Seeking Skewness

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Abstract

Using detailed disaggregated Swedish household administrative data on portfolio holdings and labor income, this paper investigates retail investors' behavior of seeking skewness in their portfolio choice. I develop a model of rational portfolio choice in which investors optimally hold portfolios with a (positively) skewed return distribution to hedge against (negatively) skewed labor income risk. I find empirical support for the model's predictions. I find that investors trade off their portfolio's Sharpe ratio against higher skewness, which explains the suboptimal Sharpe ratio found in previous studies. I also find that skewness seeking is more pronounced for investors with (i) higher overall risk in their labor income, (ii) higher downside risk in their labor income, and (iii) less wealth. Further, I find that investors hold more assets that provide insurance against the time-varying downside risk in their labor income.

Keywords: Household finance, Skewness preference, Portfolio choice, Cross-sectional heterogeneity, Labor income risk.

JEL Classification: G11, D14, D91, H31

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1 Introduction

Standard portfolio choice theory generally assumes normally distributed asset returns. However, actual return distributions are asymmetric and display fatter tails than normal distributions. Moreover, the portfolios of retail investors appear to be less diversified than in the mean-variance benchmark, and this under-diversification is associated with a tilt toward skewness (Mitton and Vorkink, 2007). Indeed, recent research finds that individuals do not behave like mean-variance investors but instead show a preference for return distributions with a small probability of large positive returns and limited downside risk, that is, for positive skewness.[1] This is important for asset pricing because skewness preference and asymmetric return distributions can generate substantial premia for skewness.[2] This is also important for portfolio choice because ignoring the skewness in returns can lead to large welfare losses.[3]

Most of the empirical work on the issue has focused on the skewness premium.[4] The few studies on portfolio choice show that retail investors' portfolios have higher skewness than those of institutional investors (Kumar, 2009) and that less sophisticated, less educated, and less wealthy investors hold portfolios with higher skewness. These findings are often rationalized by theories based on non-standard preferences or limited rationality (Barberis and Huang, 2008; Dahlquist, Farago, and Tédongap, 2017; Brunnermeier and Parker, 2005). However, we know little about the extent to which standard rational portfolio choice theory can explain investors' skewness-seeking, and about the factors that may lead investors to seek more or less skewness in their portfolios.

In this paper, I show that the skewness seeking of retail investors is consistent with a rational portfolio choice model with skewed labor income risk. Studies have shown that labor income risk, a major source of risk for retail investors, is a factor explaining investors' financial portfolio risk and their tilt toward value and growth.[5] Moreover, the skewness of labor income risk is important in explaining investors' risk-taking (Catherine, 2016) and asset pricing (Constantinides and Ghosh, 2017). I develop a standard rational portfolio choice model that incorporates skewed distributions for asset returns and labor income shock. Investors optimally hold portfolios with a (positively) skewed return to hedge against (negatively) skewed income shocks. I then test the model's predictions by using detailed disaggregated administrative Swedish data. And I find supportive evidence. First, I

[1] Many studies focus on the joint implication of asymmetries in asset returns and investors' skewness preference. See, e.g., Rubinstein (1973), Kraus and Litzenberger (1976) and Tsiang (1972).

[2] See, e.g., Beedles (1979), Aggarwal and Aggarwal (1993), and Bekaert, Erb, Harvey, and Viskanta (1998).

[3] Dahlquist, Farago, and Tédongap (2016) finds that a skewness-seeking individual who invests through a mean-variance model has a welfare loss of 16.6%. Jondeau and Rockinger (2006) finds that such an individual needs 0.4% of monthly return added to the portfolio return to become indifferent to a strategy that ignores skewness.

[4] The skewness premium is sizable, a result robust to different market settings and skewness measures. See, e.g., Harvey and Siddique (2000), Conrad, Dittmar, and Ghysels (2013), Boyer, Mitton, and Vorkink (2010), Amaya, Christoffersen, Jacobs, and Vasquez (2015), Bali, Cakici, and Whitelaw (2011) and Ghysels, Plazzi, and Valkanov (2016)

[5] See, e.g., Betermier, Jansson, Parlour, and Walden (2012), Calvet and Sodini (2014), Guiso, Jappelli, and Terlizzese (1996) and Betermier, Calvet, and Sodini (2017)

find that investors trade off their portfolio's Sharpe ratio against higher skewness, which explains the suboptimal Sharpe ratio found in previous studies. I also find that, in line with the model's predictions, skewness-seeking is more pronounced for investors (i) exposed to higher overall risk in labor income and (ii) higher downside risk in labor income and with (iii) less wealth. I also find that investors hold more assets that provide insurance against the time-varying downside risk in their labor income.

As a first step, I build a one-period portfolio choice model in which an agent chooses to invest in a risk-free asset and two risky assets with different levels of skewness. The agent has non-tradeable labor income with asymetric distribution of labor income growth and faces negatively skewed labor income risk. The skewness in labor income measures its downside risk.

I generate two sets of testable predictions. First, investors with a preference for skewness in returns trade off their portfolio's Sharpe ratio against higher skewness in their portfolio return distribution, so that optimal portfolios lie on a decreasing Sharpe ratio-skewness frontier.

Second, the model generates cross-sectional predictions. I show numerically that the skewness tilt of an investor's optimal portfolio should (i) increase with the downside risk in labor income, (ii) increase with the overall risk in labor income, and (iii) decrease with wealth. Prediction (i) comes from investors hedging the negative skewness in their labor income shock by holding portfolios with more positively skewed return distributions. Prediction (ii) comes from investors with higher (overall) risk in their labor income reducing their portfolio risk, and doing so asymmetrically due to preference for skewness. Predictions (iii) come from investors with more wealth enjoying a larger buffer against adverse shocks, and thus being able to afford riskier and less skewed portfolios.

I then take these predictions to the data. I use a Swedish administrative dataset that provides full information on investors' disaggregated financial wealth allocations at the security level for the entire Swedish population (9 million individuals) over the period from 1999 to 2007 at an annual frequency. Investors' risky portfolios consist not only of individual stocks but also of mutual funds, which account for more than half of their holdings of risky assets. Complete portfolio information is important for estimating the third moment of portfolio return distributions. The dataset also provides detailed information on labor income for the entire population from 1983 to 2007, including their various incomes and sectors of employment. The dataset also provides detailed demographics.

I first test the negative relation between portfolio Sharpe ratio and portfolio skewness. After controlling for portfolio-level characteristics such as Fama-French factor loadings and household-level characteristics such as basic demographics, I find that portfolios with lower Sharpe ratio have significantly higher skewness. The previously documented cross-sectional differences in Sharpe ratio loss relative to the market benchmark (Calvet and Sodini, 2007) can be partially captured by cross-sectional differences in portfolio skewness. On average, a one standard deviation increase in portfolio skewness corresponds to an increase in Sharpe ratio loss equal to 7.5% of the market portfolio's Sharpe ratio.[6] I also perform a placebo test to check that this negative relation does not arise mechanically from inefficient under-diversification.

The negative relation between portfolio Sharpe ratio and skewness is consistent with investors having a preference for skewness in returns (irrespective of the source of this preference). Next, I test the model's cross-sectional predictions that are more specific to the theory that labor income risk affects investors' skewness seeking.

First, I test the prediction that the skewness in an investor's portfolio should increase with the downside risk in his or her labor income. To this end, I divide individuals into 210 groups according to their sector of employment and education level and estimate the skewness of labor income shock of each group (using an extension of Carroll and Samwick (1997)'s method). About 60% of the groups have negatively skewed income shocks, and the cross-sectional heterogeneity is substantial. I find that investors in a group that face lower (i.e., more negative) skewness in their labor income shock, and hence higher downside risk, hold financial portfolios with more (positive) skewness. This is consistent with the interpretation that investors with higher downside risk in their labor income need to hedge against it by more intensively seeking skewness in their financial portfolio. An increase of one standard deviation in downside risk corresponds to an increase of a 0.02 standard deviation in portfolio skewness, which translates into a loss in Sharpe ratio of 0.16% relative to the market Sharpe ratio.

Second, I test the prediction that the skewness in an investor's portfolio should increase with the overall risk in his or her labor income. The volatility of labor income shock (labor income risk) for each group is measured using the same method as for the skewness of the shock. I find that investors in a group that faces higher volatility in their labor income shock hold financial portfolios with more (positive) skewness. The magnitude is as large as for the skewness of the shock.

Third, I test the prediction that the skewness in an investor's portfolio should decrease with his or her wealth. Financial wealth, observed at the individual level, is defined as the sum of cash, stocks, funds, bonds, derivatives, capital insurance, and other financial wealth. I find that investors with less financial wealth hold portfolios with higher skewness. A 1% increase in financial wealth corresponds to a decrease of 0.04 standard deviation in skewness. This effect is significant at 1% level.

Overall, these empirical results provide support for the key predictions in my model of rational portfolio choice in which investors hold portfolios with positive skewness to hedge against negatively skewed labor income risk. This perspective sheds new light on empirical findings established in the literature.

[6] The number corresponds to one standard deviation in the relative loss of the Sharpe ratio among Swedish investors documented in Calvet and Sodini (2007).

First, the downside risk in labor income provides a potential explanation for previously documented cross-sectional heterogeneity in skewness seeking. Previous literature finds that investors with less education and wealth, as well as low-skilled workers and immigrants hold portfolios with higher skewness (Kumar, 2009). I find that less educated, poor, unemployed, and immigrant investors tend to face high downside risk in their labor income. Indeed, including this risk reduces to a large extent the correlation between portfolio skewness and investors' level of education.

I then examine the labor income effect for different investor types. I compare investors who hold only stocks and those who also invest in mutual funds. I hypothesize that the latter may be more rational investors that should be expected to behave closer to the predictions in the model. In contrast, stock investors hold extremely under-diversified portfolios and may be less rational investors. Indeed, I find that for stock investors, the portfolio skewness is not related to their labor income risk but depends significantly on their level of education. For other investors, as for the entire population, the explanatory power of sophistication for portfolio skewness is largely weakened once labor income-related factors are included. This finding indicates that sophistication (and behavioral biases) may play a role for some investors (here stock investors), but that for others, part of the effects attributed to sophistication may in fact reflect labor risk.

This paper contributes to several strands of the literature. The macroeconomics and finance literature has extensively studied portfolio choice models with background risk in static or dynamic settings (see, e.g., Gomes and Michaelides, 2003; Cocco, Gomes, and Maenhout, 2005). A natural expectation is that background risk also has higher moment effects (see, e.g., Catherine, 2016). I contribute to this literature by describing how skewness seeking in portfolio choice is related to labor income risk, life cycle, and other demographic characteristics. Moreover, my empirical findings are overall consistent with a standard rational portfolio choice model with skewed labor income risk.

My paper also contributes to the small empirical literature on portfolio skewness. Using the holdings in online brokerage account holdings, Mitton and Vorkink (2007) were the first to show that investors hold under-diversified portfolios that have high skewness. However, investors with online brokerage accounts are unlikely to be representative of the population of investors (especially in the 1990s). Moreover, the stock holdings in online accounts are a minor part of investors' total financial wealth, so the preferences that they reveal may not be representative of actual preferences. Instead, my dataset includes the complete portfolio holdings for the full population of Swedish investors. The different results obtained for different types of investors also indicate the importance of using investors' total financial wealth instead of stock holdings when studying retail investors' portfolio choices. Thus, this paper contributes to the literature by confirming the importance of skewness in portfolio choice in a substantially more comprehensive dataset but also by connecting skewness seeking to labor income risk.[7]

The literature offers several other explanations for skewness-seeking. Studies have modeled skewness seeking as resulting from investors evaluating payoffs as for the cumulative prospect theory (Barberis and Huang, 2008), having disappointment aversion (Dahlquist, Farago, and Tédongap, 2017), or distorting their beliefs to maximize their current utility (Brunnermeier and Parker, 2005). In Shefrin and Statman (2000), investors construct layered portfolios, bottom layers being for downside protection and upper layers for upside potential. As a result, they have a higher demand for more skewed assets. My findings support an explanation in which rational investors seek skewness to hedge against the risk in their labor income.

The literature documents a strong gambling behavior by retail investors, especially among investors with less education and wealth as well as low-skilled workers and immigrants (Kumar, 2009). My results show that this behavior can be partially explained by the lower wealth and higher downside risk in their labor income, which are often characteristics shared by less educated investors, immigrants, and low-skilled workers.

The paper proceeds as follows: Section 2 presents the portfolio choice model. Section 3 presents the Swedish household dataset. Section 4 presents the key variables. Section 5 documents the Sharpe-ratio-skewness trade-off. Section 6 presents tests of the model's cross-sectional predictions. Section 7 presents the result of investors hedging time-varying downside risk in labor income. Section 8 has robustness checks. Section 9 concludes.

2 Theory and Predictions

I develop a one-period rational portfolio choice model to study the effect of income risk on the skewness in portfolios. It can be viewed as a stylized version of a standard dynamic portfolio choice model with non-tradeable labor income (Viceira, 2001). The main difference is that in my model, asset returns and labor income shocks have asymmetric distributions.

Two risky assets with different levels of skewness allow an investor to seek skewness in their portfolio. Skewed shock to labor income captures its downside risk. Holding the volatility of the shock constant, a negatively skewed shock means a higher probability of experiencing a large drop in labor income than receiving a large increase.

