Seeking Skewness

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Abstract

Using detailed disaggregated Swedish household data on portfolio holdings and incomes, this paper investigates retail investors’ skewness-seeking behavior in portfolio choice. I first show that investors trade off portfolio Sharpe ratio for higher skewness. A one standard deviation increase in portfolio skewness corresponds to a loss of about 7.5% of market Sharpe ratio. This explains the sub-optimal Sharpe ratio documented in previous studies. I mainly explore the cross-sectional heterogeneity in skewness-seeking behavior. I find that skewness seeking is more pronounced for investors (i) exposed to higher labor income risk and higher labor income downside risk and, (ii) with less financial wealth or human capital. Overall, these findings are consistent with predictions from a simple portfolio choice model with skewed payoffs and skewed background risk.

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

JEL Classification:
1 Introduction

Standard portfolio choice theory generally assume normally distributed asset returns. However, actual return distributions are asymmetric and display fatter tails than normal distributions. Recent research also found that individuals do not behave like mean-variance investors but instead exhibit a preference for positive skewness. Following Rubinstein (1973), Kraus and Litzenberger (1976), and Tsiang (1972), a large literature has focused on the joint implication of asymmetries in asset returns and skewness preference in investor’s utility. A positively skewed return distribution generates substantial positive returns with a small probability and limited downside risk. Skewness preference is that, ceteris paribus, investors favor return distributions with higher skewness. Despite the fact that preference for skewness has gained attention much later than the first two moments, exotic utility functions are not needed to capture skewness preference: with a CARA or DARA utility, the skewness of the return distribution is relevant to the investor. It is one of the first principles of portfolio choice just like maximizing mean return and minimizing volatility. Formally, an individual is averse to a decrease in the skewness (i.e. an increase of downside risk) of the payoff distribution if and only if his or her utility function has a positive third derivative. Such a Preference for skewness has been shown to be of first-order importance. For asset pricing, skewness preference can generate substantial skewness premia. For asset management, ignoring skewness in return distributions while making investment decisions can imply large welfare losses.1 As a manifestation of such a preference, investors are willing to accept either lower expected returns or higher volatility to increase payoff skewness.

Until now, most empirical work on the preference for skewness has focused on measuring the magnitude of the skewness premium in asset prices.2 However, while the skewness premium is evidence of skewness-seeking behavior at the aggregate level, it does not imply skewness-seeking behavior at the investor level as it cannot directly describe a typical household portfolio. For instance,

1Dahlquist, Farago, and Tédongap (2016) found a 16.6% welfare loss from ignoring skewness in return distribution when making investment decisions. Jondeau and Rockinger (2006) found that individual needs 0.4% of monthly return added to the portfolio return to become indifferent to a strategy that ignores skewness.

2The magnitude of the skewness premium is sizable, suggesting that investors exhibit a non-negligible preference for skewness. This result is very robust using different market settings and skewness measures. Harvey and Siddique (2000) constructed a systematic skewness factor and showed that it has a significant risk premium. Conrad, Dittmar, and Ghysels (2013) demonstrated the existence of a skewness premium in the option market. Boyer, Mitton, and Vorkink (2010) developed a methodology to predict idiosyncratic skewness using past returns and firm characteristics and showed that idiosyncratic skewness is also priced in the market. Amaya, Christoffersen, Jacobs, and Vasquez (2015) used high-frequency data to construct realized skewness and showed that it has a significant risk premium. Bali, Cakici, and Whitelaw (2011) showed that assets with a high maximum daily return in the past month have a low average return. Ghysels, Plazzi, and Valkanov (2016) proposed a quantile-based measure of conditional asymmetry.
asset prices could be driven by the behavior of wealthy individuals or institutions. The few papers studying skewness preferences at the investor level usually face two constraints. First, they use data on online brokerage account holdings, which are a minor part of investors’ total financial wealth, so these stock holdings may not reveal their preference. Thus, it is important to test the existence of skewness-seeking behavior in financial portfolio choice with a full or representative population and complete financial holdings which highlights the importance of the unique data set that I will explore in this paper. Second, it is unfortunately that skewness seeking has been addressed in isolation in the financial portfolio; no household heterogeneity factors, such as wealth, labor income, or human capital, have been explored in detail. Thus, granular studies on household behavior are essential for understanding what are the factors that affect skewness-seeking. This paper empirically test factors that drive the cross-sectional heterogeneity of skewness-seeking behavior with granular household-level data.

This paper first tests portfolio choice implication of skewness preference, namely, the trade-off between Sharpe ratio and skewness using a full population of Sweden and their complete portfolio holdings. I show that, on average, retail investors’ portfolios have higher skewness than the market. Sharpe ratio losses can be explained by investors seek higher skewness at the cost of lower expected returns or higher overall volatility. It is true not only for online stock investors’ stock portfolio, but also for investors’ entire financial wealth including fund investment. After showing that skewness matters in investment decisions by confirming the skewness-seeking induced mean-variance inefficiency, in the main part of the paper, I exploit the cross-sectional heterogeneity of portfolios regarding skewness using detailed disaggregated data on Swedish households that contains annual demographic and income information for the entire Swedish population. Most importantly, I study how skewness-seeking behavior in portfolio choice interacts with other risk sources in an investor’s life cycle, such as background risk, and what are the effects of wealth and life-cycle changes on skewness-seeking. I find that investors with higher labor income risk, especially higher left-tail risk, exhibit a more pronounced skewness-seeking behavior, as do investors with less wealth and less human capital. These findings are consistent with the behavior of an expected utility maximizer under skewed payoffs and skewed labor income risk. These findings also support some stylized facts in gambling literature that impoverished, immigrants, and low skilled workers tend to gamble in the financial market by investing in highly skewed lottery stocks, which suggest a rational explanation for gambling evidence in behavioral finance.
One implication of skewness preference is that, instead of holding a mean-variance portfolio that maximizes the Sharpe ratio, investors with different levels of skewness preference will deviate more or less from the maximum Sharpe ratio to tilt their optimal portfolio toward higher skewness. To confirm the implication of skewness preference, I examine the cross-sectional correlation between portfolio skewness and Sharpe ratio loss. Follow the previous literature (Harvey and Siddique, 2000) (Mitton and Vorkink, 2007) (Boyer, Mitton, and Vorkink, 2010), portfolio skewness is measured as the sample skewness of historical portfolio monthly returns over five years. Sharpe ratio loss is defined as the loss relative to the market benchmark Sharpe ratio to avoid bad estimation of equity premium. 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 higher Sharpe ratio losses have significantly higher skewness. The previously documented cross-sectional difference of the Sharpe ratio loss (Calvet and Sodini, 2007) can be partially explained by that in portfolio skewness. On average, one standard deviation increase in portfolio skewness corresponds to an increase in the Sharpe ratio loss equal to 7.5% of the market portfolio’s Sharpe ratio. This result stays true with a slightly higher magnitude when considering merely investors’ stock portfolio, which confirms the finding in Mitton and Vorkink (2007). To show that this trade-off is not gained mechanically due to the nature of the assets in the market, I performed a Placebo test in the robustness section. By constructing a Placebo population where portfolios are formed by randomly assigning asset or weight vector and considering the same correlation in simulated Placebo populations, I find that, in the simulated population the correlation is significant but that it cannot plausibly have the magnitude of the correlation found in the real population. The significance in the Placebo population can be due to the fact that I cannot control every channel in portfolio choice that allows for seeking skewness.

