smaller than on the unconditional equity shares. Hence, our findings appear to be mostly driven by the extensive margin: the decision not to participate. This would be consistent with a model with fixed stock market participation costs. In theory, cyclical skewness affects disproportionately workers with low financial wealth. For these workers, the presence of a fixed cost creates a discontinuity in the optimal investment policy: when their optimal equity share falls to the point that holding stocks is not worth paying the participation cost, they choose not to participate at all. Panel A reports the results of OLS regressions where the dependent variable is a participation dummy, which confirm the existence of a strong relationship between cyclical skewness and participation.

Table 3: Participation and conditional equity shares

Panel A. Stock market participation

	(1)	(2)	(3)	(4)	(5)
Cyclical skewness	-0.663***			-0.594***	-0.239***
	(-4.87)			(-5.25)	(-3.70)
Countercyclical variance		-0.456		-0.638**	-0.029
		(-1.15)		(-2.54)	(-0.18)
Covariance			0.003	-0.237	0.480**
			(0.01)	(-0.69)	(2.38)
Demographics				Yes	Yes
Wealth composition				Yes	Yes
Education group FE					Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	34,957,935	34,957,935	34,957,935	34,957,935	34,957,935
Adjusted R^2	0.006	0.002	0.002	0.129	0.147

Panel B. Conditional equity share

	(1)	(2)	(3)	(4)	(5)
Cyclical skewness	-0.241***			-0.190***	-0.042*
	(-4.82)			(-3.58)	(-1.80)
Countercyclical variance		-0.141		-0.352***	-0.024
		(-1.07)		(-3.43)	(-0.52)
Covariance			-0.028	-0.233	0.105*
			(-0.17)	(-1.48)	(1.78)
Demographics				Yes	Yes
Wealth composition				Yes	Yes
Education group FE					Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	20,047,942	20,047,942	20,047,942	20,047,942	20,047,942
Adjusted R^2	0.026	0.024	0.024	0.087	0.098

This table reports the results of OLS regressions in which the dependent variable is a stock market participation dummy (Panel A) or the equity share of participants (Panel B) and the explanatory variables are measures of countercyclical income risk and other worker characteristics. In Panel B, the sample is restricted to stock market participants. Demographic controls include age, sex, household size, and dummies identifying immigrants and entrepreneurs. Wealth composition variables control for the share of human capital, financial wealth, real-estate and debt in total wealth. Education fixed effects control for the five levels of educational attainment used to sort workers into industry×education groups. T-statistics reported in parenthesis are clustered by industry×education group.

4 Testing theoretical restrictions

For our findings to be consistent with theory, the relationship between cyclical skewness and the equity holding must be an increasing function of the human capital-to-wealth ratio and must be driven by permanent income shocks. In this section, we show that our results are consistent with these predictions.

4.1 The role of the human capital-to-wealth ratio

Equation (10) shows that the effect of countercyclical income risk depends on the importance of human capital relative to other forms of wealth. To test this prediction, we cut our sample into five groups based on the share of human capital in an individual's total wealth. Then, we run Tobit regressions of the equity shares within each subsample. Table 4 shows that when human capital represents less than 20% of total wealth, cyclical skewness and equity share are not correlated. In fact, our point estimate is close to zero with a very small standard error. The intuition behind this finding is that if human capital represents 10% of total wealth, a -50% return on human capital translates into a -5% reduction in lifetime consumption, which hardly qualifies as a tail shock.

As we move to subsamples in which human capital represents a greater share of lifetime consumption, the relationship between cyclical skewness and the equity share becomes steeper and statistically significant. The coefficient for covariance is also significant but its sign, and its evolution with the human capital-to-wealth ratio are inconsistent with theory. Just like in Table 2, the coefficient for covariance is only significant in the presence of education fixed effects.