The model relates portfolio skewness to negative skewness in the labor income shock: Labor income shocks respond negatively to latent skewed shocks to the economy, and investors hedge this risk by holding assets more likely to yield high returns in those states, that is, assets with positive

[7] See, e.g., Conine and Tamarkin (1981), Jondeau and Rockinger (2006), Guidolin and Timmermann (2008), Martellini and Ziemann (2010),Langlois (2013), Ghysels, Plazzi, and Valkanov (2016), and Dahlquist, Farago, and Tédongap (2016).

skewness.

The aim is to generate qualitative predictions on how labor income risk affects portfolio skewness. First, the model illustrates an implication of skewness preference in an investor's utility function, namely, the trade-off between portfolio Sharpe ratio and its skewness. Second, the model provides novel cross-sectional predictions for the effects of labor income risk on portfolio skewness.

2.1 Model

The model has one investment period with two dates: $t = 0$ is the start of the period, and $t = 1$ is the end. The investing universe consists of one risk-free asset and two risky assets, assets 1 and 2, both with asymmetric return distributions. The investor invests initial wealth at $t = 0$. At $t = 1$, he or she gets the liquidation value of the portfolio plus labor income and consumes. The investor can achieve different levels of portfolio skewness by adjusting the relative weight between assets 1 and 2. Without loss of generality, I assume asset 1 has positive skewness and asset 2 has slightly negative skewness. The choice between assets 1 and 2 is similar to that between a stock and a fund. A fund can be viewed as a portfolio that provides higher diversification but lower skewness than a stock. Stock returns are positively skewed on average. Funds have almost zero skewness if not a negative one. They are naturally distinct choices regarding skewness.

2.1.1 The Investor's Problem

Consider an investor with a power utility and with a risk aversion parameter γ. The investor has initial wealth W_0 at $t = 0$ and receives labor income $l = l_0(1 + r_l)$ at $t = 1$. This investor chooses the vector of portfolio weights $\alpha = (\alpha_1, \alpha_2)$ that maximizes the expected utility of consumption at $t = 1$.

$$
\begin{aligned}
&\max_{\alpha_1,\alpha_2} E\left[\frac{C^{1-\gamma}}{1-\gamma}\right], \\
\text{s.t.} \quad & C = W_0(1 + r_p) + l, \\
& r_p = r_f + \alpha_1(r_1 - r_f) + \alpha_2(r_2 - r_f),
\end{aligned}
\tag{1}
$$

where C is consumption, r_p is the portfolio's return, and r_1 and r_2 are the returns of assets 1 and 2. The model being static, labor income at $t = 1$ is a purely permanent income shock.

2.1.2 Labor income

Shocks to the investor's labor income have a skewed distribution. Following Dahlquist, Farago, and Tédongap (2017), the income shock distribution faced by the agent at $t = 1$ is obtained from the following process:

$$r_{l,\tau} = \mu_l - \sigma_l\delta_l + (\sigma_l\delta_l)\,\varepsilon_{0,\tau} + \left(\sigma_l\sqrt{1-\delta_l^2}\right)\varepsilon_{l,\tau}. \tag{2}$$

The scalar $\varepsilon_{0,\tau} \sim exp(1)$ is a latent shock that follows an exponential distribution with a rate equal to one. The exponential distribution is suitable for characterizing the occurrence of extreme events. $\varepsilon_{l,\tau}$ represents the labor income specific shock with standard normal marginal density and is independent of $\varepsilon_{0,\tau}$. The mean, variance, and skewness of l are

$$E(r_l) = \mu_l, \quad Var(r_l) = \sigma_l^2, \quad Skew(r_l) = 2\delta_l^3. \tag{3}$$

Parameter $\delta_l \in (-1, 1)$ determines the sensitivity of the labor income shock to the latent shock $\varepsilon_{0,\tau}$. A labor income shock with negative sensitivity to $\varepsilon_{0,\tau}$ is subject to infrequent negative realizations.

2.1.3 Assets

The returns of both risky assets are modeled in a similar way:

$$r_{i,\tau} = \mu_i - \sigma_i\delta_i + (\sigma_i\delta_i)\,\varepsilon_{0,\tau} + \left(\sigma_i\sqrt{1-\delta_i^2}\right)\varepsilon_{i,\tau}, \quad \text{where} \quad i \in \{1, 2\}. \tag{4}$$

Each asset receives the same latent shock (ε_0) as that on labor income. Thus, the occurrence of extreme movements is assumed to be simultaneous across assets and labor income shocks. A negative δ_i means that asset i is subject to large but infrequent negative returns (negative skewness), while a positive δ_i indicates large but infrequent positive returns (positive skewness). $\varepsilon_{i,t}$, represents asset-specific shocks; together with $\varepsilon_{l,t}$, they have a multivariate normal distribution with standard normal marginal densities and correlation matrix Ψ. The mean, variance, and skewness of asset i's return are

$$E(r_i) = \mu_i, \quad Var(r_i) = \sigma_i^2, \quad Skew(r_i) = 2\delta_i^3. \tag{5}$$

The correlation and co-skewness between l and r_i are

$$Corr(r_l, r_i) = \mathit{\Psi}_{li}\sqrt{1-\delta_l^2}\sqrt{1-\delta_i^2} + \delta_l\delta_i, \tag{6}$$

$$Coskew(r_l, r_i) = \frac{E[(l_t - E(l_t))^2(r_{i,t} - E(r_{i,t}))]}{Var(l_t)\sqrt{Var(r_{i,t})}} = 2\delta_l^2\delta_i. \tag{7}$$

Equations (2), (4), (6) and (7) illustrate how the vector of δ leads to non-zero skewness and co-skewness.

The portfolio (α_1, α_2) has the following return moments. The mean, variance, and skewness of portfolio return are

$$\mu_p = r_f + \alpha^T(\mu - r_f), \quad \sigma_p^2 = \alpha^T \Sigma \alpha, \quad 2\delta_p^3 = 2\left(\frac{\alpha^T(\sigma \circ \delta)}{\sigma_p}\right)^3, \tag{8}$$

where $\mu = (\mu_1, \mu_2)$, $\sigma = (\sigma_1, \sigma_2)$, $\delta = (\delta_1, \delta_2)$, and $\circ$ is the element-wise product.

All skewness in the model comes from the systematic component, which is the simplest process to capture asymmetric distributions. This simplification is justified by the irrelevance of idiosyncratic risk for asset pricing. The assumption of the systematic component ε_0 is also supported by empirical evidence that the downside risk in labor income has strong cyclicality (Guvenen, Ozkan, and Song, 2014). [8]

2.2 Sharpe ratio-Skewness Efficient Portfolios

To illustrate the effect of the preference for skewness, I first shut down labor income risk by assuming zero labor income.

Consider the Taylor expansion of expected utility in equation (1). The mathematical derivation is given in the appendix.

$$E(C) - \frac{\gamma}{2E(C)} Var(C) + \frac{\gamma(\gamma+1)}{6E(C)} Skew(C) + o(C). \tag{9}$$

Mean-variance investors maximize equation (9)AA with a two-term truncation: their utility function depends only on the first two moments of consumption. The preference parameter γ only drives the investor's risk aversion. If investors have mean-variance preferences, and there is a risk-free asset, then they should hold the same risky portfolio regardless of risk aversion: the maximum Sharpe ratio portfolio.

Mean-variance-skewness investors maximize the Taylor approximation with a three-term truncation. The preference parameter γ drives both risk aversion (second term) and skewness preference (third term). Their optimal portfolios no longer maximize the Sharpe ratio. Depending on the risk aversion and hence on the preference for skewness, their optimal portfolio deviates more or less from the mean-variance optimal portfolio. For investors with high risk aversion and hence high preference for skewness, the optimal portfolio is less efficient in terms of mean-variance but has higher skewness.

Figure 1 illustrates the key difference contributed by the preference for skewness in the utility function. This preference makes investors deviate from the mean-variance portfolio. Depending

[8] A possible extension of the model would be to separate the systematic shock on the financial market from that on the labor market. My model would be a special case in which the systematic shocks on both markets are perfectly correlated. As the correlation goes to zero, the hedging effect disappears, but the diversification effect remains. One should expect a lower sensitivity of skewness in optimal portfolio to the skewness in labor income shock.

on the attractiveness of skewness, they give up the Sharpe ratio in return for positive skewness. Their optimal portfolio lies on the decreasing frontier on Sharpe ratio-skewness plane. In Figure 1, the red point represents the optimal portfolio for mean-variance investors. The blue line represents the optimal portfolios for mean-variance-skewness investors. These portfolios allow the investor to achieve a high level of skewness but at the cost of a low Sharpe ratio.

To confirm that this deviation is not driven by omitted higher moments in the Taylor approximation, I plot the optimal portfolios of investors who maximize their expected power utility (1) without the Taylor approximation (Represented by the green dots). The assumption on the return distribution does not allow freedom for the fourth moment. The optimal portfolios of equation (1) coincide with those of equation (9).

As the implication of skewness preference: Investors' optimal portfolios deviate from the mean-variance optimal portfolio, and the cross-sectional heterogeneity in risk aversion causes investors to seek different levels of skewness at the cost of the Sharpe ratio. There is a negative cross-sectional relation between portfolio Sharpe ratio and skewness.

[Figure 1]

This result does not rely on power utility: any Von Neumann-Morgenstern utility with non-increasing absolute risk aversion will give the same prediction. Nor does it require any assumptions about return distributions beyond a non-zero third moment.

2.3 The Effect of Labor Income Risk

I now study the impact of the labor income risk (σ_l), its downside risk (δ_l), and initial wealth (W_0) on portfolio choice. There is no closed form solution for the optimal portfolio due to the assumed skewed distributions. Hence, I conduct a numerical analysis.

2.3.1 Parameters Choices

Table 1 gives the parameters for the baseline simulation. The parameters are calibrated to match the empirical moments in the data. Risk aversion (γ) is set to 4, and initial wealth (W_0) is set to 1. In the simulation, it varies from 1 to 6, corresponding to a variation of income to wealth ratio from 0.16 to 1. The risk-free monthly rate is set to 0.001 that is the average inflation-adjusted, post-tax, one-month Swedish treasury bill rate between 1999 and 2007.

The calibration parameter values for asset 1's mean (μ_1), variance (σ_1), and skewness ($2\delta_1^3$) are chosen to match the median value among stocks; and those for asset 2's mean (μ_2), variance (σ_2), and skewness ($2\delta_2^3$) are chosen to match the median value among funds. The correlation between asset 1 and asset 2 ($corr(\epsilon_1, \epsilon_2)$) is chosen to match the median value of the correlations between stocks and the market return.

The expected labor income l_0 is set to 0.3 to match the mean of the income to wealth ratio in the Swedish population. The volatility and skewness of the labor income shock are also chosen to match the average of estimated values for different investor groups. The detailed estimation method is given in Section 4.3. In the simulation, volatility varies from 0 to 0.2, and the skewness varies from -1 to 1.

The correlations between labor income and the assets ($corr(\epsilon_l, \epsilon_1)$ and $corr(\epsilon_l, \epsilon_2)$) are set to 0.01, which is consistent with the evidence in the literature of a very low correlation between financial and nonfinancial income.

All labor income parameters are converted to monthly bases for the consistency with monthly returns. Sensitivity tests are reported in Section 8.8. The results for different values of risk aversion, fund skewness, and the correlation between the labor and financial markets are not qualitatively different from the baseline case.

[Table 1]

2.3.2 Numerical Results

Figure 2 shows how the optimal portfolio skewness tilt varies with overall risk of labor income and its downside risk and with initial wealth. Graphs in the left column show the relation between optimal portfolio skewness and the variables of interest. Graphs in the right column show the relation between the assets' weights and the variables. Three predictions are obtained from this numerical analysis of the portfolio choice problem.

The first row in Figure 2 shows that low (more negative) skewness in labor income shock generates high skewness in the optimal portfolio. The negative skewness in labor income shock indicates a higher probability of becoming unemployed than being promoted. Investors who face this downside risk in their labor income will look for a hedge from their financial portfolio by investing less in a well-diversified fund and more in the asset that provides high skewness in the same state. It translates into higher skewness in portfolio choice.

The second row in Figure 2 shows that high volatility in the labor income shock also leads to high skewness in portfolio choice. When investors are forced to hold too much risk in labor income, they will reduce their risk-taking in the financial portfolio. As they have an asymmetric preference, they will do it asymmetrically by reducing risk more on the negative side than on the positive side and end up with a more positively skewed portfolio.

The third row in Figure 2 shows that lower wealth leads to higher skewness in the optimal portfolio. Higher wealth serves as a buffer to bad shocks. Hence, investors can afford higher risk or lower skewness in return for a higher expected return from the financial portfolio.

[Figure 2]

The numerical analysis highlights the importance of asymmetric labor income shock in explaining investors' skewness seeking. I now empirically test these predictions and see to what extend labor income can explain the stylized facts observed in the cross-sectional heterogeneity of portfolio skewness.