After confirming that there exist strong skewness seeking behavior among Swedish investors’ portfolio, I relate portfolio skewness tilt to household characteristics to study the heterogeneity of such behavior and potential explanation. Labor income risk, arguably the most important source of risk for a household, has always been the main focus in investigating household financial investment decisions. When incorporating labor income risk into portfolio choice, some skewness-seeking behavioral heterogeneity is found to be consistent with the first principle of portfolio choice. To generate clear joint prediction of skewness preference, skewed payoffs and skewed labor income risk,
I build a one period portfolio choice model where investors invest in one risk free asset and two risky assets with skewed payoffs. They have at the same time skewed labor income risk. Labor income skewness is a measurement for labor income downside risk. The lower the skewness, the higher the downside risk is. The motivation of incorporating skewed labor income risk comes from findings by Guvenen, Ozkan, and Song (2014) that skewness of labor income risk, compared to volatility, is more important for portfolio choice as it has stronger cyclicality. Empirically, I subtract permanent labor income shock moments from total labor income shock moments following a simple extension of Carroll and Sanwick (1997) method. I estimate human capital as the present value of future labor income expected which is a linear function of age. Consistent with model prediction, I find that investors exposed to substantial downside risk in their labor income seek skewness more intensively in their financial choices, and that skewness-seeking is more pronounced for investors with less financial wealth and less human capital. Other than model predictions, I also find evidence of persistent gender difference: male tend to hold more positively skewed portfolio. My empirical results support the model implication by a significant reaction of portfolio skewness to background risk, financial wealth and human capital.

The first contribution of the paper is closely related to Mitton and Vorkink (2007). Using one online brokerage account holdings data, they show that mean-variance-skewness investors appear to be mean-variance inefficient. Overcoming their data limitation of brokerage account holdings, this is the first paper that confirms the skewness-seeking-induced mean-variance inefficiency using a full population and complete portfolio holdings. This paper contributes to the literature by further confirm the importance of skewness in portfolio choice by providing robust empirical support that investors trade off Sharpe ratio and skewness on a broadly defined wealth allocation.

An extensive literature in macroeconomics and finance has studied portfolio choice models with background risk in static or dynamic settings, see, e.g., (Gomes and Michaelides, 2003), (Cocco, Gomes, and Maenhout, 2005). These studies are essential to explaining cross-sectional heterogeneity in portfolio choice. A natural expectation is that these household factors also have a higher moment effect, see, e.g., (Catherine, 2016). I contribute to this literature by describing how skewness-seeking behavior observed in portfolio choice is related to background risk variation, life-cycle variation, and other demographic characteristics. Moreover, I showed that empirical findings are overall consistent.

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with a simple portfolio choice model under skewed labor income risk where investors simply maximize their power utility.

The behavioral finance literature documents that retail investors of a particular type, usually poor, less educated, immigrants, and male, tend to gamble in the stock market by holding highly skewed assets (Kumar, 2009). My result suggests a potential rational explanation for the gambling behavior of some retail investors. As less educated investors, immigrants, and low-skilled workers also often have less wealth accumulation, lower expected human capital, and higher labor income downside risk. Ultimately, this paper bridges the gap between behavioral evidence and rational explanation. Gambling behavior in the stock market documented in previous literature can be partially explained when investors have less wealth and a higher labor income risk, especially higher downside risk.

The paper proceeds as follows. Section 2 gives the conceptual framework. Section 3 presents the data and defines the key variables. Section 4 confirms the important role of skewness preference in investment decisions for Swedish investors. Section 5 introduces risky labor income with asymmetry into the portfolio choice model to explain an important heterogeneity found in skewness-seeking behavior across investors. Section 6 presents a battery of robustness checks. Section 7 concludes.

2 Conceptual Framework

I present the conceptual framework for my empirical strategy in the following parts by analyzing a comprehensive expected utility approach. I then distinguish my approach from the behavioral approach by illustrating two essential differences.

2.1 Expected Utility Approach

Theoretical work on skewness preference has a long history. The influential works by Arditti (1967), Rubinstein (1973), Kraus and Litzenberger (1976), and Tsiang (1972) looked at skewness preference in expected utility theory by linear approximation of utility function. Menezes, Geiss, and Tressler (1980) and Chiu (2005) provided the preference for skewness with a firm choice-theoretic foundation by introducing the concept of increasing downside risk. An increase in downside risk implies a lower third moment, and an individual is averse to it if and only if his or her Von Neumann-Morgenstern utility function has a positive third derivative. As a manifestation of such a preference, investors are willing to accept either a lower expected return or higher volatility if their return distribution
provides higher skewness.\(^4\)

I use a Taylor expansion of the expected utility because a Taylor expansion is a practical and effective way of separating preferences for different moments and gaining insights on the effects of each moment on the optimal portfolio. Expected utility is often presented in a certainty equivalent (CE) form; maximizing expected utility is equivalent to maximizing the CE. The Taylor expansion of the CE of the expected power utility is as follows. The mathematical derivation is given in Appendix.

\[
CE = E(W) - \frac{\gamma}{2E(W)} Var(W) + \frac{\gamma(\gamma + 1)}{6E(W)} Skew(W) + o(W),
\]

where \(E(W), Var(W)\) and \(Skew(W)\) are the mean, variance, and skewness of wealth, respectively, and \(o(W)\) is the residual term of the Taylor expansion. The mean-variance investors can be obtained by truncating equation (1) at the second moment.

\[
CE = E(W) - \frac{\gamma}{2E(W)} Var(W)
\]

If mean-variance investors maximize equation (2), we should observe that investors with different levels of risk aversion (i.e., \(\gamma\) all lie on the capital market line (CML) and have the same risky portfolio composition (i.e., market portfolio) that provides the maximum Sharpe ratio. Empirical evidence is inconsistent with this theory. Investors, especially retail investors, face some dead loss due to excessive exposure to idiosyncratic risk. Calvet and Sodini (2007) defined welfare loss as Sharpe ratio loss and found that, in general, investors are below but not far from the CML and that loss contains a high level of heterogeneity. The following analysis shows that investors’ exposure to portfolio skewness can explain the Sharpe ratio loss when taking into account the third moment preference.

When increasing the accuracy of the CE Taylor expansion by considering the third moment,\(^4\) Jondeau and Rockinger (2006) showed that under a large deviation from normality in asset returns, allocating a portfolio focusing only on mean variance induces major welfare losses. Harvey, Liechty, Liechty, and Müller (2010) used a Bayesian decision framework to show that it is important to incorporate higher moments in portfolio selection. Dahlquist, Farago, and Tédongap (2016) characterized the optimal portfolio when returns are skewed and demonstrated that investors have generalized disappointment aversion preferences. Barberis and Huang (2008) and Barberis, Mukherjee, and Wang (2016) described how cumulative prospective theory generates a strong preference for skewness.
preference for skewness naturally emerges:

\[ CE = E(W) - \frac{\gamma}{2E(W)} Var(W) + \frac{\gamma(\gamma + 1)}{6E(W)} Skew(W). \] (3)

For power utility, the skewness preference parameter is a nonlinear transformation of risk aversion with only one degree of freedom: the relative risk aversion \( \gamma \) simultaneously defines risk aversion and skewness preference. Other utility functions may give a higher degree of freedom to the preference parameters. Investors who maximize CE for three terms no longer aim to maximize their Sharpe ratio. Depending on their level of risk aversion, they are willing to give up more or less mean-variance efficiency in return for a higher moment of payoffs. This is a first principle result of skewness preference, and it does not depend on power utility per se. Any Von Neumann-Morgenstern utility with non-increasing absolute risk aversion will give the same prediction. This result of skewness preference does not demand any further assumptions about return distribution beyond a non-zero third moment.

Figure 1 illustrates the key difference contributed by the presence of the third moment term in CE: only investors with skewness preference are willing to deviate from a mean-variance optimal portfolio that maximizes the Sharpe ratio, and the cross-sectional heterogeneity in risk aversion causes investors to seek a different level of skewness. The blue point represents the optimal portfolio for mean-variance investors. Regardless of the difference in their level of risk aversion \( \gamma \), they hold the same risky portfolio that provides the maximum Sharpe ratio. The red line are optimal portfolios for mean-variance-skewness investors with different levels of risk aversion. For an individual who has a high risk aversion, and so a high skewness preference, the optimal portfolio lies on the right tail of the red line. This portfolio allows the investor to achieve a high level of skewness, but at the cost of a low Sharpe ratio level. There is a negative cross-sectional relation between portfolio Sharpe ratio and skewness. Though the graph is based on a setting with two risky assets and a skewed distribution is used to describe risky assets’ returns, the Sharpe ratio to skewness trade-off does not depend on either of these two specific settings.