Table 4: **Role of the human capital-to-wealth ratio**

	Human Capital share of Total Wealth				
	< 20%	20 to 40%	40 to 60%	60 to 80%	> 80%
	(1)	(2)	(3)	(4)	(5)
Cyclical skewness	0.004	-0.081**	-0.147***	-0.202***	-0.205***
	(0.13)	(-2.09)	(-3.02)	(-3.47)	(-3.26)
Countercyclical variance	0.097	-0.012	-0.033	-0.023	0.046
	(0.95)	(-0.11)	(-0.26)	(-0.15)	(0.28)
Covariance	-0.191*	-0.050	0.083	0.327**	0.557***
	(-1.89)	(-0.38)	(0.54)	(1.98)	(2.69)
Demographics	Yes	Yes	Yes	Yes	Yes
Wealth composition	Yes	Yes	Yes	Yes	Yes
Education group FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	822,221	1,615,779	2,913,871	6,591,654	23,014,410
Pseudo R^2	0.150	0.138	0.133	0.128	0.164

This table reports the result of tobit regressions of the equity share on measures of countercyclical income risk, for different levels of the share of human capital in the households' total wealth. Demographic controls include age, sex, household size, and dummies identifying immigrants and entrepreneurs. Wealth composition variables control for the share of human capital, financial wealth, real-estate and debt in the household's overall endowment. Education fixed effects control for the five levels of educational attainment used to sort workers into industry×education groups. T-stats are clustered by industry×education groups and reported in parenthesis.

4.2 Permanent income shocks

Theoretically, the effect of cyclical skewness should be driven by permanent income shocks because they reduce earnings for many years. To test this prediction, we try to disentangle moments from the distributions of permanent and transitory income shocks. Then, we show that cyclical skewness only predicts lower equity share when measured using permanent income shocks.

4.2.1 Decomposing countercylical income risk

Because we cannot observe the permanent and transitory components of earnings in the data, we build an approximate measure of permanent disposable income. Previous studies have used rolling average of log income to build such proxy (Bonaparte et al., 2014; Krueger and Lustig, 2010) by computing the average log disposable income over a k-year window. More recently, Busch et al. (2020) also use this method to decompose cyclical skewness. In this paper, we use a 3-year window and show this proxy effectively skim away most of transitory shocks from our measures of countercyclical income risk. Our proxy for log permanent income is:

$$\hat{z}_{it} = \frac{y_{it-1} + y_{it} + y_{it+1}}{3}. \tag{18}$$

Assuming the income process of Section 1.1, our empirical measure of permanent income shocks is therefore:

$$\hat{\eta}_{it} = \hat{z}_{it} - \hat{z}_{it-1} = \frac{\eta_{it+1} + \eta_{it} + \eta_{it-1} + \epsilon_{it+1} - \epsilon_{it-2}}{3}. \tag{19}$$

If η_{it-1} to η_{it+1}, ϵ_{it-2} and ϵ_{it+1} are independently distributed, and μ_n denotes the n-th moment of a distribution, then for for $n \leq 3$:

$$\mu_n(\hat{\eta}_{it}) = \frac{\mu_n(\eta_{it+1}) + \mu_n(\eta_{it}) + \mu_n(\eta_{it-1}) + \mu_n(\epsilon_{it+1}) - \mu_n(\epsilon_{it-2})}{3^n} \tag{20}$$

As before, we assume a linear relationship between cross-sectional moments and contemporaneous and lag market returns, that is, for permanent shocks:

$$\mu_n(\eta_{it}) = \beta_{\eta,n,1} \cdot r_{s,t} + \beta_{\eta,n,2} \times \cdot r_{s,t} + u_{\eta,n,t} \tag{21}$$

and similarly for transitory shocks. Assuming that the distribution of income shocks does not depend on returns from two or more years ago, we can replace all moments in Equation (20) as linear functions of returns to obtain:

$$\mu_n(\hat{\eta}_{it}) = \frac{(\beta_{\eta,n,1} + \beta_{\eta,n,2} + \beta_{\xi,n,2}) \cdot r_{s,t} + (\beta_{\eta,n,1} + \beta_{\eta,n,2}) \cdot r_{s,t-1}}{3^n} + v_{\eta,n,t} \tag{22}$$