3 Data and Statistics

3.1 Individual Panel Data

The Swedish Wealth and Income Registry is a high-quality 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.[9] The whole population of Sweden consists of around 9 million distinct individuals. For each individual in the population, I observe disaggregated wealth, such as equity holdings, fund holdings, savings, leverage, and real estate holdings at the level of each security or property. The disaggregate wealth panel is available from 1999 to 2007, and the disaggregate income panel is available from 1983 to 2007.

This dataset has significant advantages relative to previously available datasets. Most studies on the household behavior of portfolio choice rely on surveys such as the US Survey of Consumer Finances (SCF) that provides the household asset allocation on several broad asset classes and other demographics. The drawback to the SCF data is that it 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, which are important in estimating higher moments of portfolio return distribution. Other data that can provide detailed information on holdings are the data on brokerage records, (see, e.g., Odean, 1998, 1999). The drawback to these data is that only holdings of stocks in the investor's brokerage account are observed, which may not give a representative portrait of the investor's entire wealth allocation and do not have detailed demographic and income data for the investor. Online investors in the 90s likely belonged to a special group that does not represent the average population. Compared to brokerage records, the Swedish data provides the investors' overall wealth distribution, which is very important in identifying investors' true preference. At the same time, detailed income and also the demographic information are important in heterogeneity studies.

[9] See, for instance, Calvet and Sodini (2007), Calvet, Campbell, and Sodini (2009a), Calvet, Campbell, and Sodini (2009b), Calvet and Sodini (2014), and Betermier, Calvet, and Sodini (2017).

Individual-level information is observed annually. This information is available for each resident 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. Income is reported by individual source. For capital income, the database reports the income earned on each bank account and from each security. For labor income, the database reports gross labor income, business sector, unemployment benefits, and pensions. For disaggregated wealth, the data contain the assets owned worldwide by each resident on December 31 of each year, including the bank account[10] for 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.

In this study, I concentrate on individuals' holdings of cash and risky assets outside defined contribution pension accounts, and individuals between 20 and 100 years old. 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.[11] For Swedish households, 65% held risky assets (stocks or funds) at the end of 2002. Risky holdings account for 52% of total financial wealth. Risky mutual funds refer to all funds other than Swedish money market funds. 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. Total wealth is defined as the sum of financial wealth and real estate wealth. Net wealth is defined as the total wealth minus debt. The leverage ratio is defined as the ratio between debt and total wealth. All values are expressed in Swedish Kronor.

For the empirical analysis on labor income, I impose several filters on the panel. First, I exclude students. In order to estimate labor income risk by business sector, I also exclude individuals for which the sector of employment is not available. In each year, I winsorize the nonfinancial real disposable income to $1,000$ kronor.

Table 2 gives the main financial and demographic characteristics of Swedish retail investors at the end of 2002.

[Table 2]

[10]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. I follow methods developed in Calvet and Sodini (2007) to impute bank account balances. Details can be found in Calvet and Sodini (2007) (Appendix)

[11]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.

3.2 Market Return Data

Data on Nordic stocks and mutual funds for the 1983 to 2009 period are available from FINBAS, which is a financial database maintained by the Swedish House of Finance. The data include monthly stock and mutual fund returns. For securities not covered by FINBAS, I use price data from Datastream and Morningstar. The returns are winsorized at the 1% level due to errors in price data.

At year t, I focus on stocks and funds that have at least three years of available data over a five-year span because skewness is evaluated on a five-year rolling window of historical monthly returns. I end up with a universe of approximately 2,500 stocks and 1,500 funds in 2003. This number goes up to 2,900 and 1,600 respectively in 2007. I drop individuals who put more than 10% of their financial wealth into assets that do not appear in my dataset of asset returns as this preference may be different from the observable part. About 3.9% of the population are dropped. Dropped individuals have similar characteristics compared to the rest of the population.

The risk-free rate is represented by the monthly average yield on the one-month Swedish Treasury bill. The return on the local market portfolio is represented by the SIX return index (SIXRX) that tracks the value of all the shares listed on the Stockholm Stock Exchange. I use the All Country World Index (henceforth 'world index') compiled by Morgan Stanley Capital International (MSCI) in US dollars as the global market index. 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. Table 3 provides the summary statistics for the asset returns and the correlations. The results reported in Section 5 are based on the SIXRX index as a benchmark. I also report results from the world index in the robustness section.

[Table 3]

4 Construction of Main Variables

I use measures for the Sharpe ratio and skewness to test the negative relation between them. The measure for the Sharpe ratio is the same as in Calvet and Sodini (2007). This consistency makes the quantitative result comparable with the under-diversification loss measured in Calvet and Sodini (2007). The measure for portfolio skewness is the same as the one in Mitton and Vorkink (2007). To test the model predictions on how labor income affects skewness seeking, I estimate the investors' labor income risk, labor income downside risk and their human capital using an extension of Carroll and Samwick (1997)'s method. Human capital estimation is as in Betermier, Calvet, and Sodini (2017). In this section, I describe the methodologies used in estimating the main variables used in my paper and report the cross-section distributions of these variables.

4.1 Portfolio Sharpe Ratio

Expected return

The measurement error is a crucial issue for the estimation of expected returns due to slow convergence of the mean. As the observation period is short, the mean return of the portfolio is difficult to estimate. To gain a better estimation, I follow Calvet and Sodini (2007) and infer the mean return vector from an asset pricing model. Model-implied return delivers better estimates of the mean returns than a historical sample mean due to the significant reduction in the standard error. I assume that assets are priced with CAPM, and the market portfolio has the return of the SIXRX index.[12]

$$r^e_{i,\tau} = \beta_{i,M,t} r^e_{m,\tau} + \varepsilon_{i,\tau} \quad \tau \in [t-59, t]. \tag{10}$$

At the end of each year from 1999 to 2007, I estimate the time varying β_i in equation (10) using the previous 60 monthly returns. The estimated mean monthly return of asset i and year t is

$$\bar{r}_{i,t} = \beta_{i,M,t} \bar{r}_m, \tag{11}$$

where $\bar{r}_m$ is the average of the market excess return over a long sample period from 1983 to 2009. The average of the monthly excess return in the Swedish market is 0.7%. The portfolio mean return at year t is the weighted average of the assets' mean return. Individual portfolios are indexed by $p \in 1, \ldots, P$. The portfolio market beta at time t $\beta_{p,M,t}$ is the weighted average of each individual asset's market beta, $\beta_{p,M,t} = \sum_{j=1}^{N} w_{j,p,t} \beta_{j,M,t}$, where $w_{j,p,t}$ is the weight of asset j in portfolio p at time t. The portfolios' estimated mean return can be obtained by

$$\bar{r}_{p,t} = \beta_{p,M,t} \bar{r}_m. \tag{12}$$

Volatility

The sample variance converges faster to its expectation than the sample average. The sample variance of a short time series of 60 periods is an accurate estimation of the variance in returns. The variance in a portfolio at time t is estimated by using the sample variance over 60 months of historical monthly returns. I compute the portfolio's return as if the portfolio was fully rebalanced every month to the same weight as the weight vector observed at time t:

$$\sigma^2_{p,t} = \frac{1}{60} \sum_{\tau=1}^{60} \left(r^e_{p,t-\tau} - \mu_{p,t-60:t} \right)^2 . \tag{13}$$

[12] I also report the results from using CAPM with world index and Fama-French three-factor model as the asset pricing model in the robustness checks. Results are identical.

where $r^e_{p,t-\tau}$ is the excess return of portfolio p at time $t-\tau$; and $\mu_{p,t-60:t}$ is the mean of portfolio excess returns over the period $t-59$ to t. The portfolio's volatility $\sigma_{p,t}$ is the square root of its variance.

Sharpe ratio

The portfolio Sharpe ratio at time t is defined as

$$SR_{p,t} = \frac{\bar{r}_{p,t}}{\sigma_{p,t}}. \tag{14}$$

where $\sigma_{p,t}$ is the portfolio's volatility at time t, and $\bar{r}_{p,t}$ is the CAPM implied expected return at time t. Instead of using the level of the Sharpe ratio, I follow Calvet and Sodini (2007) and use the relative loss in the Sharpe ratio compared to the market Sharpe ratio. The relative loss $RSRL_{p,t}$ is defined as $1 - \dfrac{SR_{p,t}}{SR_B}$, where SR_B is the market Sharpe ratio. As the dependent variable is always relative to the market benchmark, there is no need to worry about the measurement issue of the equity premium. As the measure of the Sharpe ratio is identical to the diversification measure used in Calvet and Sodini (2007), the under-diversification can be directly related to the skewness in the portfolio.

4.2 Portfolio Skewness

Similar to variance, the portfolio skewness at time t is the sample skewness of its excess return over the past 60 months.

$$skew_{p,t} = \frac{1}{60}\sum_{\tau=1}^{60}\left(\frac{r^e_{p,t-\tau} - \mu_{p,t-60:t}}{\sigma_{p,t-60:t}}\right)^3. \tag{15}$$

Note that, as the measure of the sample skewness is the third moment scaled by volatility to the power of three, the portfolio's complete skewness equals its risky skewness and does not depend on its risky share. The risky share indicates the aversion to volatility, and the asymmetry in the risky portfolio shows the preference for skewness. Although skewness is a good statistical measure for distribution asymmetry, empirically it is very positively correlated with volatility. To have a skewness measure that is orthogonal to volatility, I follow Mitton and Vorkink (2007) and construct a volatility-adjusted skewness (noted skewIV) by regressing the portfolio skewness on its volatility and use the residual as the measure for its skewness.

Panel A in Table 4 shows the cross-sectional distribution of the mean return, volatility, skewness, Sharpe ratio, and the number of assets in the retail investors' portfolio. It also gives the world market portfolio as a benchmark. The retail investors' portfolio has, on average, a lower expected return, higher volatility, higher skewness, and a lower Sharpe ratio than the benchmark.

[Table 4]

4.3 Labor Income Risk

To estimate the variance and skewness in the permanent income shock from the data[13], I consider the following specification for labor income based on Cocco, Gomes, and Maenhout (2005):

$$log(L_{h,t}) = a_h + b' x_{h,t} + \nu_{h,t} + \varepsilon_{h,t}, \tag{16}$$

where $L_{h,t}$ denotes the observed nonfinancial disposable income for individual h in year t that is obtained by subtracting the post-tax financial gain from the observed disposable income, a_h is the individual fixed effect, and $x_{h,t}$ is a vector of age dummies. $\nu_{h,t}$ is a permanent component, and $\varepsilon_{h,t}$ is a transitory shock with stationary distribution. The permanent component $\nu_{h,t}$ follows the random walk process:

$$\nu_{h,t} = \nu_{h,t-1} + \xi_{h,t}, \tag{17}$$

$\xi_{h,t}$ has the same distribution as equation (2) and is the permanent shock to income in period t. $\varepsilon_{h,t}$ and $\xi_{h,t}$ are uncorrelated with each other at all leads and lags.

After retirement, labor income risk collapses to 0. Therefore, I consider only non-retired individuals. Model (16) is estimated separately for three different education levels: basic or missing education, high school, and post-high school diploma. Individuals with different educational levels face different growth paths for their labor income.

To explore the heterogeneity of labor income shock distribution, I divide the population into different groups according to their similar business sectors and educational levels. I assume individuals within the same group face the same labor income shock distribution. There are in total 71 business sectors and 3 levels of education defined in the data. Within each group, I follow the procedure of Carroll and Samwick (1997) and estimate the variances of cumulative income growth innovations over different horizons (2 to 5) at the individual level and use the estimates to infer the variances of permanent and transitory income shocks and the third central moment of the permanent shock.

$$\begin{aligned} y_{h,t} - y_{h,t-\tau} &= (\nu_{h,t} + \varepsilon_{h,t}) - (\nu_{h,t-\tau} + \varepsilon_{h,t-\tau}) \\ &= (\xi_{h,t} + \xi_{h,t-1} + \ldots + \xi_{h,t-\tau+1}) + \varepsilon_{h,t} - \varepsilon_{h,t-\tau+1}. \end{aligned}$$

[13] Transitory shocks are reverted quickly and have little impact on long-term portfolio choice.

The variance and the third central moment of $y_{h,t} - y_{h,t-\tau}$ have the following expression:

$$var(y_{h,t} - y_{h,t-\tau}) = \tau\sigma_\xi^2 + 2\sigma_\varepsilon^2, \tag{18}$$

$$m^3(y_{h,t} - y_{h,t-\tau}) = \tau m_\xi^3, \tag{19}$$

where σ_ξ^2 is the variance of permanent shock, σ_ε^2 is the variance of transitory shock, and m_ξ^3 is the third central moment of the permanent shock. For each group, σ_ξ^2 and σ_ε^2 can be estimated by regressing $var(y_{h,t} - y_{h,t-\tau})$ on τ and a vector of 2 without a constant. Similarly, m_ξ^3 can be estimated by regressing $m^3(y_{h,t} - y_{h,t-\tau})$ on τ without a constant. The maximum τ equals five.

Following Guvenen, Ozkan, and Song (2014), I estimate the variance and skewness in the permanent income shock using males between the ages of 25 and 55. The reason being that males within this age range have a relatively stable employment rate and labor supply. At the same time, they are less affected by endogenous choice in the labor market such as voluntary part-time jobs. I then apply the estimated labor income shock distribution to all individuals within the same group regardless of age and gender.