2.2 Rational or Irrational

This section justifies my expected utility approach. A series of papers studying retail investors’ gambling behavior in the stock market showed that they overweight assets with high skewness.
Nevertheless, as early as 1972, Tsiang (1972) pointed out that "skewness preference is certainly not necessarily a mark of an inveterate gambler, but a common trait of a risk avert person with decreasing or constant absolute risk-aversion." Investors’ skewness preference does not necessarily need to be based on an exotic utility; the simple non-increasing Von Neumann-Morgenstern utility offers this preference. For this reason, I conduct studies within the expected Von Neumann-Morgenstern utility framework to identify to what extent it can explain patterns in the data. First, I measure skewness on the portfolio level, which is consistent with the expected utility maximizer evaluating utility over the entire wealth distribution and does not have mental accounting. Second, I do not distinguish positive from negative skewness in the main test. Chiu (2005) defined a downside risk increase, which implies a lower third moment, as dispersion transferred from higher wealth levels to lower ones without distinguishing the positive and negative sides. An increase in skewness on the negative side creates satisfaction identical to that resulting from the same increase on the positive side. The statistical measure of skewness captures two different aspects compared to a normal distribution: the upside, extreme positive return realization, and the downside, less frequent extreme negative return realization. For a rational investor who maximizes the expected utility, these two aspects should provide equal satisfaction. Chiu (2005) defined an increase of skewness, holding everything else equal, as a precedence relationship: a mean-preserving spread (MPS) precedes a mean-preserving contraction (MPC) of equal size, and it is not necessary for the MPS to be on the right side of the distribution while the MPC is on the left side.

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. It covers the whole population of Sweden which consists of around 9 million distinct individuals and is available for the 1999 to 2007 period. For each in the population,  

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5 In fact, looking at the asset level should not change the result, as retail investors usually hold fewer than 5 assets. Asset level distribution characterizes the portfolio level distribution to a very large extent.

6 We start with only financial wealth whose skewness is easier to measure. In section 5, we further consider other sources of skewness such as labor income.

we observe disaggregated wealth, such as individual equity holdings, fund holdings, savings, leverage, real estate holdings, and various types of income. This dataset has significant advantages relative to those previously available. Most studies on the household behavior of portfolio choice rely on surveys such as U.S. Survey of Consumer Finances (SCF) which provide household asset allocation on several broad asset class and other demographics. The drawback of SCF data is that it does not provide detailed holdings on each asset and many answers are imputed. Compared to the SCF data, the Swedish data covers accurate individual asset holdings, such as stocks, funds, derivatives, which are important in estimating higher moments of portfolio return distribution. Other data that can provide detailed holdings information are the brokerage records data, see, e.g., (Odean, 1998) and (Odean, 1999). The drawback of the brokerage account data is that we can only observe holdings of stocks in one brokerage account, which may not give a representative portrait of the investor’s entire wealth allocation. Compared to brokerage records, the Swedish data provides investors’ overall wealth distribution, which is very important in revealing investors’ true preference and detailed income and also demographic information, which is important in heterogeneity studies.

Individual-level information is observed annually. Information available on each resident 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 contains the assets owned worldwide by each resident on December 31 of each year, including bank account, mutual funds, and holdings of stocks, bond, and derivatives. The database also records contributions made during the year to private pension savings, as well as debt outstanding at year-end and interest paid during the 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

\footnote{Bank accounts information is only available if the interest during the year exceed 100SEK. Missing bank account data can distort the estimates of the share held by a household in risky assets but do not affect our estimates of portfolio standardized skewness, which only depends on the composition of risky portfolio. We follow methods developed in Calvet and Sodini (2007) to impute bank account balances. Details can be found in Calvet and Sodini (2007) (Appendix).}
assets, that is directly held stocks and risky mutual funds.\textsuperscript{9} 65 percent of Swedish households hold risky assets at the end of 2002. Risky holding accounts for 52 percent 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 participant individuals have strictly positive risky share. 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. In Table 1, we report a summary statistics of retail investors' wealth allocation as well as other income and demographic characteristics.

Table 1 inserted here.

### 3.2 Market Return Data

Data on Nordic stocks and mutual funds for the 1983 to 2009 period are available from FINBAS, a financial database maintained by the Swedish House of Finance. The data include monthly stock returns and mutual fund returns. For securities not covered by FINBAS, I use price data from Datastream and Morningstar. 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 out of five years history, because skewness is evaluated on five years rolling window of historical monthly returns. We end up with a universe of approximately 2,500 stocks and 1,500 funds in 2003. This number went 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 our dataset of asset returns as their preference revealed in total financial investment 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 proxied by the monthly average yield on the one-month Swedish Treasury

\textsuperscript{9}Swedish investors rarely hold bonds and derivatives. Holdings on these two assets categories are small enough to be ignored from the analysis.
The return on the local market portfolio is proxied by the SIX return index (SIXRX), which 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 U.S. 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 2 reports the summary statistics of asset returns and the correlations. Results reported in section 4 are based on the SIXRX index as a benchmark. We also report results using world index in section 6.

Table 2 inserted here.

3.3 Main Variables Construction

3.3.1 Portfolio Expected Return

Measurement error is a crucial issue for the estimation of expected return due to slow convergence of the mean. As the observation period is short, the mean return of the portfolio is difficult to estimate. To have a better estimation, I infer the mean return vector from an asset pricing model. Model implied return delivers better estimates of mean returns than historical sample mean due to the significant reduction of standard error. I assume that assets are priced with CAPM, and the market portfolio has the return of the SIXRX index return. (I also report results using CAPM with world index and Fama-French three-factor model as asset pricing model in robustness checks):

\[ r_{i,t}^e = \beta_{i,M,t} \bar{r}_m + \epsilon_{i,t}, \quad \tau \in [t-59,t]. \]  

(4)

At the end of each year from 1999 to 2007, I estimate the time varying \( \beta_i \) in equation (4) using the previous 60 monthly returns. The estimated mean return of asset \( i \) and year \( t \) is

\[ \bar{r}_{i,t} = \beta_{i,M,t} \bar{r}_m, \]  

(5)

where \( \bar{r}_m \) is the average of the market excess return over a long sample period from 1983 to 2009. The average of Swedish market monthly return excess to risk-free rate is 0.7%. The portfolio mean return at year \( t \) is the weighted average of 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 market beta, ∑ \limits_{j=1}^{N} w_{j,t}\beta_{j,M,t}, where \( w_{j,t} \) is the portfolio weight in asset \( j \) at time \( t \). Portfolio estimated mean return can be obtained by

\[
\bar{r}_{p,t} = \beta_{p,M,t}\bar{r}_m.
\]

### 3.3.2 Portfolio Variance

As the sample variance converges faster to its expectation than the sample average, a short time series of 60 periods is shown to be enough to give an accurate estimation. Variance of portfolio at time \( t \) is estimated using the sample variance over 60 months of historical monthly return. I compute portfolio return as if the portfolio was fully rebalanced every month to the same weight as the weight vector observed at time \( t \):

\[
\sigma^2_{p,t} = \frac{1}{60} \sum_{\tau=1}^{60} (r_{p,t-\tau}^e - \mu_{p,t-60:t})^2.
\]

where \( r_{p,t-\tau}^e \) is the excess return of portfolio \( p \) at time \( t - \tau \); \( \mu_{p,t-60:t} \) is the mean of portfolio excess returns over the period \( t - 59 \) to \( t \). Portfolio volatility \( \sigma_{p,t} \) is the square root of portfolio variance.