where $v_{\eta,n,t}$ is a random variable independent of contemporaneous and lag returns. Equation(22) shows that if we measure permanent cyclical skewness by regressing our moments of $\hat{\eta}$ on market returns and lag market returns, we need to multiply the resulting coefficients by $3^3/2$. More generally, our measure of the cyclicality of the n-th moment will be:

$$\frac{3^n}{2}\left(\beta_{\hat{\eta},n,1} + \beta_{\hat{\eta},n,2}\right) = \beta_{\eta,n,1} + \beta_{\eta,n,2} + \frac{\beta_{\xi,n,2}}{2} \tag{23}$$

This measure should capture 100% of the cyclicality of permanent shocks ($\beta_{\eta,n,1} + \beta_{\eta,n,2}$) and, relative to our previous countercylical risk measures, skims away roughly three quarters of transitory shocks. Indeed, the remaining term $\frac{\beta_{\xi,n,2}}{2}$ represents one quarter of transitory cyclical skewness ($\beta_{\xi,n,1} + \beta_{\xi,n,2}$) provided that $\beta_{\xi,n,1} \approx \beta_{\xi,n,2}$.

4.2.2 Portfolio effects of permanent countercyclical risk

Table 5: Equity share and countercyclical permanent income risk

	(1)	(2)	(3)	(4)	(5)
Cyclical skewness	-0.740***			-0.691***	-0.130
	(-5.25)			(-3.94)	(-1.63)
Countercyclical variance		-0.011		0.205	0.124
		(-0.02)		(0.38)	(0.50)
Covariance			-0.078	-0.585	0.268
			(-0.16)	(-1.19)	(1.41)
Demographics				Yes	Yes
Wealth composition				Yes	Yes
Education group FE					Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	34,961,392	34,961,392	34,961,392	34,958,722	34,958,722
Pseudo R^2	0.007	0.003	0.003	0.114	0.134

This table reports the results of Tobit regressions in which the dependent variable is the equity share and the explanatory variables are measures of countercyclical permanent income risk and other worker characteristics. Demographic controls include age, sex, household size, and dummies identifying immigrants and entrepreneurs. Wealth composition variables control for the share of human capital, financial wealth, real-estate and debt in total wealth. Education fixed effects control for the five levels of educational attainment used to sort workers into industry×education groups. T-statistics reported in parenthesis are clustered by industry×education group.

Table 5 reports our findings when we regress equity shares on measures of countercyclical permanent income risk. Se find coefficients that are quantitatively close to Table 2, which show that our main findings are driven by permanent income shocks during recessions, as theory would predict. In Column (1) and (4), our point estimates for cyclical skewness are very close to those reported in Table 2. Column (5) shows that the coefficient for cyclical skewness is no longer statistically significant in the presence of education fixed effects. However, we find this coefficient to be significant in other unreported specifications: when the dependent variable is participation, when the sample is restricted to middle-age workers, or when the sample is restricted to individuals with high human capital-to-wealth ratios.

Finally, under the assumption that permanent and transitory shocks are independently distributed, we can proxy the cyclical skewness of transitory shocks as the difference between cyclical skewness of total and permanent shocks. We find this measure to be uncorrelated with equity shares.

5 Implications for quantitative models

Countercyclical income risk has received attention in the finance literature because its introduction in quantitative models helps explain important empirical puzzles. First, life-cycle models with countercyclical income risk can generate an equity share that does not decreases with age (Storesletten et al., 2007; Lynch and Tan, 2011; Catherine, 2019). Second, asset pricing models with countercyclical risk generate a higher equity premium and greater volatility (Constantinides and Ghosh, 2017; Schmidt, 2016). In this section, we expand our empirical analysis to shed light on the predictions of these models.

5.1 Cross-section of portfolio choices

Portfolio choice models generally struggle to match three aspects of the data: (i) the low average equity share, (ii) the lack of a strong positive relationship between equity shares and the model main state variable: the human capital-to-wealth ratio and (iii) a life-cycle profile that does not rapidly decline with age. Our findings show that cyclical skewness can help models match the data along these three dimensions.