Table 5 shows the cross-sectional distribution of total permanent shock moments. On average, labor income shock has negative skewness. Individuals in more than half of the groups face downside risk in their labor income. The skewness ranges from -0.316 to 0.171. Table 7 gives the top 10 and bottom 10 business sectors in terms of labor income downside risk. There are reasonable differences across sectors with relatively high downside risk in sales, repair of motor vehicles, and real estate activities. The public sector appears neither in the bottom nor in the top of shock skewness.

[Table 5]

[Table 7]

Table 6 shows the total permanent income shock for different education levels. Highly educated individuals have higher volatility in the labor income shock but at the same time have higher skewness in the shocks, hence lower downside risk in their labor income. These findings show that highly educated individuals have higher dispersion in their labor income but rarely receive downside shocks. In contrast, less educated individuals have lower volatility in the shocks as many of them are close to minimum wage. However, they have higher downside risk. This is consistent with earlier studies that show that in the United States, less educated people have "layoff risk" and highly educated people have "career risk". This table emphasizes the difference between overall risk and downside risk in labor income.

[Table 6]

4.4 Human Capital

Expected human capital is defined as:

$$HC_{h,t} = \sum_{n=1}^{T_h} \pi_{h,t,t+n} \frac{\mathbb{E}_t(L_{h,t+n})}{(1+r)^n}, \tag{20}$$

where T_h denotes the difference between 100 and the age of individual h at time t, and $\pi_{h,t,t+n}$ is the survival probability that the individual alive at t is still alive at date $t+n$. The survival probability is imputed from the life tables for the period 2004 - 2008 (both sexes) that is provided by Statistics Sweden. The expected labor income is obtained by estimating model (16) for different education groups and on non-retired people who are older than 20. The expected labor income is replaced by a discounted amount of constant income after retirement. The replacement ratios are measured as the average income of retired individuals over 65 and the average income of non-retired individual under 64 for each education group. The discount rate r is set to be flat to 4.1%, following the estimation in Calvet, Campbell, Gomes, and Sodini (Working paper). For every individual h, I compute the expected income $\mathbb{E}_t(L_{h,t+n})$ from the estimates of equation (16) conditional on age, educational level, and whether retired at time $t+n$. I winsorize human capital at 50 million kronor (approximately \$6 million).

Table 8 gives the average human capital by educational level and by age. Highly educated and younger individuals have higher human capital.

[Table 8]

5 Portfolio Skewness and Mean-variance Efficiency

In this section, I conduct the empirical test of the effect of the skewness preference mentioned in Section 2.1 that is, in cross-section, a portfolio with higher loss in the Sharpe ratio have also higher skewness. Mitton and Vorkink (2007) use a regression model to investigate the skewness preference by using data on stock portfolios held by a broker's retail investor clients. My sample contains the whole Swedish population and the entire wealth portfolio that is required to investigate skewness preferences. Also, to further study the important factors that affect investors' skewness seeking, it is important to first show that the effect of the skewness preference is observed among Swedish population.

The baseline regression is a pooled OLS on an unbalanced panel:

$$\mathrm{RSRL}_{p,t} = \alpha_0 + \alpha_1 skewIV_{p,t} + \alpha_2 X_{p,t} + \alpha_3 X_{h,t} + FE_t + \varepsilon_{p,t}, \tag{21}$$

where $\text{RSRL}_{p,t}$ is the relative loss in the Sharpe ratio, and $shewIV$ is the volatility adjusted skewness. $X_{p,t}$ is the portfolio-level control variables. $X_{h,t}$ is the individual-level control variables. I also control for some additional interaction terms. As a pooled regression, I also include the year fixed effect. To eliminate the non-fixed time effect, I cluster on two dimensions simultaneously.[14] As I do not have a sufficiently large number of time periods, in the robustness section, I also perform a Newey-West Fama-MacBeth with the number of lags equal to four. The result is robust and significant in both cases.

Portfolio-level controls $X_{p,t}$ include the portfolio's concentration and size and its factor loadings. I control for the concentration of the portfolio to rule out the case that investors acquire skewness as a by-product of holding a small number of assets.[15] I measure the concentration of the portfolio with the Herfindahl Index defined as $\sum_{i=1}^{N}\omega_i^2$ where N is the number of assets in the portfolio, and ω_i is the weight of asset i. This concentration measure takes into account both the number of assets and the weights of each asset in the portfolio. This mechanical relation can affect the baseline results if investors invest in a small number of assets not for seeking skewness but for other risk factors, or for an irrational or cognitive reason. I measure the size of the portfolio by the number of assets in the portfolio. It is highly correlated with the Herfindahl Index.

I also control for empirical factor loadings on value, size, and momentum. By doing this, I rule out the possibility that skewness seeking is a side effect of chasing other factors. The local value, size, and momentum factors are constructed as in Fama and French (1993) and Carhart (1997). Details are given in the appendix. Empirically, I find that skewness has little correlation with the market cap and the BM ratio and has a positive correlation with momentum on the asset level. (Cf. Table 9)

[Table 9]

Investor-level controls include education, age, and gender. The idea is to capture the investors' irrationality that correlates with some demographics. Under the rational framework, one should expect that controlling for irrationality will not change the trade-off effect between the Sharpe ratio and skewness. Indeed, I find that adding controls on individual characteristics does not drive away the significance and the magnitude of the trade-off coefficient.

Table 10 reports the estimation of equation (21). The first column reports the estimation without

[14] Petersen (2009) shows that, when there are both individual and time effects, a good empirical approach to get an unbiased standard error is to add dummy variables to each period to absorb the time effect and then cluster by the individual.

[15] The number of assets in the portfolio mechanically affects its skewness: Simkowitz and Beedles (1978) and Albuquerque (2012) show both theoretically and empirically that skewness decreases as the number of assets in the portfolio increases and as the concentration of the portfolio decreases. The proof is given in the appendix. For this reason, the market portfolio has negative skewness while individual assets are usually positively skewed, and this divergence between the individual and market levels is because of the stylized fact that assets tend to be negatively co-skewed with each other.

controls. α_1 is significantly different from zero and rejects the null hypothesis that investors are mean-variance maximizers. α_1 is positive and indicates that there is indeed a systematic trade-off between the Sharpe ratio and skewness. Moving to the right columns of the table, I control for the portfolio's concentration as measured by the Herfindahl index, demographic characteristics, size, value, momentum loadings, the interaction term between volatility and demographics, and the interaction term between beta loadings and demographics. The significance and the magnitude of α_1 stay very consistent. Regarding the economic magnitude, the *magnitude* line shows that one standard deviation increase in the skewness of the portfolio corresponds to a loss of about 7.5% of the market benchmark. To put this number in perspective: moving from the 10th percentile to the 90th percentile of skewness, the Sharpe ratio's loss increases from 5% to 35% of the market Sharpe ratio.

[Table 10]

Two robustness tests are provided in Robustness Section to further confirm that the significant trade-off is not just picking up mechanical relation and is obtained only through investors' portfolio choice.

6 Labor Income and Cross-Sectional Heterogeneity

In this section, I first empirically test the predictions in Section 2 that investors with higher downside risk in labor income, higher overall risk in labor income, and lower wealth hold portfolios with higher skewness. Then, I link the results to observed stylized facts of cross-sectional heterogeneity of skewness seeking and shed light on what are consistent with rational portfolio choice and what are investors' behavioral biases.

I estimate the effects of labor income risk and wealth using the following linear specification for portfolio skewness:

$$\begin{aligned} skewIV_{p,t} =& \beta_0 + \beta_1 IncSkew_h + \beta_2 IncVar_h + \beta_3 log(FinWealth)_{h,t} + \beta_4 log(HumanCapitial)_{h,t} \\ &+ \beta_5 X_{p,t} + \beta_6 FE_t + \varepsilon_{p,t}, \end{aligned} \tag{22}$$

where $skewIV$ is the volatility adjusted portfolio skewness, $IncSkew$ is the skewness of labor income shock to the group the investor belongs to, $IncVar$ is the variance of labor income shock to the same group, $log(FinWealth)$ is the log of the investor's financial wealth, and $log(HumanCapitial)$ is the log of estimated human capital.

I control for the log of real estate holdings, log of leverage, immigrant dummy, and the number of assets in the portfolio. All regressions are pooled OLS estimates that include the year and zip-code fixed effect. Standard errors are clustered at the group level (business sector $\times$ education) at which the distribution of the income shocks distribution is estimated. The coefficients of interest are β_1 to β_3 and especially β_1 and β_2. The model in Section 2 predicts that $\beta_1 < 0$, $\beta_2 > 0$, and $\beta_3 < 0$.

Columns 2 and 3 in Table 11 show the results of model prediction tests. The estimates show that consistent with model predictions, higher labor income downside risk (i.e., lower skewness in the shock), higher overall risk, and lower financial wealth correspond to higher skewness in the portfolio. Lower human capital also correspond to higher portfolio skewness.

The choice of the job may be endogenous, and the preference may define both their financial investment decision and choice of work. Though, it predict an opposit sign from prediction in my model. To control for risk preferences, although I could not observe their preference, I compare investors with similar individual characteristics that may be correlated with their risk preference. As is shown in column 3, inclusion of these additional controls increases the magnitude and the significancy of the coefficents. Age no longer has explanatory power after including the control variables.

Columns 4 to 6 give the regression on the four different age groups. For investors between 25 and 65 who are in the work force and are exposed to risky labor income, their skewness seeking in portfolio choice is significantly correlated with their background risk.

In column 1 of Table 11, I report the regression of portfolio skewness on observed characteristics. The estimates show that poor, less educated, and elder males hold portfolios with higher skewness. This result is consistent with the findings for the heterogeneity in skewness seeking in the literature. Compare to column 2, including human capital decreases to a large extent the explanatory power of education.

[Table 11]

Table 12 reports the regression estimated on different subgroups of investors: those who invest all their financial wealth exclusively in stocks, and those who hold both stocks and funds in their portfolio. Mixed investors are those who actively and more rationally manage their portfolios and behave close to the predictions of the model. Stock investors are those who only directly hold a very small number of stocks, usually 2 to 3 stocks, and are considered irrational investors. Indeed, in column 2, for mixed investors, the skewness tilt in their portfolio choice correlates with labor income risk distribution. In contrast, column 1 shows that for stock investors, although they can extract high skewness by investing in stocks, they do not react to background risk. This finding confirms that stock investors may seek skewness for reasons other than compensating for their risk exposure in the background. Column 3 reports the regression on the stock portfolio of mixed investors. Compared with column 1, the skewness in the portfolios of mixed investors correlates with the risk in their labor income, which indicates that they have different investment strategies than stock investors. The difference between stock and mixed investors confirms the irrationality of holding only a small number of stocks in a financial portfolio. It also supports the importance of using retail investors' entire financial holdings to study their investment behavior. They may appear irrational in a small set of portfolios, but overall, they may rationally optimize their financial investments.

[Table 12]

How does the risk in labor income relate to the characteristics of the heterogeneity in skewness seeking? Table 13 shows some individual characteristics by their level of skewness in the labor income shock. It shows that the stylized heterogeneities in skewness seeking found in the previous literature are indeed correlated with the downside risk in the labor income. Individuals with lower income shock skewness (higher downside risk) tend to be those who have a low level of education, less wealth, and are more likely to be unemployed and immigrants. They also tend to hold a lower share of risky assets. Columns 1 and 2 in Table 11 show that education is not significant in explaining portfolio skewness once human capital, labor income risk, and downside risk are included. Moreover, the gender difference is always persistent and indicates that the heterogeneity in the skewness preference also drives the skewness seeking in portfolio choice.

[Table 13]

7 Hedging Time-varying Labor Income Downside Risk

The empirical results above show that the downside risk in labor income is a crucial factor for understanding the heterogeneity in investors' skewness seeking in portfolio choice. When investors face high downside risk and hence low (more negative) skewness in the income shock, they compensate by seeking higher skewness in their financial portfolios.

Further, the downside risk is countercyclical (Guvenen, Ozkan, and Song, 2014). Labor income downside risk is high when the market is in recession, and vie versa. The level of this contercyclicality affects invesotrs' investment in financial market (Catherine, 2016). Investors whose sector of employment has stronger downside risk cyclicality reduce investment in financial market. I next show that retail investors hedge time-varying downside risk in their labor income by investing in assets that are less negatively correlated with the income downside risk of their sector of employment.

The permanent component (ν) of unpredicted labor income defined in Equation 16 can be decomposed into a group-level component ω_t and an idiosyncratic component $w_{h,t}$:

$$\nu_{h,t} = \omega_t + w_{h,t}. \tag{23}$$

The group-level and idiosyncratic components follow independent random walks:

$$\omega_t = \omega_{t-1} + \kappa_t, \tag{24}$$

$$w_{h,t} = w_{h,t-1} + u_{h,t}. \tag{25}$$

The transitory component (ε) of labor income can also be decomposed as a sum of a group-level component η_t and an idiosyncratic component $e_{h,t}$,

$$\varepsilon_{h,t} = \eta_t + e_{h,t}. \tag{26}$$

Both η_t and $e_{h,t}$ have a stationary distribution.