### 3.3.3 Portfolio Sharpe Ratio

Portfolio Sharpe Ratio at time \( t \) is defined as

\[
SR_{p,t} = \frac{\bar{r}_{p,t}}{\sigma_{p,t}}
\]

where \( \sigma_{p,t} \) is the portfolio volatility at time \( t \), \( \bar{r}_{p,t} \) is CAPM implied portfolio expected return at time \( t \). Instead of using the level of Sharpe ratio, I choose to follow Calvet and Sodini (2007) and use the relative Sharpe ratio loss compared to the market Sharpe ratio. The relative Sharpe ratio loss \( RSRL_{p,t} \) defined as \( 1 - \frac{SR_{p,t}}{SR_B} \), where \( SR_B \) is the market portfolio 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 this portfolio Sharpe ratio measure is identical to the diversification measure used in Calvet and Sodini (2007), the result can be directly explained based on previous result in the literature.
3.3.4 Portfolio Skewness

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

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

(8)

Note that complete portfolio skewness equals risky portfolio skewness, and does not depends on risky share, as sample skewness measure is the third moment scaled by volatility to the power of three. Risky share reveals the risk aversion to the volatility, and the asymmetry of risky portfolio reveals the skewness preference. Though skewness is a good statistic measure for distribution asymetry, empirically, it is very positively correlated with volatility. To have a skewness measure that is orthogonal to volatility, I follow Mitton and Vorkink (2007), construct an instrument variable of portfolio skewness by regressing portfolio skewness on portfolio volatility, and taking the residual as the instrument for portfolio skewness.

The sample skewness measure is sensitive to outliers in returns. In robustness checks section, I also report result using an alternative measure of skewness: quantile-based measure of skewness which is defined as follows,

$$ skew_{p,t} = \frac{q(95) + q(5) - 2q(50)}{q(95) - q(5)}, $$

(9)

where $q(n)$ is the $n^{th}$ percentile of portfolio excess return over past 60 months. This measurement is robust to outliers, which may impact the estimation of the skewness measure. Both skewness measures lead to the same conclusion showing that the result is not driven by few outliers.

3.3.5 Portfolio Size and Concentration

The size and the concentration of the portfolio is used as a control in the baseline regression in Section 4. The number of assets affects portfolio skewness in a mechanical way: Simkowitz and Beedles (1978) and Albuquerque (2012) show both theoretically and empirically that portfolio skewness decreases as the number of assets in the portfolio increases and as the concentration of the portfolio decrease. Proof is given in appendix. For this reason, market portfolio exhibits negative skewness while individual assets are usually positively skewed, and this divergence between individual and market level is because of the stylized fact that assets tend to be negatively coskewed with each other. I measure the size of the portfolio by the number of assets in the portfolio. I measure the
concentration of portfolio by the Herfindahl Index defined as \( \sum_{i=1}^{N} \omega_i^2 \) where \( N \) is the number of assets in the portfolio and \( \omega_i \) is the weight of asset \( i \). This concentration measure takes into account both number of asset and weights put in each asset in the portfolio. This mechanical relation may 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. By controlling for portfolio size or concentration, I rule out small size portfolio both as skewness seeking channel and behavior bias.

### 3.3.6 Factor Loadings

Portfolio value, size, and momentum loadings are also controls in the baseline regression in Section 4. 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:

\[
\begin{align*}
    r_{i,\tau}^e &= \alpha_{i,t} + \beta_{i,t} MKT_{\tau} + v_{i,t} HML_{\tau} + s_{i,t} SMB_{\tau} + m_{i,t} MOM_{\tau} + u_{i,\tau}, \\
    \tau &\in \{t-59, t\}
\end{align*}
\]

(10)

where \( r_{i,\tau}^e \) denotes the excess return of asset \( i \) in month \( \tau \) 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:

\[
v_{p,t} = \sum_{i=1}^{N} w_{p,i,t} v_{i,t}
\]

(11)

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 \( m_{p,t} \).
3.3.7 Labor Income Risk

In order to empirically test the implications of bringing risky labor income into a portfolio choice model, one need to have an accurate estimation of different moments of labor income shock. To estimate the labor income shock skewness from the data, I consider the following specification of household labor income:

\[ \log(L_{h,t}) = a_h + b' x_{h,t} + \nu_{h,t} + \varepsilon_{h,t}, \]  

where \( L_{h,t} \) denotes non financial disposable income for individual \( h \) in year \( t \) obtained by subtracting post-tax financial gain from observed disposable income, \( a_h \) is individual fixed effect, \( x_{h,t} \) is a vector of age dummies to take away life-cycle deterministic part away from labor income process. As we believe that individuals with different education level face different labor income growth path, model (12) is estimated separately for three different education level: before high school, high school and post high school diploma. The unpredicted labor income \( y_{h,t} \),

\[ y_{h,t} = \log(L_{h,t}) - \hat{a}_h - \hat{b}'x_{h,t}, \]

is the sum of a permanent component \( \nu_{h,t} \) and a transitory component \( \varepsilon_{h,t} \). The permanent component of labor income is the sum of a group level component \( \omega_t \) and an idiosyncratic component \( w_{h,t} \):

\[ \nu_{h,t} = \omega_t + w_{h,t} \]  

The group level and idiosyncratic components follow independent random walks:

\[ \omega_t = \omega_{t-1} + \kappa_t \]
\[ w_{h,t} = w_{h,t-1} + u_{h,t} \]

Therefore, the permanent component \( \nu_{h,t} \) itself is also a random walk:

\[ \nu_{h,t} = \nu_{h,t-1} + \xi_{h,t} \]  

The transitory component of labor income can also be decomposed as a sum of a group level component \( \eta_t \) and an idiosyncratic component \( \varepsilon_{h,t} \):

\[ \varepsilon_{h,t} = \eta_t + \varepsilon_{h,t} \]  

16
Both $\eta_t$ and $e_{h,t}$ have stationary distribution. Above is the standard way of modeling labor income shock. We are interested in extracting the permanent labor income shock $\nu_{h,t}$ from the total labor income shock, as transitory shocks are reverted quickly and have little impact on long term portfolio choice. To this end, I divide the population into different groups according to their similarity in business sector and education level, and assume individuals within the same group face the same labor income shock distribution. Within each group, I follow the procedure of Carroll and Samwick (1997) and estimate the variances of cumulative income growth innovations at the household level and use the estimates to infer the variances of permanent and transitory income shocks and the third central moment of permanent income shock.

$$y_{h,t} - y_{h,t-\tau} = (\nu_{h,t} + \varepsilon_{h,t}) - (\nu_{h,t-\tau} + \varepsilon_{h,t-\tau})$$

$$= (\xi_{h,t} + \xi_{h,t-1} + \ldots + \xi_{h,t-\tau+1}) + \varepsilon_{h,t} - \varepsilon_{h,t-\tau+1}$$

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

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

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

Where $\sigma_{\xi}^2$ is the variance of permanent income shock, $\sigma_{\varepsilon}^2$ is the variance of transitory income shock, and $m_{\xi}^3$ is the third central moment of permanent income shock. For each group, the time constant $\sigma_{\xi}^2$ and $\sigma_{\varepsilon}$ for each group can be estimated by regressing $\text{var}(y_{h,t} - y_{h,t-\tau})$ on $\tau$ and a vector of 2 without a constant. Similarly, $m_{\xi}^3$ can be estimated by regressing $m^3(y_{h,t} - y_{h,t-\tau})$ on $\tau$ without a constant. I take maximum $\tau$ equals to 5. Following Guvenen, Ozkan, and Song (2014), we estimate this model for males between age 25 and 55 as the true labor income shock is better estimated only with males in the workforce. Males within this age range have relatively stable employment rate and labor supply. At the same time, they are less affected by endogenous labor market choice such as the voluntary part-time job. I then apply the estimated labor income shock distribution to all individuals within the same group at that year regardless of age and gender.

I apply the same method on idiosyncratic labor income shock, defined as the deviation of individual...
ual 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 permanent income shock. The objective is to show that variance and skewness of total income shocks are predominated by variance and skewness of idiosyncratic income shocks, and the systematic income shocks has much lower volatility and asymmetry. Table 3 reports the cross-sectional distribution of total and idiosyncratic permanent labor income shock moments. The total permanent shock can almost be captured by only idiosyncratic permanent shock, and the group level permanent shock counts for a tiny fraction of total permanent shock. Table 4 reports some individual characteristics by their level of labor income shock skewness. Low educated, less wealthy people tend to have lower labor income shock skewness. Also, individuals with low labor income shock skewness are more likely to be unemployed, immigrant. They also tend to hold a lower risky asset share.