We have already documented that cyclical skewness help solve the first two issues. To see how countercyclical income risk might shape the life-cycle profile of the equity share, we run our main Tobit regression by age group. Table 6 shows that we can cut an investor's working life into two periods. Before 40 years old, the negative relationship between cyclical skewness and the equity share becomes more important with age. After 40, the relationship weakens as a consequence of the relative decline in the importance of human capital in the agent's total wealth. In unreported results, we find that the coefficient for cyclical skewness is statistically insignificant after age

63. Hence, cyclical skewness appears to make the relationship between equity holdings and age more positive (or less negative) above age 40. 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 recessions and safer portfolios, but less so as they get closer to retirement.

The evolution of the coefficient for cyclical skewness after age 40 is fully consistent with theory whereas the weak relationship at the beginning of the life-cycle could be explained by two things. First, the majority of young households do not participate in the stock market, which reduces the amount of variation on the left-hand side of our regressions. Second, young workers face less permanent left-tail risk than their colleagues (Guvenen et al., 2014), which means that our measure of cyclical skewness could overstate how much left-tail risk they face in recessions, which would bias our coefficient for cyclical skewness towards zero.

Interestingly, the relationship between education and the equity share also declines with age: the dummy coefficient for Bachelor graduates falls from 0.314 for the 25-29 age group to .135 for the 60-64 age group. This finding would be consistent with education increasing equity share because it moderates labor income risk.

Table 6: Equity share and countercyclical income risk over the life cycle

	Age							
	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64
Cyclical skewness	-0.103	-0.158**	-0.232***	-0.264***	-0.245***	-0.213***	-0.184***	-0.104**
	(-1.41)	(-2.17)	(-3.20)	(-3.59)	(-3.44)	(-3.25)	(-3.25)	(-2.33)
Countercyclical variance	-0.136	-0.073	0.052	0.019	-0.009	0.061	0.008	-0.030
	(-0.78)	(-0.36)	(0.25)	(0.09)	(-0.04)	(0.33)	(0.05)	(-0.20)
Covariance	0.404*	0.462**	0.489**	0.483**	0.420*	0.217	0.044	-0.062
	(1.91)	(2.29)	(2.15)	(2.11)	(1.83)	(0.95)	(0.22)	(-0.42)
High School	0.206***	0.186***	0.153***	0.116***	0.091***	0.075***	0.067***	0.065***
	(12.49)	(10.76)	(9.00)	(7.08)	(5.75)	(5.15)	(5.36)	(7.28)
Bachelor	0.314***	0.307***	0.274***	0.227***	0.191***	0.161***	0.139***	0.135***
	(16.82)	(15.31)	(13.61)	(12.05)	(10.95)	(9.91)	(10.78)	(15.16)
Master	0.418***	0.383***	0.332***	0.278***	0.238***	0.204***	0.179***	0.171***
	(22.57)	(19.44)	(16.62)	(14.67)	(13.84)	(14.08)	(15.28)	(19.40)
Doctorate	0.450***	0.401***	0.365***	0.321***	0.284***	0.249***	0.223***	0.215***
	(23.47)	(20.37)	(17.52)	(15.48)	(12.85)	(11.48)	(12.26)	(15.07)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wealth composition	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,518,313	4,110,335	4,488,441	4,390,917	4,244,899	4,357,830	4,228,513	2,362,406
Pseudo R^2	0.121	0.122	0.129	0.140	0.155	0.170	0.191	0.219

This table reports the result of tobit regressions of the equity share on measures of countercyclical income risk, for different age groups. Demographic controls include sex, household size, and dummies identifying immigrants and entrepreneurs. Wealth composition variables control for the share of human capital, financial wealth, real-estate and debt in the household's overall endowment. Education fixed effects control for the five levels of educational attainment used to sort workers into industry×education groups. T-stats are clustered by industry×education groups and reported in parenthesis.