I apply the same method as Section 4.3 to the idiosyncratic labor income shock, which is defined as the deviation in individual shocks from the group-level average shock, to estimate the variance of idiosyncratic permanent and idiosyncratic transitory income shocks and the third central moment of the permanent income shock. Table 14 reports the cross-sectional distribution of the total and idiosyncratic permanent labor income shock. The total permanent shock can almost be captured by only the idiosyncratic permanent shock, and the group level permanent shock counts for a tiny fraction of the total permanent shock. This result indicates that the variance and skewness of the total income shocks are predominated by the variance and skewness of idiosyncratic income shocks, and the systematic income shocks have much lower volatility and asymmetry.

[Table 14]

In order to measure the time-varying skewness in the income shock, I rely on the result in Table 14 that the total permanent shock $\xi_{h,t}$ can almost be captured by the idiosyncratic permanent shock $u_{h,t}$, and the group-level permanent shock κ_t counts for a tiny fraction of the total permanent shock.

As individuals within the same group at year t face the same idiosyncratic labor income distribution of $u_{h,t}$ together with the independent and identically distributed assumption, the distribution of $u_{h,t}$ for a specific group can be estimated by the cross-sectional realization of one-year innovation of labor income. This setting allows for the estimation of the time-varying labor income shock moments.

$$E(y_{h,t} - y_{h,t-1}) \approx E(u), \tag{27}$$

$$m^3(y_{h,t} - y_{h,t-1}) \approx m_u^3. \tag{28}$$

As each group has a time-varying mean and skewness of idiosyncratic labor income shock, I then compute the pair-wise correlation between labor income moments and asset returns over22 years annual returns. To reduce the noise, instead of using the individual portfolio weight, I use aggregate portfolio weights at the group level. The results for the following regression model are reported in Table 15.

$$w_{i,g} = \alpha + \beta_1 corr\_mean_{i,g} + \beta_2 corr\_skew_{i,g} + \beta_3 X_g + FE_t + FE_i + \epsilon_{i,g}, \tag{29}$$

Where $w_{i,p}$ is the weight of asset i in the aggregate portfolio of group g; $corr\_mean_{i,g}$ is the correlation between the return of asset i and the mean of labor income shock for group g; $corr\_skew_{i,g}$ is the correlation between the return of asset i and the labor income shock skewness of group g; and X_g is the group level controls that are the mean, variance, and skewness of idiosyncratic labor income shock. I also include time fixed effect and asset fixed effect. The standard error is clustered on the group-times-asset level where the correlations are computed. Popular assets, which are defined as the five top held assets, are excluded from the regression.

[Table 15]

As shown in Table 15, the correlation with the skewness of labor income shock has a negative effect on the asset's weight, which shows that investors do hedge against their downside risk by holding more assets that provide a high return when the skewness of their labor income shock is low. The asset return's correlation with the mean of labor income shock has a positive effect on the asset weight in the portfolio, which shows that investors invest more on assets that are positively correlated with their labor income shock. This is consistent with previous finding and may be explained by home bias or familiarity. I also include the correlation with the labor income shock volatility. It shows that investors also hedge against the overall risk in their labor income. But, as the variance in the one-year shock to labor income is a sum of permanent and transitory shock[16], I cannot conclude on which part of the shock investors are hedging against. I perform both an OLS with fixed effects and a Tobit regression, as the dependent variable is constrained between zero and one.

8 Robustness Checks

This section present a battery of robustness checks mentioned previously.

[16]The sample mean and the skewness of the one-year shock to labor income is the correct estimation for the mean and the skewness of permanent labor income shock, as transitory parts always cancel away with each other.

8.1 Newey-West Fama-MacBeth Regression

As the panel contains only 9 years of data, OLS regression's standard error clustered on year may not be consistence. To deal with both time effect (cross-sectional dependence) and firm effect (potentially decay over time), I estimate model (21) using Fama-MacBeth regressions, and compute heteroscedasticity and autocorrelation consistent Newwey and West (1987) standard error estimates with a lag length of 4. Table 16 report the regression results. The trade-off coefficients are significant and have the same magnitude as in the baseline case.

[Table 16]

8.2 CAPM (world index) Implied Expected Return

Table 17 reports the regression result of model (21) using CAPM implied expected return for the Sharpe ratio computation using the world index as the proxy for the market portfolio. The trade-off between portfolio Sharpe ratio and skewness is robust and have similar magnitude compared to the case with CAPM using the Swedish index as the proxy for the market portfolio.

[Table 17]

8.3 Fama-French Three-Factor Model Implied Expected Return

Table 18 reports the regression result of model (21) using Fama-French Three-factor model implied expected return. The local market factor is the SIXRX index, the local value and size factors are constructed as in Fama and French (1993) with Swedish listed stocks. Assets' factor loadings are constructed by estimating the three-factor model over 60 months rolling window. The portfolio factor loadings are the weighted average of individual asset factor loadings. The results are robust, and the magnitude is slightly bigger.

[Table 18]

8.4 Quantile-based Skewness

Table 19 reports the estimation of model (21) using quantile-based skewness measure. The trade-off coefficients are robust though with different magnitude. The magnitude is not comparable to the baseline case, as sample skewness and quantile-based skewness, though highly correlated, have different scale.

[Table 19]

8.5 Placebo Test

Ideally, in a Placebo test, one should compare the real population with a population without skewness preference. However, I do not observe portfolio choice by non-skewness preference investors in the real world. In this section, I will shut down possible channels through which investors seek skewness and construct a pseudo placebo population. It is natural to view individual's portfolio formation as a three-step choice. First, decide how many stocks and how many funds to invest – the number of assets. Second, decide which asset to include in the portfolio – discrete choice; third, what is the weight to allocate to each asset in the portfolio – continuous choice. They can happen simultaneously or sequentially. If skewness investors seek for skewness through one or several channels among these three, I should observe the Sharpe skewness trade-off I found in the data become weaker if one or several channels are shut down.

In this section, I use a simulated method to shut down respectively the third channel: continuous choice and the second channel: discrete choice, and show that, the trade-off found in the real data significantly decreases if I randomize part of the portfolio formation process. In the first randomization, I shut down the third channel by keeping assets in the portfolio as observed and randomize portfolio weights. I drop out single asset portfolios from both real population and simulated population, as there is no randomization in portfolio weight in single asset portfolio. Each path of the randomization is a simulated population with the same size as real population. I perform a Monte Carlo simulation by generating 200 paths. I estimate the Sharpe skewness trade-off on every simulated population and obtain a Monte Carlo distribution of α_1 under randomization. The average asymptotic standard error and the finite sample standard error are given in the first line of Table 20. The α_1 estimated in real portfolio is 0.14 with asymptotic standard error of 0.00025. It lies far out of the confidence interval of the Monte Carlo distribution under randomization. This result means that investors do seek for skewness via portfolio weight allocation, and the Sharpe skewness trade-off found in real population is too large to be explained by chance. In the second randomization, I use the same analogy and shut down both the second and the third channel. I keep the number of stocks and the number of funds as observed and randomize assets within each category, stock or fund. Following the same analogy, I get the same conclusion that the magnitude of the Sharpe skewness trade-off cannot be obtained under randomization. The average asymptotic standard error and the finite sample standard error under the second randomization are given in Table 20 in the second line. Shutting down both channel 2 and channel 3 gives a α_1 that is closer to 0 than shutting down only channel 3. Investors seek for skewness via both weight allocation and asset picking.

[Table 20]

Though, under both randomization, the Monte Carlo distribution of the estimation is still significantly different from zero. It can be caused by not able to shut down all possible channels, such as the first channel – under-diversification decision on portfolio formation. Under-diversification can serve as a channel through which investors seek for skewness. If investors go through the under-diversification channel to achieve for high skewness, I can still obtain a non-zero correlation.

8.6 Portfolio Rebalancing

In the baseline regression, I show that in cross-section, higher skewness corresponds to lower Sharpe ratio. In this section, I focus on the portfolio rebalancing and show that, when investors rebalance their portfolio, an increase in portfolio skewness corresponds to an increase in portfolio relative Sharpe ratio loss and vice versa. Instead of looking at investors' whole financial portfolio, I focus on the stock portfolio with daily frequency returns. When studying portfolio rebalance, I need non-overlapped periods for return estimation ideally. Hence, I increase return frequency to be able to estimate return moments with short period (one year). As daily return is only available for stocks listed on Stockholm Stock Exchange (SSE), I concentrate on stock portfolio instead of the risky portfolio in this section. As 95% of investors direct stock holdings are SSE listed, dropping foreign exchanges listed stocks held by Swedish investors does not affect the result.

I observe at the end of year t the stock portfolio owned by investor i. Let $\omega_{p,t}$ denote the corresponding vector of portfolio weights. The portfolio generates a random return between the end of year t and the next time the portfolio is rebalanced which is observde at the end of year $t+1$. I do not observe rebalancing within the year, but investor progressively rebalance from $\omega_{p,t}$ to $\omega_{p,t+1}$. Counterfactually, without rebalancing, investor should buy and hold the portfolio $\omega_{p,t}$ until end of year $t+1$. I call this portfolio the "passive portfolio", and denoted by $\omega_{p,\widetilde{t+1}}$. I call the portfolio observed at the end of year $t+1$ the "active portfolio", denoted $\omega_{p,t+1}$. I denote the portfolio skewness of passive and active portfolio by $skew_{p,\widetilde{t+1}}$ and $skew_{p,t+1}$ respectively. I denote the portolio relative Sharpe ratio loss of passive and active portfolios by $RSRL_{p,\widetilde{t+1}}$ and $RSRL_{p,t+1}$ respectively. I denote also the change in skewness and relative Sharpe ratio loss:

$$\Delta skew_{p,t+1} = skew_{p,t+1} - skew_{p,\widetilde{t+1}},$$
$$\Delta RSRL_{p,t+1} = RSRL_{p,t+1} - RSRL_{p,\widetilde{t+1}}.$$

As I do not know which model investors use for return estimation (using historical returns or having more complicated forward-looking models). I estimate $skew_{p,t+1}$, $skew_{p,\widetilde{t+1}}$, $RSRL_{p,t+1}$, and $RSRL_{p,\widetilde{t+1}}$ using both year $t+1$ daily returns and year $t+2$ returns, denoted backward and forward measures.

I regress $\Delta RSRL_{p,t+1}$ on $\Delta skew_{p,t+1}$ controlling for changes in portfolio volatility and changes in portfolio's factor loadings. I do not control for demographic changes, as these variables are relatively constant from one year to another for each investor. I consider the following regression,

$$\Delta RSRL_{p,t} = \alpha_0 + \alpha_1 \Delta skew_{p,t} + \alpha_2 \Delta vol_{p,t} + \alpha_3 \Delta X_{p,t} + FE_t + \varepsilon_{p,t}, \tag{30}$$

where $\Delta vol_{p,t}$ is the change in portfolio volatility, $\Delta X_{p,t}$ represent for changes in portfolio's factor loadings, including size, value, and momentum.

Table 21 shows the result for regression (30). The change of portfolio skewness is significantly positively correlated with the change of portfolio relative Sharpe ratio loss, for both backward and forward measures. Going from the passive portfolio to the active portfolio, an increase of relative Sharpe ratio is compensated by an increase of portfolio skewness; a decrease of relative Sharpe ratio is at the cost of a decrease in portfolio skewness. I exclude the year 2006 and 2007 from the analysis. For the year 2006 and 2007, I obtain the same result – a positive relation between skewness change and RSRL change with backward measure; but I obtain an opposite relation for a forward measure. The reason is that investors do not have a "good model" to predict Sharpe ratio during the crisis.

[Table 21]

8.7 Heterogeneity in skewness-seeking measured by Sharpe-skewness slope

From the Sharpe ratio-skewness efficient frontier obtained in the Section 2, skewness has an increasing marginal cost in terms of Sharpe ratio. Investors who are willing to tilt their portfolio more to positive skewness have to give up more than proportional Sharpe ratio compared to investors who seek for less skewness in their portfolio. One expects the heterogeneity of the magnitude of Sharpe-skewness trade-off goes to the same direction as the level of skewness itself, i.e. α_1 in model (21) varies in the same direction as portfolio skewness.

$$\alpha_{1,h,t} = \beta_0 + \beta_1 log(FinWealth)_{h,t} + \beta_2 log(HumanCap)_{h,t} + \beta_3 IncVar_h + \beta_4 IncSkew_h + \epsilon_{p,t}. \tag{31}$$

Table 22 shows the result of the following regression.

$$\begin{aligned} \mathrm{RSRL}_{p,t} = \alpha_0 &+ \beta_0 skewIV_{p,t} \\ &+ \gamma_1 skewIV_{p,t} \times log(FinWealth)_{h,t} + \gamma_2 skewIV_{p,t} \times log(HumanCap)_{h,t} \\ &+ \beta_3 skewIV_{p,t} \times IncVar_h + \beta_4 skewIV_{p,t} \times IncSkew_h \\ &+ \alpha_2 X_{p,t} + \alpha_3 X_{h,t} + FE_t + \varepsilon_{p,t}. \end{aligned} \tag{32}$$

[Table 22]

8.8 Sensitivity Test for Calibration

In the model, investors have homogeneous preference. It is important to check whether the value of risk aversion affect the way labor income skewness, labor income volatility, wealth and human capital affect portfolio skewness tilt. First row in Figure 3 shows how each of the four factors affect optimal portfolio skewness when risk aversion takes different value. There is no qualitative change, though the effect is less strong when investors have lower risk aversion. Secondly, I look at the change in fund type asset skewness. It is known that fund's skewness is almost zero or slightly negative. It is important to check the skewness goes above or below the zero threshold does not affect qualitatively the result. Second row in Figure 3 shows that the fund skewness being above, below or equal to 0 does not affect the way labor income skewness and volatility affect optimal portfolio skewness. Not surprisingly, when fund skewness increases, it moves horizontally optimal portfolio skewness upwards. Last, I look at whether the correlation between labor income shock and asset returns being different from 0 moves the result. Third row in Figure 3 shows that zero correlation is not a crucial threshold. When correlation deviate from 0, there is no dramatic change in the result.