Table 3 inserted here.

Table 4 inserted here.

3.3.8 Human Capital

Expected human capital is computed as the present value of future expected labor income:

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

I assume that no individual lives longer than 100. Individuals over 100 have zero human capital. $T_h$ is the number of years left to 100, $\pi_{h,t,t+n}$ is the survival probability given by the life tables for the period 2004 - 2008, both sexes provided by Statistics Sweden. The expected labor income is obtained by estimating model (12) for different education group and on non-retired people who are older than 20. Expected labor income is replaced by a discounted amount of constant income after retirement. The replacement ratios are measured as the average income of 65 retired individual over the average of 64 non-retired individual 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 (12) conditional on his age, education level and whether retired at time $t + n$. I winsorize human capital at 50 million Swedish Kronor (approximately $6 million). Table 5 reports the average human capital by education level and by age.
4 Portfolio Skewness and Mean-variance Efficiency

As mentioned in Section 2.1, one important implication of skewness preference compared to mean-variance preference is that, in cross-sectional, investors’ optimal portfolios have lower Sharpe ratio and higher skewness for those who express higher skewness preference. This section conduct the empirical test of this implication. Mitton and Vorkink (2007) use a regression model to investigate skewness preference using data on stock portfolio held by a broker’s retail investor clients. Our sample contains the whole Swedish population and entire wealth portfolio which is required to investigate skewness preferences. Also, to further study the important factors that affect investors’ skewness seeking behavior, it is important to first show that implication of skewness preference is observed among Swedish population.

Table 6 panel A reports the cross-sectional distribution of retail investors’ portfolio mean return, volatility, skewness, Sharpe ratio and number of assets. It also reports world market portfolio as a benchmark. Retail investors’ portfolio has, on average, lower mean return, higher volatility, higher skewness, and lower Sharpe ratio than the market portfolio benchmark.

Empirical prediction is directly obtained from expected utility analysis in section 2.1. However, carrying this prediction to empirical test and obtaining a reliable result face some challenges. I will discuss each one of these issues and show that the positive relation between portfolio skewness and Sharpe ratio loss is robust.

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

$$RSRL_{p,t} = \alpha_0 + \alpha_1 skewIV_{p,t} + \alpha_2 X_{p,t} + \alpha_3 X_{h,t} + FE_t + \varepsilon_{p,t},$$

where $RSRL_{p,t}$ is the relative Sharpe ratio loss. $X_{p,t}$ 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. Petersen (2009) shows that, when there...
exists both individual and time effect, a good empirical approach to get an unbiased standard error is to include dummy variables for each period to absorb the time effect and then cluster by the individual. To eliminate the non-fixed time effect, I clustered on two dimensions simultaneously. As I do not have a sufficiently large number of time periods, in robustness, I also perform Newey West Fama-MacBeth with the number of lags equal to 4. The result is robust and significant in both cases.

I first control for portfolio volatility by using the instrument portfolio skewness described in Section 3.3.4. There are two reasons to do so. First, though skewness is a good statistic measure for distribution asymmetry, it is very positively correlated with volatility. To capture the relation between Sharpe ratio and skewness, one should extract skewness measure that is not explained by volatility. The second reason for controlling volatility is borrowing constraint. When mean-variance investors face borrowing constraint, they have to deviate from the capital market line and long assets on the efficient frontier, which causes a decrease of Sharpe ratio that can be achieved by borrowing constrained investors. If efficient assets that have higher volatility than the market portfolio also tend to be positively skewed, borrowing constrained investors acquire skewness inattentively by longing assets on the right tail of efficient frontiere.

Second, for the reason explained in section 3.3.5. I control for the concentration of portfolio to rule out the case that investors acquire skewness inattentionally by holding small number of assets. I use the Herfindahl Index as the measure of concentration. It is highly correlated with the number of assets.

I also control for empirical factors such as value, size, and momentum. By doing this, I rule out the possibility that skewness seeking is a side effect of chasing other factors. Empirically, I find that skewness has little correlation with market cap and BM ratio and has a positive correlation with momentum on asset level. (Cf. Table 7)

Moreover, I add controls for some demographic characteristics, such as level of education, age, and gender. The idea is to capture investors’ irrationality if there exists any, such as gambling behavior, cognitive limitation. Under the rational framework, one should expect that controlling
for irrationality will not change the trade-off effect between 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 8 reports the estimation of equation (18). The first column reports the estimation without controls. $\alpha_1$ being significantly different from 0 rejects the null hypothesis that investors are mean-variance maximizers. $\alpha_1$ being positive suggests that there is indeed a systematic trade-off between Sharpe ratio and skewness. Moving to the right columns of the table, I control for portfolio concentration 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 $\alpha_1$ stay very consistent. Put it in economic magnitude, the magnitude line reports that one standard deviation increase in portfolio skewness corresponds to a loss of about 7.5% of market Sharpe ratio. To put this number in perspective: moving from the 10th percentile to the 90th percentile of portfolio skewness, Sharpe ratio loss increases from 5% to 35% of market Sharpe ratio.

Table 8 inserted here.

Two more robustness tests are provided in Section 6. To further confirm that the significant trade-off is not just picking up mechanical relation and is obtained only through investors’ portfolio choice, I conduct a Placebo test where a Placebo population only pick asset randomly. I show that the trade-off found in the data cannot be achieved by random portfolio construction, and is too large to be explained by chance. The second robustness test focus on portfolio rebalancing. Instead of looking at levels of Sharpe ratio and skewness, I look at the changes of Sharpe ratio and skewness when investors rebalance their portfolio. I find again an increase in portfolio skewness corresponds to an increase in portfolio relative Sharpe ratio loss and vice versa.

5 Cross-Sectional Heterogeneity

Having confirmed from previous exercise that skewness preference plays an important role in investors’ financial investment decision, a deeper and more interesting question that has not been answered is what are the key factors that drive the heterogeneity of this behavior. In previous literature, skewness seeking behavior is often connected with gambling behavior, which says that retail
investors tend to gamble in stock market by irrationally invest in lottery like stocks. Especially less wealthy, low skilled, less educated males. But skewness preference, before anything else, is one of the first principles of portfolio choice. In this section, I build background risk, which is an important factor for household life-cycle decision, in a portfolio choice model, to see to which extent the background risk characteristics can explain the heterogeneity of skewness seeking in portfolio choice within the expected utility framework, and whether behavior evidence, such as gamblers’ behavior, can be partially explained by their specific labor income characteristics. At the end, I also explored other potential effect of hedging labor income skewness on portfolio choice.

5.1 Theoretical Framework

Background risk, as the most important source of uncertainty for households, affects investor’s portfolio choice. It has been shown that higher background risk is compensated by lower portfolio risk for a risk vulnerable (decreasing and convex absolute risk aversion) agent. This interaction between background risk and portfolio choice also extends to the higher moment. Guvenen, Ozkan, and Song (2014) shows that, compared to background risk (measured by volatility), background left tail risk (measured by skewness) changes over business cycle more aggressively, which suggest that hedging against background downside risk with financial investment can be potentially very important. We should expect that higher labor income downside risk is compensated by higher skewness loading in portfolio. Another important source of variation for retail investors is the life-cycle variation. As investors gaining age, several forces play roles in investors’ portfolio third moment structure. Their financial wealth accumulate. At the same time, as investors are getting old, their human capital de-cumulate, they also lose labor supply flexibility and consumption adjustment ability which can serve as self-insurance against (downside) risk. As they become less able to buffer bad outcomes outside their financial investment, their demand for downside risk protection in the portfolio should increase.