5.2 Asset prices

Current models that solve asset pricing puzzles with countercyclical tail risk calibrate the consumption process directly, or indirectly by assuming a linear, calibrated, relationship between income and consumption shocks (Constantinides and Ghosh, 2017; Schmidt, 2016). On the other hand, when the consumption response is endogenous, tail labor income shocks only translate into consumption shocks for low-wealth individuals (Catherine, 2019) which means that the effect of countercyclical risk on equity shares is small for individuals with higher financial wealth.

Table 7 shows that consistent with models with endogenous consumption, 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. As the top three deciles concentrate 88% of total financial wealth, it is unlikely 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.

Importantly, high-wealth individuals are exposed to other forms tail shocks during recessions: in particular entrepreneurial risk. Salgado et al. (2020) document a high level of cyclical skewness in various business performance metrics, which may reduce wealthy owners of private businesses to invest less in publicly traded stocks.

Table 7: Equity share and countercyclical income risk by decile of financial wealth

	Decile of Financial Wealth									
	Bottom	2	3	4	5	6	7	8	9	Top
Cyclical skewness	-0.349***	-0.257***	-0.210***	-0.136***	-0.109***	-0.088***	-0.068***	-0.009	0.023	-0.002
	(-3.20)	(-4.18)	(-4.28)	(-4.35)	(-4.92)	(-3.75)	(-2.87)	(-0.36)	(0.92)	(-0.06)
Countercyclical var.	0.475*	0.121	0.035	0.003	-0.006	0.036	0.040	0.069	0.096	0.029
	(1.77)	(0.80)	(0.31)	(0.04)	(-0.10)	(0.55)	(0.55)	(0.96)	(1.42)	(0.48)
Covariance	1.032***	0.694***	0.488***	0.181**	0.129**	0.114	0.036	-0.080	-0.111	-0.072
	(3.30)	(3.70)	(3.53)	(2.11)	(2.00)	(1.49)	(0.42)	(-0.96)	(-1.39)	(-1.00)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wealth composition	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,409,059	3,437,049	3,443,205	3,500,359	3,523,650	3,527,567	3,528,276	3,529,170	3,529,821	3,529,779
Pseudo R^2	0.093	0.168	0.273	0.332	0.182	0.094	0.073	0.066	0.071	0.120

This table reports the result of tobit regressions of the equity share on measures of countercyclical income risk, by decile of financial wealth. Demographic controls include sex, household size, and dummies identifying immigrants and entrepreneurs. Wealth composition variables control for the share of human capital, financial wealth, real-estate and debt in the household's overall endowment. Education fixed effects control for the five levels of educational attainment used to sort workers into industry$\times$education groups. T-stats are clustered by industry$\times$education groups and reported in parenthesis.

6 Robustness

In this section, we show that (i) there is a negative relationship between cyclical skewness and equity shares within education groups and (ii) that our main findings remain statistically significant when we collapse the data by education×industry group. Finally, we show that our findings regarding covariance risk and equity share differ from those of Bonaparte et al. (2014) because, unlike these authors, we do not estimate income risk at the group level.

6.1 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 find that workers with higher variance and covariance have lower equity shares.

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

Table 8: **Equity shares in 2000 and individual-level measures of income risk**

	(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

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.

As reported in Table 8, variance and covariance only have negative and significant effects when they are estimated using past shocks. This finding is difficult to interpret but raises concerns regarding the interpretation of previous studies. Indeed, the correlation between equity shares and past experiences is only consistent with a rational hedging story if it results in workers with higher future covariance/variance investing less in stocks. The absence of such correlation suggests another interpretation. One example is investor "scarring." Malmendier and Shen (2021) find that consumers who personally experienced unemployment spells remain pessimistic and reduce their consumption even when these experiences do not predict future earnings. If scars increase precautionary savings, they may also lead to more conservative portfolio choices. This hypothesis is consistent with Table 8: past variance/covariance is negatively correlated with equity shares in a way that does not help workers hedge against labor income risk.