[Figure 3]

9 Conclusion

In this paper, I document strong evidence of a preference for skewness among retail investors. Controlling for diversification and other factors, investors seek skewness in their portfolois at the expense of a lower mean return and/or higher overall riskiness, which explains the suboptimal Sharpe ratio.

I further document that the cross-sectional heterogeneity of skewness seeking in portfolio choice shows strong patterns that are consistent with a rational portfolio choice under skewed payoffs and labor income shocks. I focus on how background risk and wealth affect a portfolio's third-moment tilt. I show that there is hedging effect between the skewness in labor income shock and the skewness in a portfolio. Investors who face more downside risk in their labor income tend to seek higher skewness in their portfolio, which indicates a hedging demand in financial investment. I also show that investors seek more skewness in their portfolio when they have more overall risk in their labor income, less financial wealth, and less human capital. In order to hedge against downside risk shocks to their labor income, investors overweight assets that provide a high return when their downside risk is high.

The results provide new directions for future research on skewness preference. The data show a relatively high skewness preference among retail investors. However, retail investors are not necessarily marginal investors. Whether the level of skewness preference found in retail investors matches the magnitude of the skewness premium in asset prices is unknown. My results indicate that labor income and life-cycle changes may have major impacts on investors' demand for skewness. Their importance affects policy making and could be investigated in further research.

A Appendix

A.1 Taylor Expansion of CE

Investors have power utility over the second period wealth:

$$U(W) = \frac{W^{1-\gamma}}{1-\gamma}$$

Apply Taylor expansion on $E[U(W)]$ around EW:

$$\begin{aligned} E[U(W)] &= E[U(EW) + U'(EW)(W-EW) + \frac{U''(EW)}{2}(W-EW)^2] \\ &= U(EW) + \frac{U''(EW)}{2}Var(W) \end{aligned}$$

Apply Taylor expansion on $U(CE)$ around EW:

$$U(CE) = U(EW) + U'(EW)(CE-EW)$$

As $U(CE) \equiv E[U(W)]$,

$$\begin{aligned} CE &= EW + \frac{U''(EW)}{2U'(EW)}Var(W) \\ &= EW - \frac{\gamma}{2EW}Var(W) \end{aligned}$$

Higher moment case can be applied directly.

A.2 Portfolio Factor Loadings

The market factor MKT_t is the monthly SIX return index (SIXRX) minus the risk-free rate proxied by Swedish one-month T-bill rate of return. The local value, size, and momentum factors are constructed as in Fama and French (1993) and Carhart (1997). Every month, stocks traded on the major Nordic exchanges are sorted by book-to-market value, market size, and past one year cumulative performance, and then use these bins to compute the monthly rebalanced value factor

HML_t, the size factor SMB_t, and the momentum factor MOM_t, same procedure can be found in Betermier, Calvet, and Sodini (2017).

Stocks and funds are indexed by i. For every asset i at time t, I estimate the four-factor model over the past 60 months:

$$r_{i,\tau}^e = \alpha_{i,t} + \beta_{i,t} MKT_\tau + v_{i,t} HML_\tau + s_{i,t} SMB_\tau + m_{i,t} MOM_\tau + u_{i,\tau}, \quad \tau \in \{t-59, t\} \tag{33}$$

where $r_{i,\tau}^e$ denotes the excess return of asset i in month τ between $t-59$ and t and $u_{i,\tau}$ is the residual uncorrelated to the factors.

The factor loading of individual risky portfolio at time t is the weighted average of individual asset loadings. The portfolio p's value loading is:

$$v_{p,t} = \sum_{i=1}^{N} w_{p,i,t} v_{i,t} \tag{34}$$

where $w_{p,i,t}$ denotes the weight of asset i in portfolio p at time t. The same method applies for portfolio size loading $s_{p,t}$ and portfolio momentum loading $m_{p,t}$.

A.3 Portfolio Skewness Decomposition

Portfolio skewness decreases as the number of assets in the portfolio increases and as the concentration of the portfolio decreases. Albuquerque (2012) shows that, positive skewness in asset level aggregate into negative skewness in market level is due to the negative co-movement term between assets in the market. He shows that equal weighted portfolio with N components, its sample non-standardized skewness can be decomposed in the following way:

$$\begin{aligned}
T^{-1} \sum_t (r_{p,t} - \bar{r}_p)^3 &= \frac{1}{N^3} \sum_{i=1}^{N} \frac{1}{T} \sum_t (r_{p,t} - \bar{r}_p)^3 \quad \text{(mean of asset skewness)} \\
&+ \frac{3}{TN^3} \sum_t \sum_{i=1}^{N} (r_{p,t} - \bar{r}_p) \sum_{p' \neq p}^{N} (r_{p',t} - \bar{r}'_p)^2 \quad \text{(co-vol)} \\
&+ \frac{6}{TN^3} \sum_t \sum_{i=1}^{N} (r_{p,t} - \bar{r}_p) \sum_{p' > p}^{N} \sum_{l > p'}^{N} (r_{p',t} - \bar{r}'_p)(r_{l,t} - \bar{r}_l) \quad \text{(co-cov)}
\end{aligned}$$

The coskewness terms capture the average comovement in one firm's return with the variance of the portfolio that comprises the remaining firms. As there are$N$ asset level skewness terms, $N((N-1)$ terms on co-vol, and $N!/[3!(N-3)!]$ terms in co-cov, when the number of assets in the portfolio increases, the number of terms associated with coskewness increases faster than the number of terms associated with asset level skewness. He also points out in his paper that the coskewness term is negative, and monotonically decreasing in N. When the number of assets in portfolio increase from

1 to 25, coskewness drives the portfolio skewness from, on average, 0.8 to 0.

I expand the case for non-equal weighted portfolio where the weighting vector is $\omega = (\omega_1, \omega_2, \dots, \omega_N)$,

$$
\begin{aligned}
T^{-1}\sum_t (r_{p,t} - \bar{r}_p)^3 = & \sum_{i=1}^{N} \omega_i^3 \frac{1}{T}\sum_t (r_{p,t} - \bar{r}_p)^3 \quad \text{(mean of asset skewness)} \\
& + \frac{3}{T}\sum_t \sum_{i=1}^{N} \omega_i (r_{p,t} - \bar{r}_p) \sum_{p' \neq p}^{N} \omega_{i'}^2 (r_{p',t} - \bar{r}'_p)^2 \quad \text{(co-vol)} \\
& + \frac{6}{T}\sum_t \sum_{i=1}^{N} \omega_i (r_{p,t} - \bar{r}_p) \sum_{p' > p}^{N} \sum_{l > p'}^{N} \omega_{i'} (r_{p',t} - \bar{r}'_p) \omega_l (r_{l,t} - \bar{r}_l) \quad \text{(co-cov)}
\end{aligned}
$$

Then the portfolio weight concentration, which takes into account both asset number and weight distribution, affect portfolio skewness in a similar way to number of asset. When portfolio is very concentrated, portfolio coskewness has less weight in the decomposition and portfolio skewness is higher.

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Table 1: Benchmark calibration parameters

Parameters		Value
Financial assets and labor income		
r_f	Monthly risk-free rate	0.001
μ_1	Expected monthly return of asset 1	0.0032
μ_2	Expected monthly return of asset 2	0.0031
μ_l	Expected labor income	0.025
σ_1	Volatility of asset 1	0.094
σ_2	Volatility of asset 2	0.052
σ_l	Volatility of labor income shock	0.02
$2\delta_1^3$	Skewness of asset 1	0.38
$2\delta_2^3$	Skewness of asset 2	-0.12
$2\delta_l^3$	Skewness of labor income shock	-0.04
$corr(\epsilon_1, \epsilon_2)$	Correlation of asset specific shock between asset 1 and asset 2	0.32
$corr(\epsilon_1, \epsilon_l)$	Correlation between asset 1 specific shock and labor income shock	0.01
$corr(\epsilon_2, \epsilon_l)$	Correlation between asset 2 specific shock and labor income shock	0.01
Preferences		
γ	Risk aversion	4
Wealth		
W_0	Initial wealth	1

Table 2: Summary Statistics

This table reports the main financial and demographic characteristics of Swedish retail investors at the end of 2002. All financial variables are converted to U.S. dollars using the exchange rate at the end of 2002 (1 SEK = $ 0.1127). 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. Net wealth is total wealth net of debt. Income is inflation adjusted, using CPI index of 2009. Education takes value among 0, 1, and 2, represent respectively basic or missing education, high school, and post high school diploma.

	All individuals					Participants				
	p10	p50	p90	mean	s.d.	p10	p50	p90	mean	s.d.
Financial wealth ($)	953	3,623	34,928	16,233	1,198,126	1,946	7,035	53,640	25,150	1,622,923
Total wealth ($)	1,195	10,493	140,974	54,394	1,219,009	2,169	29,494	182,356	76,476	1,647,632
Net wealth ($)	-7,344	5,102	111,118	38,144	1,212,971	-2,013	15,040	152,123	57,886	1,640,870
Cash:										
Bank account ($)	904	2,363	12,946	6,530	27,830	1,095	2,959	17,144	8,252	34,953
Money market fund ($)	0	0	0	792	9,907	0	0	283	1,121	12,685
Risky assets:										
Stocks ($)	-	-	-	-	-	0	0	5566	5989	1607389
Funds ($)	-	-	-	-	-	0	1286	15293	6396	48507
Risky share	-	-	-	-	-	0.05	0.36	0.83	0.40	0.29
Incomes:										
Non-financial disposable real income ($)	0.00	14,075.22	27,939.91	14,365.36	31,281.19	0.00	15,427.84	30,388.88	15,611.91	41,277.21
Demographics:										
Age	9.00	39.00	74.00	40.43	23.64	8.00	40.00	72.00	40.08	23.55
Education	0.00	1.00	3.00	1.15	1.01	0.00	1.00	3.00	1.28	1.05

Table 3: Summary Statistics

This table reports the summary statistics of Swedish T-bill return, MSCI world index return, and SIXRX index return over the period January 1983 to December 2009 (Full period) and the period January 1995 to December 2007 (Study period).

	Annual. Ret (%)	Annual. Vol (%)	Correlation	
	Panel A: Full period			
Interest rate	7	1.23		
MSCI world index	10.8	15.5	0.048	
SIXRX index	15.7	22.6	0.004	0.715
	Panel B: Study period			
Interest rate	3.9	0.53		
MSCI world index	9.18	14.5	-0.03	
SIXRX index	15.5	20.2	-0.05	0.729

Table 4: Summary Statistics

This table reports the cross-sectional distribution of portfolio characteristics. All portfolio characteristics are computed as in Section 4, then taken the average cross years (1999-2007). Expected mean return, volatility, and skewness are annualized by multiplying by 12, $\sqrt{12}$, and $1/\sqrt{12}$ respectively. The last column, market portfolio return is the MSCI world index return, the expected return, volatility and skewness of market portfolio is the historical sample mean, volatility and skewness of MSCI world index return over 1983 - 2009.

	Risky portfolio			Stock portfolio			Fund portfolio			Mkt
	p10	p50	p90	p10	p50	p90	p10	p50	p90	
Annual. ExpRet (%)	2.19	3.71	5.22	2.52	3.85	9.61	2.04	3.69	4.31	3.76
Annual. Vol (%)	11.91	19.03	32.99	23.40	32.53	61.46	9.65	17.92	22.13	15.44
Annual. Skewness (%)	-13.6	-6.64	6.06	-7.79	5.2	15.3	-14.4	-8.66	-1.44	-10.97
Sharpe ratio (%)	11.5	19.5	22.3	8.7	12.9	18.0	16.4	20.4	22.9	24.2
Number of assets	1.00	2.00	6.44	1.00	1.56	6.25	1.00	1.71	4.33	–

Table 5: Distribution of Labor Income Shock Moments

This table reports the cross-sectional distribution of total labor income shock volatility, third-central moment and skewness measured by Carroll and Samwick (1997) method.

	mean	s.d.	p10	p25	p50	p75	p90
total permanent shock volatility	0.082	0.036	0.046	0.056	0.074	0.103	0.128
total permanent shock third central moment	-0.001	0.010	-0.007	-0.003	0.000	0.001	0.004
total permanent shock skewness	-0.011	0.091	-0.069	-0.033	-0.005	0.009	0.057

Table 6: Labor Income Shock Distribution by Education

This table reports the average of total labor income shock volatility, third-central moment and skewness by education level.