This section uses the simplest model possible to illustrate formally the effect of labor income, human capital and wealth effect on portfolio skewness tilt. To this end, I develop a one-period portfolio choice model with risky labor income. The economy has three assets: one risk-free asset and two risky assets with skewed payoffs. Investor invests initial wealth in the first period, get the liquidation value of his portfolio plus the realization of a random labor income in the second period and consume everything. Investors have power utility. As market provides skewed assets, investor reveals his skewness preference by investing relatively more or less into a positively skewed
asset. Investors have homogenous preferences, but face different background risk, expected labor income level, and wealth endowment. Each of them optimizes their expected utility by choosing their financial portfolio composition holding assets’ returns exogenous.

5.1.1 Financial Assets

The riskless asset has a fixed simple return \( r_f \), two risky assets have random simple returns \( r_1 \) and \( r_2 \). Both risky assets’ returns have asymmetric distributions. Two risky assets with different level asymmetry provide distinguish choices in terms of skewness. In reality, this choice can be proxied by the choice between stock and fund. Table 6 panel B on assets’ return moments shows that, stocks are on average positively skewed, while funds, as they provide a diversified portfolio, have almost 0 skewness if not negative. They are naturally distinguish choices in terms of skewness. Following Dahlquist, Farago, and Tédongap (2017), we use a simple extension to the multivariate normal distribution in order to capture the asymmetry of asset returns. We assume that simple excess returns on two risky assets are described by the following model,

\[
    r_{i,t} = \mu_i - \sigma_i \delta_i + (\sigma_i \delta_i) \varepsilon_{0,t} + \left( \sigma_i \sqrt{1 - \delta_i^2} \right) \varepsilon_{i,t}. \quad \text{where} \quad i \in \{1, 2\}
\]

\{1, 2\} represent respectively, risky asset 1 and 2. The scalar \( \varepsilon_{0,t} \) is a common shock across all assets that follows an exponential distribution with a rate parameter equal to one. \( \varepsilon_{i,t} \), represents asset-specific shocks and has a multivariate normal distribution, independent of \( \varepsilon_{0,t} \), with standard normal marginal densities and correlation matrix \( \psi \). Parameters \( \mu, \sigma, \psi \) define the return generation process. It is straightforward to show that the mean, variance and skewness of asset \( i \) are given by

\[
    E(r_{i,t}) = \mu_i, \quad Var(r_{i,t}) = \sigma_i^2, \quad Skew(r_{i,t}) = 2\delta_i^3.
\]

The correlation and coskewness between \( r_i \) and \( r_j \) is

\[
    Corr(r_{i,t}, r_{j,t}) = \Psi_{ij} \sqrt{1 - \delta_i^2} \sqrt{1 - \delta_j^2} + \delta_i \delta_j,
\]

\[
    Coskew(r_{i,t}, r_{j,t}) = \frac{E[(r_{i,t} - E(r_{i,t}))^2(r_{j,t} - E(r_{j,t}))]}{Var(r_{i,t})\sqrt{Var(r_{j,t})}} = 2\delta_i^2 \delta_j.
\]

Together with asset returns generating model, it can be shown that, the portfolio return has the
following moments expressions,

\[ \mu_p = r_f + \alpha^T \mu^*, \quad \sigma_p^2 = \alpha^T \Sigma \alpha, \quad \delta_p = \frac{\alpha^T (\sigma^* \circ \delta^*)}{\sigma_p}, \]

where \( \mu^* = (\mu_1, \mu_2), \sigma^* = (\sigma_1, \sigma_2) \) and \( \delta^* = (\delta_1, \delta_2) \).

### 5.1.2 Labor income

Individuals also have skewed labor income shock distribution. A negative skewness in labor income shock can be interpreted as a left tail or downside risk of labor income. Holding labor income shock volatility constant, a lower skewness of labor income shock means a higher probability of receiving a large labor income drop than receiving a large labor income upward jump. Labor income shock is defined similarly to the one for asset returns:

\[ l_t = \mu_l - \sigma_l \delta_l + (\sigma_l \delta_l) \varepsilon_{0,t} + \left( \sigma_l \sqrt{1 - \delta_l^2} \right) \varepsilon_{l,t}. \]

\( \varepsilon_{0,t} \) is the same common shock that for stock returns, representing an aggregate shock to the economy. I allow \( \varepsilon_{l,t} \) to be correlated with \( \varepsilon_{i,t} \). The correlation matrix among asset 1, asset 2 and \( l \) is noted as \( \Psi \). In one period model, labor income shock is the labor income received in the second period and is purely permanent shock.

### 5.1.3 Agent’s Utility

Agent has power utility function. Each investor’s optimization problem is to choose the portfolio weight vector \( \alpha_h = (\alpha_{1,h}, \alpha_{2,h}) \) that maximizes the expected utility of his consumption at the end of the second period. For simplicity, index \( h \) is omitted in the following maximization problem.

\[
\max_{\alpha_1, \alpha_2} E \left[ \frac{C^{1-\gamma}}{1-\gamma} \right]
\]

s.t. \( C = W_0 (1 + r_p) + l, \)

where \( r_p = r_f + \alpha_1 (r_1 - r_f) + \alpha_2 (r_2 - r_f) \).

### 5.2 Calibration and Model Predictions

There is no simple close form solution for the optimal portfolio due to the presence of skewed pay-offs. To obtain the effect of each variable of interest on optimal portfolio choice, I use instead a
numerical calibration. I choose parameters for baseline calibration as shown in Table 15. Calibration parameters are chosen to be as close as possible to the empirical value in the data to get realistic predictions. The monthly risk-free rate is set to be 0.001, which is the average inflation adjusted post-tax one-month Swedish treasury bill rate between 1999 and 2007. Parameters for two risky assets in the model are set to fit the best stock and fund respectively. The calibration parameter values for assets' mean, variance, and skewness are chosen to be the cross-sectional median value among stocks and funds respectively. The correlation between asset 1 and asset 2 is chosen to be the median correlation with market return among all stocks. The expected labor income equals to 0.3 which is the mean of income to wealth ratio among Swedish population. In the simulation, it varies from 0 to 2, covers 0.07 to 1.8 which are the 1th and 99th percentile of income to wealth ratio. Volatility and skewness of labor income shock are also chosen to be equal to the mean of estimated values. In the simulation, volatility varies from 0 to 0.2 and skewness varies from $-1$ to 1. The correlation between labor income and financial assets is set to be close to 0, which is consistent with the standard results in the literature that find a very low or zero correlation between financial and nonfinancial income. Risk aversion is set to be 4, and initial wealth is normalized to 1. All parameters about labor income shock are converted to monthly bases, consistent with monthly returns. Sensitivity tests are carried and reported in appendix for debatable parameters. Results with different values of risk aversion, fund skewness and the correlation between labor market and financial market are reported. No qualitative change in the calibration results.

Table 15 inserted here.

Figure 2 shows how optimal portfolio skewness varies with the different level of labor income risk, initial wealth and human capital. Three empirical implications are obtained from the model. First, low skewness in labor income risk generates high skewness in the portfolio. A negative skewness in labor income risk suggests a higher probability of becoming unemployed than being promoted. Investors who face this kind of downside risk in their labor income will look for more downside protection from their financial portfolio position, which translates into seeking for higher skewness in portfolio choice. Second, high volatility of labor income shock also leads to high skewness in portfolio choice. When investors are forced to hold too high labor income risk, they reduce their risk taking in financial portfolio. As they have asymmetric preference, they will do it asymmetrically by reducing risk more on the negative side than on the positive side. Third, low expected labor income
lead to strong skewness seeking. Low expected labor income decrease the expected consumption in the second period, which needs to be compensated by lower volatility and higher skewness in consumption, and the only way is by decreasing the volatility or increasing the skewness of financial portfolio.

Figure 2 inserted here.