6.2 Education

As mentioned earlier, the relationship between cyclical skewness and equity shares is partially explained by the fact that more educated workers invest more in stocks and are less exposed to left-tail risk during recessions. In Table 9, we report the results of our main regression after cutting our sample by education group. We find that, within each level of educational achievement, workers employed in industry with higher cyclical skewness have lower equity share. The coefficient for skewness is not statistically significant within workers whose highest achievements are Bachelor or Doctorate degrees but, relative to our previous regressions, the number of clusters is reduced from 327 to roughly 60, which strongly weakens our statistical power.

Table 9: Equity share and countercyclical income risk by highest degree

	High School		Bachelor	Master	Doctorate	Higher Education	
	Dropouts	Degree				No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cyclical skewness	-0.258*	-0.422*	-0.065	-0.216**	-0.022	-0.444**	-0.271***
	(-1.81)	(-1.75)	(-0.55)	(-2.13)	(-0.63)	(-2.03)	(-3.68)
Countercyclical variance	0.248	0.174	0.047	-0.423**	-0.055	-0.160	-0.247
	(0.53)	(0.31)	(0.15)	(-2.12)	(-0.62)	(-0.36)	(-1.28)
Covariance risk	0.479	0.017	0.516*	0.482**	0.447**	0.125	0.252
	(0.73)	(0.03)	(1.79)	(2.30)	(2.36)	(0.21)	(1.31)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wealth composition	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,968,462	15,883,454	6,161,004	7,408,524	536,491	20,851,916	14,106,019
Pseudo R^2	0.150	0.112	0.113	0.107	0.130	0.116	0.110

This table reports the result of tobit regressions of the equity share on measures of countercyclical income risk, for different levels of highest educational achievement. Demographic controls include age, sex, household size, and dummies identifying immigrants and entrepreneurs. Wealth composition variables control for the share of human capital, financial wealth, real-estate and debt in the household's overall endowment. T-stats are clustered by industry group and reported in parenthesis.

6.3 Collapsed regressions

As our main explanatory variables are measured on the group level, we run collapsed regressions as a robustness test. We collapse all variables into averages at the education×industry level to obtain one cross-section of different groups. As reported in Table 10, the coefficient for cyclical skewness remains statistically significant at the 1% level.

Table 10: **Collapsed regression – Equity share and countercyclical income risk**

	(1)	(2)	(3)	(4)	(5)
Cyclical skewness	-0.461***			-0.123***	-0.076***
	(-5.69)			(-2.94)	(-2.67)
Countercyclical variance		0.299*		0.278***	0.132**
		(1.88)		(3.25)	(2.25)
Covariance			-0.014	0.061	0.337***
			(-0.10)	(0.66)	(5.13)
			(-0.04)	(-0.92)	(2.40)
Demographics				Yes	Yes
Wealth composition				Yes	Yes
Education group FE					Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	327	327	327	327	327
Adjusted R^2	0.088	0.008	-0.003	0.815	0.915

This table reports the result of tobit regressions of the equity share on measures of countercyclical income risk, controlling for worker and households characteristics. All variable are collapsed by industry×education group. Demographic controls include age, sex, household size, and dummies identifying immigrants and entrepreneurs. Wealth composition variables control for the share of human capital, financial wealth, real-estate and debt in the household's overall endowment. Education fixed effects control for the five levels of educational attainment used to sort workers into industry×education groups. T-stats are reported in parenthesis.

7 Conclusion

In this paper, we document that workers who face more left-tail income risk following low stock market returns are less likely to participate in the stock market and, when they participate, invest less in stocks. We show that the relationship between cyclical skewness and equity shares is stronger when human capital represents a larger share of total wealth, as predicted by theory.

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 labor income 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. But many wealthy investors are exposed to other sources of risk during recessions, in particular capital losses on undiversified investment in private businesses. It is therefore possible that, despite our findings, tail consumption risk is important for asset pricing.

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