	Basic education	High School	Post High School
total permanent shock volatility	0,075	0,078	0,095
total permanent shock third central moment	-0,004	-0,001	0,002
total permanent shock skewness	-0,023	-0,014	0,004

Table 7: Business sectors with lowest and highest labor income shock skewness

This table reports the 10 business sectors with the lowest labor income shock skewness (i.e. highest labor income downside risk) and the 10 business sectors with the highest labor income shock skewness (i.e. lowest labor income downside risk). There are in total 70 business sectors.

Rank	Business Sector	Labor income shock skewness
1	Sale, maintenance and repair of motor vehicles and accessories	-0.316
2	Book-keeping and auditing activities; tax consultancy	-0.155
3	Publishing and printing of books; sound recordings and video production	-0.091
4	Miscellaneous business activities n.e.c.	-0.084
5	Real estate activities	-0.068
6	Advertising	-0.066
7	Industrial cleaning	-0.060
8	Manufacture of rubber and plastic products	-0.058
9	Banking	-0.057
10	Water transport and supporting activities	-0.052
61	Technical testing and analysis	0.041
62	Hotels, camping sites and other provision of short-stay accommodation	0.042
63	Manufacture of electrical machinery and apparatus n.e.c.	0.044
64	Museums; botanical and zoological gardens; other entertainment activities	0.047
65	Manufacture of aircraft and spacecraft	0.048
66	Higher education	0.051
67	Investigation and security activities	0.066
68	Activities of travel agencies and tour operators; tourist assistance activities n.e.c.	0.097
69	Secondary education	0.152
70	Activities auxiliary to financial intermediation, insurance and pension funding	0.171

Table 8: Human Capital by Education and Age

This table reports the average of the estimated human capital by education level and by age group. Young people with high education level have more human capital.

	age group			
	20-35	35-50	50-65	65+
Basic education	3,725,770	3,075,792	1,956,964	1,287,151
High School	4,241,160	3,537,456	2,354,112	1,786,048
Post High School	5,155,551	4,644,504	3,175,708	2,366,382

Table 9: Correlation of firm characteristics

This table reports summary statistics and correlations of firm characteristics. It is based on daily return of stocks listed on major Nordic exchanges. *tskew qskew* and *tvol* are based on past year daily excess returns, the measures are described in Section 4. I take December market size (in billion kr) and BM ratio. *mom* is past year cumulative daily excess return. *aMAX* is the average of 10 maximum daily return over the past year. *aMIN* is defined in the same way as *aMAX*. *price* is the last price in December.

	tskew	qskew	tvol	mktcap	BM ratio	mom	aMAX	aMIN	price
mean	-0.908	0.030	0.062	4.43	0.170	0.154	1.336	-1.292	106
s.d.	4.253	0.151	0.319	24.01	6.885	1.151	5.145	1.519	2205
tskew	1.000								
qskew	0.053	1.000							
tvol	-0.199	-0.177	1.000						
mktcap	0.020	0.010	-0.115	1.000					
BM ratio	-0.010	-0.011	0.014	-0.049	1.000				
mom	0.024	0.322	-0.048	0.043	-0.038	1.000			
aMAX	0.190	-0.089	0.757	-0.148	0.010	-0.017	1.000		
aMIN	0.275	0.251	-0.820	0.129	-0.016	0.085	-0.541	1.000	
price	-0.034	0.015	-0.028	0.094	-0.024	0.050	-0.070	0.039	1.000

Table 10: Regression of portfolio Sharpe ratio on skewness

This table reports the result of pooled OLS regression of portfolio Sharpe ratio on skewness based on 9 years unbalanced panel. Standard error clustered on individual and year level. *Magnitude* reports the losses in percentage of Market benchmark Sharpe ratio correspond to one standard deviation increase in portfolio skewness.

	(1)	(2)	(3)	(4)	(5)	(6)
skewness(IV)	0.246***	0.245***	0.237***	0.227***	0.226***	0.224***
	(6.82)	(7.09)	(6.88)	(6.26)	(6.34)	(6.36)
Concentration		0.167***	0.182***	0.196***	0.191***	0.191***
		(8.78)	(10.52)	(8.22)	(8.15)	(8.19)
Demographics	No	No	Yes	Yes	Yes	Yes
4-factor loadings	No	No	No	Yes	Yes	Yes
vol x Demographics	No	No	No	No	Yes	Yes
factor loadings x Demographics	No	No	No	No	No	Yes
Magnitude (%)	7.9***	7.8***	7.6***	7.2***	7.2***	7.2***
Observations	35,847,540	35,847,540	35,777,262	35,777,262	35,777,262	35,777,262
Adjusted-R2	0.332	0.364	0.375	0.391	0.398	0.402

Table 11: Pooled regression of the portfolio skewness

This table reports the pooled regression of the portfolio volatility adjusted skewness on estimated labor income shock moments and individual characteristics with year and zip-code fixed effects. Column (1) reports estimates of regression of portfolio skewness on observed individual characteristics. Column (2) reports estimates with estimated labor income shock variance, skewness and expected human capital. Column (3) reports the same regression controling for log of real estate holdings, log of leverage, immigrant dummy, and number of assets in the portfolio. Column (4) to (6) reports estimates on four age groups.

				Age Groups		
				<25	25-55	55-65
LaborInc Skew		-0.2077***	-0.2744***	-0.0671*	-0.2918***	-0.2371***
		(-3.20)	(-4.16)	(-1.83)	(-4.43)	(-3.99)
LaborInc Var		0.5298***	0.6781***	0.1140	0.7142***	0.5286***
		(3.03)	(3.23)	(0.74)	(3.22)	(3.16)
log(HumanCap)		-0.0078*	-0.0081*	-0.0002	-0.0066	-0.0117**
		(-1.72)	(-1.75)	(-0.10)	(-1.58)	(-2.24)
log(FinWealth)	-0.0067***	-0.0098***	-0.0130***	-0.0020*	-0.0132***	-0.0135***
	(-3.53)	(-5.09)	(-5.55)	(-1.66)	(-6.42)	(-4.30)
Male	0.0290***	0.0285***	0.0294***	0.0225***	0.0314***	0.0216***
	(12.03)	(8.13)	(8.91)	(11.15)	(9.28)	(6.36)
Education	-0.0054**	-0.0032	-0.0042*	0.0069***	-0.0044	-0.0039**
	(-2.05)	(-1.40)	(-1.86)	(2.75)	(-1.57)	(-2.30)
age 25-55	0.0175***	0.0155***	0.0034			
	(4.21)	(4.25)	(1.08)			
age 55-65	0.0233***	0.0152***	0.0033			
	(4.77)	(4.92)	(0.88)			
age >65	0.0310***	0.0185***	0.0089*			
	(4.70)	(3.66)	(1.68)			
Controls	No	No	Yes	Yes	Yes	Yes
Observations	19,887,939	16,598,786	9,927,847	263,260	7,519,118	1,873,801
Adjusted R^2	0.006	0.007	0.015	0.013	0.016	0.014

Table 12: Portfolio skewness regression on subgroups

This table reports the estimates of regression (22). Column (1) reports the estimates on stock holders who only invest in stocks. The dependent variable is the volatility adjusted skewness of their stock portfolio/ Column (2) reports the estiamtes of mix holders who hold both stocks and funds. The dependent variable is the volatility adjusted skewness of their risky portfolio. Column (3) reports the estimates on mix holders, but dependent variable is the stock portfolio skewness.

	(1) Stock Pf of Stock holders	(2) Risky Pf of Mix holders	(3) Stock Pf of Mix hodlers
LaborInc Skew	-0.1904	-0.2718***	-0.2023***
	(-1.61)	(-4.65)	(-2.76)
LaborInc Var	0.9042*	0.6429***	0.8330***
	(1.81)	(3.12)	(3.04)
log(HumanCap)	-0.0216***	0.0079***	-0.0069
	(-4.44)	(2.75)	(-1.37)
log(FinWealth)	-0.0346***	-0.0125***	-0.0263***
	(-11.53)	(-8.83)	(-15.45)
Male	0.0174***	0.0103***	0.0118***
	(3.83)	(5.45)	(3.57)
Education	-0.0240***	-0.0020	-0.0186***
	(-6.91)	(-1.05)	(-6.49)
Controls	Yes	Yes	Yes
Observations	1,607,395	3,443,357	3,309,156
Adjusted R^2	0.225	0.013	0.030

Table 13: Demographics by Labor Income Shock Skewness

This table reports the average of characteristics by level of labor income shock skewness. Individuals are sorted into three categories by their estimated total labor income shock skewness, and the average of labor income shock skewness, characteristics and risky share within the top 30%, middle 40%, and bottom 30% groups are reported.

	Labor income shock skewness		
	Low	Middle	High
Skewness	-0.059	-0.003	0.046
Education	0.953	1.085	1.307
Wealth (thousand)	438.6	464.5	668.8
Unemployment (%)	12.367	13.042	10.005
Immigrant (%)	12.579	11.868	11.168
Risky share	0.245	0.245	0.294

Table 14: Distribution of Labor Income Shock Moments

This table reports the cross-sectional distribution of total labor income shock volatility, third-central moment and skewness measured by Carroll and Samwick (1997) method.

	mean	s.d.	p10	p25	p50	p75	p90
total permanent shock volatility	0.082	0.036	0.046	0.056	0.074	0.103	0.128
total permanent shock third central moment	-0.001	0.010	-0.007	-0.003	0.000	0.001	0.004
total permanent shock skewness	-0.011	0.091	-0.069	-0.033	-0.005	0.009	0.057
idiosyncratic permanent shock volatility	0.075	0.038	0.035	0.046	0.066	0.097	0.124
idiosyncratic permanent shock third central moment	-0.001	0.009	-0.008	-0.003	0.000	0.001	0.004
idiosyncratic permanent shock skewness	-0.005	0.092	-0.077	-0.037	-0.005	0.013	0.071

Table 15: Hedging time-varying labor income downside risk

This table reports the result of regression (29). Dependent varialbe is the weight of asset i in aggregate portfolio of group g. Independent variables are correlation between asset i return and expected mean, variance and skewness of labor income shock of group g. Column (1) to (3) reports the estimates on risky portfolio, stock portfolio and fund portfolio respectively. Column (4) to (6) report the results of Tobit regression estimation.

	OLS			Tobit		
	Risky pf	Stock pf	Fund pf	Risky pf	Stock pf	Fund pf
corr mean	0.002***	0.003**	0.001**	0.010***	-0.017***	0.034***
	(2.63)	(2.13)	(2.07)	(6.01)	(-5.97)	(18.17)
corr var	0.001***	0.002***	0.000	0.033***	0.029***	0.033***
	(3.01)	(3.02)	(0.17)	(21.87)	(11.80)	(19.39)
corr skewness	-0.001***	-0.003***	-0.000	-0.012***	-0.013***	-0.010***
	(-3.54)	(-3.64)	(-0.69)	(-8.42)	(-5.91)	(-6.33)
mean	-0.009**	0.001	-0.022***	-0.066***	-0.197***	0.064***
	(-2.28)	(0.10)	(-6.56)	(-11.83)	(-22.02)	(9.02)
variance	0.008***	0.018***	-0.004***	0.019***	0.049***	-0.013**
	(6.83)	(9.22)	(-4.10)	(4.48)	(7.69)	(-2.35)
skewness	0.000	-0.001	0.001***	-0.016***	-0.025***	-0.007***
	(0.57)	(-1.10)	(2.74)	(-18.88)	(-18.78)	(-6.84)
Observations	2,561,211	1,335,357	1,225,854	2,561,211	1,335,357	1,225,854
Adjusted R^2	0.475	0.402	0.607			

Table 16: Fama-MacBeth regression of portfolio Sharpe ratio on skewness

This table reports the result of Fama-MacBeth regression of portfolio Sharpe ratio on skewness based on 9 years unbalanced pannel. Newey-West with lag number of 4 is applied. The last line reports the average R^2 of cross-sectional regression.

skewness(IV)	0.247***	0.229***	0.221***	0.228***	0.225***	0.224***
	(5.01)	(4.86)	(4.76)	(4.73)	(4.79)	(4.70)
concentration		0.163***	0.175***	0.191***	0.186***	0.186***
		(6.27)	(7.20)	(5.05)	(5.00)	(5.12)
Demographics	No	No	Yes	Yes	Yes	Yes
4-factor loadings	No	No	No	Yes	Yes	Yes
tvol x Demographics	No	No	No	No	Yes	Yes
factor loadings x Demographics	No	No	No	No	No	Yes
Observations	35,847,540	35,847,540	35,777,262	35,777,262	35,777,262	35,777,262
Average-R2	0.128	0.181	0.200	0.261	0.273	0.289

Table 17: Regression of portfolio Sharpe ratio on skewness (World index)

This table reports the result of pooled OLS regression of portfolio Sharpe ratio on skewness based on 9 years unbalanced panel. Standard error clustered on individual and year level. Expected returns are estimated using CAPM model with world index as proxy for market portfolio return.

skewness(IV)	0.234***	0.228***	0.225***	0.215***	0.215***	0.215***
	(5.03)	(5.00)	(5.15)	(5.59)	(5.65)	(5.59)
concentration		0.185***	0.213***	0.221***	0.210***	0.210***
		(9.87)	(10.48)	(10.81)	(9.50)	(9.52)
Demographics	No	No	Yes	Yes	Yes	Yes
4-factor loadings	No	No	No	Yes	Yes	Yes
tvol x Demographics	No	No	No	No	Yes	Yes
factor loadings x Demographics	No	No	No	No	No	Yes
Observations	28,192,669	28,192,669	28,192,669	28,192,669	28,192,669	28,192,669
Average-R2	0.100	0.155	0.168	0.212	0.227	0.233

Table 18: Regression of portfolio Sharpe ratio on skewness (Fama-French Three-factor model)

This table reports the result of pooled OLS regression of portfolio Sharpe ratio on skewness based on 9 years unbalanced panel. Standard error clustered on individual and year level. Expected returns are estimated using Fama-French Three-factor model with SIXRX local index as proxy for market portfolio return.

skewness(IV)	0.477***	0.474***	0.471***	0.424***	0.423***	0.419***
	(3.35)	(3.33)	(3.42)	(3.11)	(3.07)	(3.12)
Number of Assets		-0.010**	-0.006	-0.009***	-0.009***	-0.009***
		(-2.51)	(-1.61)	(-2.88)	(-2.79)	(-2.64)
Demographics	No	No	Yes	Yes	Yes	Yes
4-factor loadings	No	No	No	Yes	Yes	Yes
tvol x Demographics	No	No	No	No	Yes	Yes
factor loadings x Demographics	No	No	No	No	No	Yes
Observations	28,192,669	28,192,669	28,192,669	28,192,669	28,192,669	28,192,669
Average-R2	0.076	0.081	0.091	0.237	0.241	0.252

Table 19: Regression of portfolio Sharpe ratio on skewness (World index)

This table reports the result of pooled OLS regression of portfolio Sharpe ratio on skewness based on 9 years unbalanced panel. Standard error clustered on individual and year level. Portfolio skewness is measured by quintile-based skewness defined by $skew_{p,t} = \frac{q(95) + q(5) - 2q(50)}{q(95) - q(5)}$.