5.3 Empirical Results

In this section, I first test empirically the predictions mentioned in section 5.2. Then, I link the results to other existing findings in the literature and shed lights on some issues in asset pricing and household finance. I estimate the following pooled regression:

\[
\text{skewIV}_{p,t} = \beta_0 + \beta_1 \log(\text{FinWealth})_{p,t} + \beta_2 \log(\text{HumanCapital})_{p,t} + \beta_3 \text{IncVar}_p + \beta_4 \text{IncSkew}_p \\
+ \beta_5 X_{p,t} + \beta_6 FE_t + \epsilon_{p,t},
\]

(19)

(20)

where \(X_{p,t}\) is a vector of controls including log of labor income level, log of real-estate wealth, log of leverage, gender, education level, immigrant dummy, unemployed dummy and urban dummy. Standard errors are clustered on group level. Results are shown in Table 16 where the first column is regressing portfolio skewness only on individual characteristic, the second column is regression model (19) on the full sample, and the third and fourth columns are regression model (19) on two investor types: exclusive stock holders and mixed holders who invest in both stocks and funds. Regression on the full sample gives consistent sign with the model predictions. I estimate the same regression model separately on individuals with negative labor income shock skewness and positive skewness. I find that income shock skewness affects portfolio skewness tilt only when it is negative, which confirm the model prediction that investors are only concerned by negative income shock skewness and seek for compensation from financial portfolio. I also estimate the regression model on two subgroups of investors: exclusive stockholders and investors who hold both stocks and funds in their portfolio. One expects mixed holders are, among retail investors, those who actively and rationally manage their portfolio and behave close to the predictions of the model. We do observe that, for mixed holders, skewness tilt in portfolio choice correlates with labor income risk distribution. For exclusive stockholders, though they can extract high skewness from stock holding, they do not react to background risk situation when they do so, confirming that exclusive stockholders may seek for
skewness for reasons other than compensating their risk exposure in the background. These findings
give some rational explanations for some stylized facts in gambling literature that poor, low skilled
workers tend to gamble in the financial market, as these investors are often those who have lower
wealth accumulation and higher left tail risk in labor income. The summary statistic in Table 4
shows that, investors with low labor income shock skewness also tend to be less educated, have less
net wealth, be more likely unemployed and immigrants, and hold less risky share. One difference be-
tween the model prediction and the gambler characteristics is that, in the model, younger investors,
as they have higher human capital, should hold less skewness in their financial portfolio while gam-
bling literature documents that younger investors are more likely to gamble in the stock market.
Evidence found in Swedish investors is consistent with the model prediction – younger investors
hold less skewed financial portfolio. Besides model predictions, I also look at some key demographic
characteristics such as gender and education. Males tend to have higher skewness tilt compared to
female, but it is not significant among mixed holders. Lower educated investors hold significantly
more skewness in their portfolio, and it is more pronounced among exclusive stockholders.

Table 16 inserted here.

6 Robustness Checks

This section present a battery of robustness checks mentioned previously.

6.1 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 (18) using Fama-MacBeth regressions, and compute
heteroscedasticity and autocorrelation consistent Newwey and West (1987) standard error estimates
with a lag length of 4. Table 9 report the regression results. The trade-off coefficients are significant
and have the same magnitude as in the baseline case.

Table 9 inserted here.
6.2 CAPM (world index) Implied Expected Return

Table 10 reports the regression result of model (18) 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 10 inserted here.

6.3 Fama-French Three-Factor Model Implied Expected Return

Table 11 reports the regression result of model (18) 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 11 inserted here.

6.4 Quantile-based Skewness

Table 12 reports the estimation of model (18) 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 12 inserted here.

6.5 Placebo Test

Ideally, in a Placebo test, one should compare the real population with a population without skewness preference. However, we 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, we should observe the Sharpe skewness trade-off we 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 we 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 $\alpha_1$ under randomization. The average asymptotic standard error and the finite sample standard error are given in the first line of Table 13. The $\alpha_1$ 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 13 in the second line. Shutting down both channel 2 and channel 3 gives a $\alpha_1$ that is closer to 0 than shutting down only channel 3. Investors seek for skewness via both weight allocation and asset picking.

Table 13 inserted here.

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, we can still obtain a non-zero correlation.

6.6 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, we need
non-overlapped periods for return estimation ideally. Hence, we 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), we 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 we observe at the end of year
$t + 1$. We 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 $t + 1$. We call this portfolio the "passive portfolio", and denoted by $\omega_{p,\tilde{t}+1}$. 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 $\text{skew}_{p,\tilde{t}+1}$ and $\text{skew}_{p,t+1}$ respectively. I denote
the portfolio relative Sharpe ratio loss of passive and active portfolios by $\text{RSRL}_{p,\tilde{t}+1}$ and $\text{RSRL}_{p,t+1}$
respectively. I denote also the change in skewness and relative Sharpe ratio loss:

$$
\Delta \text{skew}_{p,t+1} = \text{skew}_{p,t+1} - \text{skew}_{p,\tilde{t}+1}
$$
$$
\Delta \text{RSRL}_{p,t+1} = \text{RSRL}_{p,t+1} - \text{RSRL}_{p,\tilde{t}+1}.
$$

As we do not know which model investors use for return estimation (using historical returns or hav-
ing more complicated forward-looking models). I estimate $\text{skew}_{p,t+1}$, $\text{skew}_{p,\tilde{t}+1}$, $\text{RSRL}_{p,t+1}$, and
\(RSRL_{p,t+1}\) 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,

\[
\Delta RSRL_{p,t} = \alpha_0 + \alpha_1 \Delta skew_{p,t} + \alpha_2 \Delta vol_{p,t} + \alpha_3 \Delta X_{p,t} + FE_t + \varepsilon_{p,t},
\]

(21)

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 14 shows the result for regression (21). 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, we obtain the same result – a positive relation between skewness change and RSRL change with backward measure; but we 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 14 inserted here.

7 Conclusion

This paper first documents the strong evidence of skewness preference among retail investors. Controlling for diversification and other factors, investors seek for portfolio skewness at the expense of lower mean return and/or higher overall riskiness, which explains the deviation from the capital market line and the heterogeneity in risky portfolio composition.

This paper further documents that the cross-sectional heterogeneity of skewness seeking behavior in portfolio choice shows strong patterns that are consistent with many first principals of portfolio
choice. I focus on how background risk and wealth affect portfolio third-moment tilt. I show that there exists substitution effect between background downside risk and portfolio skewness. Investors face more downside risk in their labor income tend to seek for higher skewness in the portfolio, suggesting a hedging demand of financial investment. I also show that investors seek for more skewness in the portfolio when they have less financial wealth or less human capital. In order to hedge against labor income shock downside risk, investors overweight assets that provide high return when their labor income downside risk is high.

The results provide new directions for future research on skewness preference. The data reveals relatively high skewness preference among retail investors. However, retail investors are not necessarily the 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 suggest that demographic changes may have major implications for the skewness premium, showing an importance in policy making, which can be investigated in further research.
Appendix

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 \( EW \):

\[
E[U(W)] = E[U(EW) + U'(EW)(W - EW) + \frac{U''(EW)}{2}(W - EW)^2]
= U(EW) + \frac{U''(EW)}{2}Var(W)
\]

Apply Taylor vexpansion on \( U(CE) \) around \( EW \):

\[
U(CE) = U(EW) + U'(EW)(CE - EW)
\]

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

\[
CE = EW + \frac{U''(EW)}{2U'(EW)}Var(W)
= EW - \frac{\gamma}{2EW}Var(W)
\]

Higher moment case can be applied directly.