Quintile skewness	0.743***	0.833***	0.822***	0.811***	0.778***	0.768***	0.765***
	(6.04)	(7.64)	(7.50)	(7.46)	(6.84)	(6.73)	(6.77)
Volatility		-0.823***	-0.824***	-0.828***	-1.094***	-1.112	-2.196**
		(-4.60)	(-4.73)	(-4.75)	(-4.13)	(-1.46)	(-2.13)
Number of Assets			-0.009***	-0.008***	-0.009***	-0.008***	-0.008***
			(-9.89)	(-10.11)	(-8.79)	(-8.22)	(-7.78)
Demographics	No	No	Yes	Yes	Yes	Yes	
4-factor loadings	No	No	No	Yes	Yes	Yes	
tvol x Demographics	No	No	No	No	Yes	Yes	
factor loadings x Demographics	No	No	No	No	No	Yes	
Observations	28,192,669	28,192,669	28,192,669	28,192,669	28,192,669	28,192,669	
Average-R2	0.108	0.118	0.140	0.147	0.164	0.174	0.178

Table 20: Estimation of α_1 on randomized population

This table reports the sample average of α_1 estimation over 200 simulated population, the sample average of asymptotic standard error (AASE), and the finite sample standard error (FSSE). The 95% confidence interval is the 2.5 and 97.5 percentile of finite sample distribution.

	mean	AASE	FSSE	95% CI	
Random. of weights	0.0764	0.00026	0.00004	0.07638	0.07642
Random. of assets	0.0516	0.00048	0.00004	0.05158	0.05162

Table 21: Robustness: Portfolio Rebalance

This table reports the regression result of model (30). Column 1 and 2 report the result using backward measure for portfolio skewness and Sharpe ratio; column 3 and 4 report the result using forward measure for portfolio skewness and Sharpe ratio. Column 1 and 3 do not include controls; column 2 and 4 include volatility difference as a control. Regressions include year fixed effect. Error clustered on the individual level. Regressions are based on from the year 2000 to 2005. Error clustered on individual and year level.

	Backward measures		Forward measures	
	(1)	(2)	(3)	(4)
$\Delta skew$	-0.00240***	-0.00224***	-0.00305***	-0.00202***
	(-38.93)	(-35.85)	(-33.88)	(-21.50)
Δvol		-0.148***		-0.716***
		(-47.39)		(-156.35)
year FE	Yes	Yes	Yes	Yes
Observations	9,125,862	9,125,862	8,063,009	8,063,009
Adjsuted-R2	0.030	0.031	0.038	0.062

Table 22: Skewness-seeking Heterogeneity

	(1) Full sample	(2) Full sample	(3) Stock holders	(4) Mix holders
skewness	1.2956***	1.3363***	0.4878***	0.8196***
	(14.18)	(15.56)	(13.83)	(7.81)
skewness × log(FinWealth)	-0.0196***	-0.0254***	-0.0172***	-0.0205***
	(-20.96)	(-19.04)	(-13.37)	(-14.16)
skewness × log(HumanCap)	-0.0560***	-0.0547***	-0.0062**	-0.0279***
	(-10.05)	(-11.03)	(-2.47)	(-4.57)
skewness × LaborIncVar	-0.6069*	-0.2958	-0.3103	0.1897
	(-1.85)	(-0.80)	(-1.21)	(0.62)
skewness × LaborIncSkew	-0.2023***	-0.2126***	-0.0119	-0.3928***
	(-2.71)	(-2.93)	(-0.14)	(-4.54)
Male × skewness	0.0236***	0.0312***	0.0096***	0.0195***
	(4.18)	(5.85)	(3.58)	(4.03)
edu	-0.0169***	-0.0116***	-0.0042	-0.0071***
	(-14.83)	(-5.09)	(-1.65)	(-6.47)
age 25-55	0.0136***	0.0079***	0.0096***	-0.0032**
	(9.76)	(4.82)	(3.95)	(-2.01)
age 55-65	0.0020	0.0081***	0.0073***	-0.0097***
	(1.54)	(5.20)	(3.23)	(-6.04)
age >65	0.0126***	0.0216***	0.0141***	-0.0003
	(6.34)	(12.06)	(5.19)	(-0.19)
Controls	No	Yes	Yes	Yes
Observations	16598786	9927847	1607395	3443357
Adjusted R^2	0.274	0.300	0.369	0.398

Figure 1: Trade-off between Sharpe ratio and skewness

Optimal portfolios are computed in an economy with one risk-free asset and two risky assets with different level of skewness. Mean-variance investors maximize $CE = E(W) - \frac{\gamma}{2E(W)}Var(W)$, and mean-variance-skewness investors maximize $CE = E(W) - \frac{\gamma}{2E(W)}Var(W) + \frac{\gamma(\gamma+1)}{6E(W)}Skew(W)$. Risk aversion γ varies from 0.05 to 10. For mean-variance investors, changes in γ does not change the risky portfolio composition. For mean-variance-skewness investors, when γ increases, the optimal portfolio moves to the right along the red frontier.

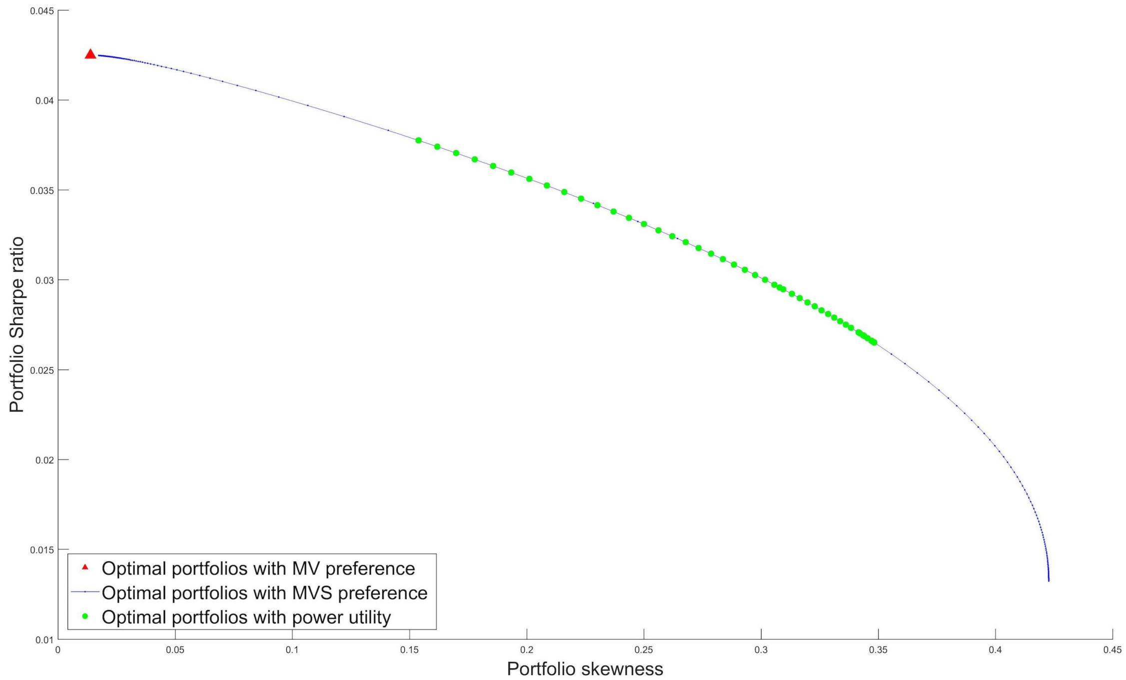

Figure 2: Baseline calibration of portfolio skewness

This figure illustrates the four predictions from model calibration. Graphs on the left show how variables of interest: labor income shock skewness, volatility, inital wealth and human capital affect optimal portfolio skewness tilt. Graphs on the right show the corresponding change in weight allocation in asset 1 and 2.

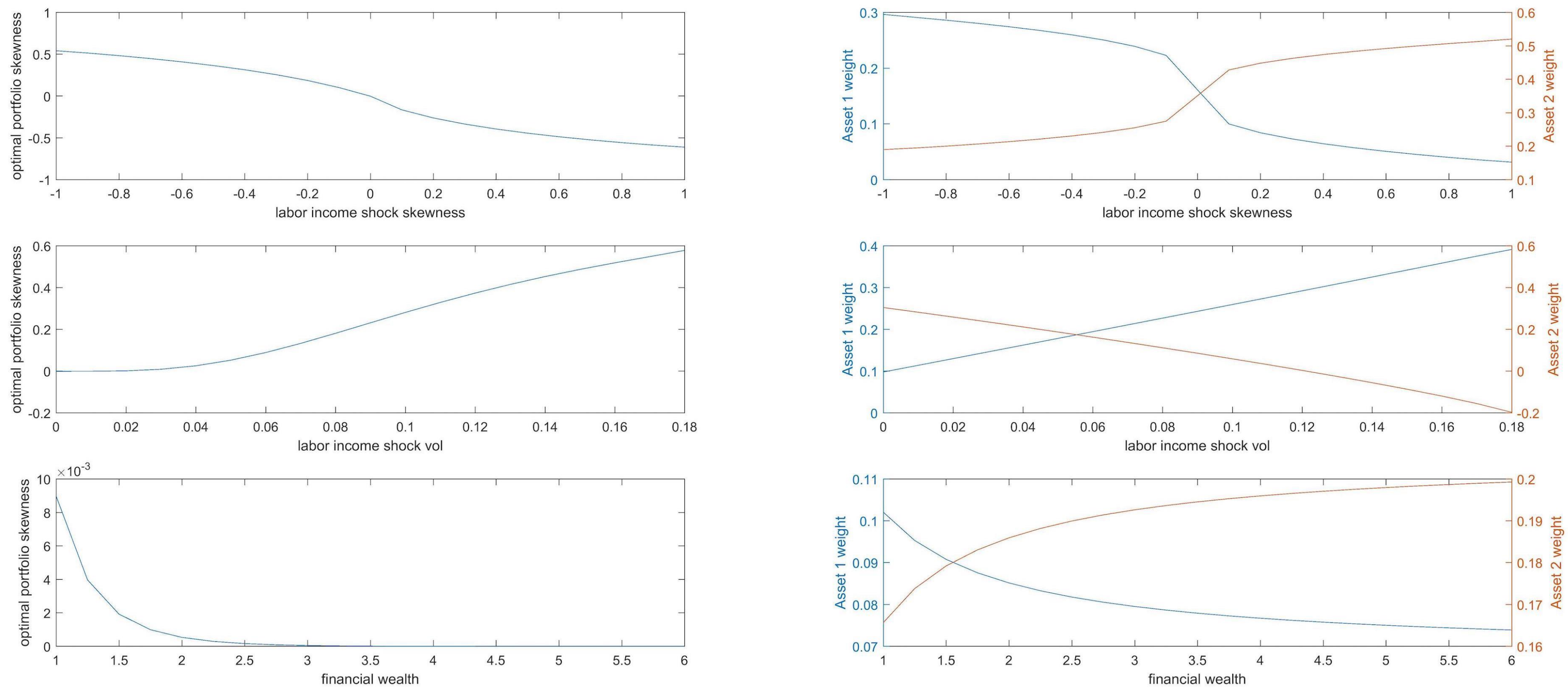

Figure 3: Calibration sensitivity to key parameters

This figure shows how sensitive the prediction in Figure 2 is to risk aversion, asset return skewness and the correlation between labor income shock and asset return.