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 comement 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:

\[
T^{-1} \sum_{t} (r_{p,t} - \bar{r}_p)^3 = \frac{1}{N^3} \sum_{i=1}^{N} \frac{1}{T} \sum_{t} (r_{p,t} - \bar{r}_p)^3 \quad \text{(mean of asset skewness)}
\]

\[
+ \frac{3}{TN^3} \sum_{t} \sum_{i=1}^{N} (r_{p,t} - \bar{r}_p) \sum_{p' \neq p} (r_{p',t} - \bar{r}_{p'})^2 \quad \text{(co-vol)}
\]

\[
+ \frac{6}{TN^3} \sum_{t} \sum_{i=1}^{N} (r_{p,t} - \bar{r}_p) \sum_{p' > p} \sum_{l > p'} \omega_i (r_{p',t} - \bar{r}_{p'}) \omega_l (r_{l,t} - \bar{r}_l) \quad \text{(co-cov)}
\]

The coskewness terms capture the average movement in one firm’s return with the variance of the portfolio that comprises the remaining firms. As there are \(N\) asset level skewness terms, \(N((N - 1) \text{ terms on co-vol, and } N!/[3!(N - 3)!] \text{ terms in co-cov, when the number of assets in the portfolio increases, the number of terms associated with coskewness increases faster than the number of terms associated with asset level skewness. He also points out in his paper that the coskewness term is negative, and monotonically decreasing in } N. \) 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 \(\omega = (\omega_1, \omega_2, \ldots, \omega_N)\),

\[
T^{-1} \sum_{t} (r_{p,t} - \bar{r}_p)^3 = \sum_{i=1}^{N} \omega_i^3 \frac{1}{T} \sum_{t} (r_{p,t} - \bar{r}_p)^3 \quad \text{(mean of asset skewness)}
\]

\[
+ \frac{3}{T} \sum_{t} \sum_{i=1}^{N} \omega_i (r_{p,t} - \bar{r}_p) \sum_{p' \neq p} \omega_{p'}^2 (r_{p',t} - \bar{r}_{p'})^2 \quad \text{(co-vol)}
\]

\[
+ \frac{6}{T} \sum_{t} \sum_{i=1}^{N} \omega_i (r_{p,t} - \bar{r}_p) \sum_{p' > p} \sum_{l > p'} \omega_{i'} (r_{p',t} - \bar{r}_{p'}) \omega_l (r_{l,t} - \bar{r}_l) \quad \text{(co-cov)}
\]

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.

**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. 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 slitley negative. It is important to check the skewness goes above or below the zero threshold does not affect qualitatively the result. Figure 4 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 suprisingly, when fund skewness increases, it moves horizontally optimal portfolio skewness upwards. Last, I look at whether the correlation between labor income shock and asset’s return being different from 0 moves the result. Figure 5 shows that zero correlation is not a crucial threshold. When correlation deviate from 0, there is no dramatic change in the result.

Figure 3 inserted here.

Figure 4 inserted here.

Figure 5 inserted here.
References


BETERMIER, S., L. CALVET, AND P. SODINI (2017): “Who are the Value and Growth Investors?,” The Journal of Finance, 72(1), 5–46. 9, 15


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 $\gamma$ varies from 0.05 to 10. For mean-variance investors, changes in $\gamma$ does not change the risky portfolio composition. For mean-variance-skewness investors, when $\gamma$ increases, the optimal portfolio moves to the right along the red frontier.
Table 1: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>All individuals</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>p10</td>
<td>p50</td>
<td>p90</td>
<td>mean</td>
<td>s.d.</td>
<td>p10</td>
<td>p50</td>
<td>p90</td>
<td>mean</td>
<td>s.d.</td>
</tr>
<tr>
<td>Financial wealth ($)</td>
<td>953</td>
<td>3,623</td>
<td>34,928</td>
<td>16,233</td>
<td>1,196,126</td>
<td>1,946</td>
<td>7,035</td>
<td>25,150</td>
<td>1,622,923</td>
<td>53,640</td>
</tr>
<tr>
<td>Total wealth ($)</td>
<td>1,195</td>
<td>10,493</td>
<td>140,974</td>
<td>54,394</td>
<td>1,219,009</td>
<td>2,169</td>
<td>29,494</td>
<td>76,476</td>
<td>1,647,632</td>
<td>182,356</td>
</tr>
<tr>
<td>Net wealth ($)</td>
<td>-7,344</td>
<td>5,102</td>
<td>111,118</td>
<td>38,144</td>
<td>1,212,971</td>
<td>-2,013</td>
<td>15,040</td>
<td>152,123</td>
<td>1,640,870</td>
<td>57,886</td>
</tr>
<tr>
<td>Cash:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bank account ($)</td>
<td>904</td>
<td>2,363</td>
<td>12,946</td>
<td>6,530</td>
<td>27,830</td>
<td>1,095</td>
<td>2,959</td>
<td>17,144</td>
<td>8,252</td>
<td>34,953</td>
</tr>
<tr>
<td>Money market fund ($)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>792</td>
<td>9,907</td>
<td>0</td>
<td>0</td>
<td>283</td>
<td>1,121</td>
<td>12,685</td>
</tr>
<tr>
<td>Stock assets:</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Stocks ($)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Funds ($)</td>
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<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Risky share</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Incomes:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-financial disposable real income ($)</td>
<td>0.00</td>
<td>14,075.22</td>
<td>27,939.91</td>
<td>14,365.36</td>
<td>31,281.19</td>
<td>0.00</td>
<td>15,427.84</td>
<td>30,388.88</td>
<td>15,611.91</td>
<td>41,277.21</td>
</tr>
<tr>
<td>Demographics:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>9.00</td>
<td>39.00</td>
<td>74.00</td>
<td>40.43</td>
<td>23.64</td>
<td>8.00</td>
<td>40.00</td>
<td>72.00</td>
<td>40.08</td>
<td>23.55</td>
</tr>
<tr>
<td>Education</td>
<td>0.00</td>
<td>1.00</td>
<td>3.00</td>
<td>1.15</td>
<td>1.01</td>
<td>0.00</td>
<td>1.00</td>
<td>3.00</td>
<td>1.28</td>
<td>1.05</td>
</tr>
</tbody>
</table>

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 consist of cash, direct stock holding, fund holding, bond holding, derivatives, capital insurance and other financial wealth. Total wealth consist 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 before high school, high school, and post high school diploma.
Table 2: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Annual. Ret (%)</th>
<th>Annual. Vol (%)</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Full period</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interest rate</td>
<td>7</td>
<td>1.23</td>
<td></td>
</tr>
<tr>
<td>MSCI world index</td>
<td>10.8</td>
<td>15.5</td>
<td>0.048</td>
</tr>
<tr>
<td>SIXRX index</td>
<td>15.7</td>
<td>22.6</td>
<td>0.004 0.715</td>
</tr>
<tr>
<td><strong>Panel B: Study period</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interest rate</td>
<td>3.9</td>
<td>0.53</td>
<td></td>
</tr>
<tr>
<td>MSCI world index</td>
<td>9.18</td>
<td>14.5</td>
<td>-0.03</td>
</tr>
<tr>
<td>SIXRX index</td>
<td>15.5</td>
<td>20.2</td>
<td>-0.05 0.729</td>
</tr>
</tbody>
</table>

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).
Table 3: Summary Statistics

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

This table reports the summary statistics of total and idiosyncratic labor income shock volatility, third-central moment and skewness measured by applying Carroll and Samwick (1997) method on total labor income shock and idiosyncratic labor income shock respectively.
### Table 4: Summary Statistics

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

This table reports the characteristics by level of labor income shock skewness. Individuals are sorted into three categories by their level of total labor income shock skewness, and the average of labor income shock skewness, characteristics and risky share are reported.

### Table 5: Summary Statistics

<table>
<thead>
<tr>
<th>age group</th>
<th>20-35</th>
<th>35-50</th>
<th>50-65</th>
<th>65+</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before High School</td>
<td>3,725,770</td>
<td>3,075,792</td>
<td>1,956,964</td>
<td>1,287,151</td>
</tr>
<tr>
<td>High School</td>
<td>4,241,160</td>
<td>3,537,456</td>
<td>2,354,112</td>
<td>1,786,048</td>
</tr>
<tr>
<td>Post High School</td>
<td>5,155,551</td>
<td>4,644,504</td>
<td>3,175,708</td>
<td>2,366,382</td>
</tr>
</tbody>
</table>

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

### Table 6: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Risky portfolio</th>
<th>Stock portfolio</th>
<th>Fund portfolio</th>
<th>Mkt</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>p10</td>
<td>p50</td>
<td>p90</td>
<td>p10</td>
</tr>
<tr>
<td>Annual. ExpRet (%)</td>
<td>2.19</td>
<td>3.71</td>
<td>5.22</td>
<td>2.52</td>
</tr>
<tr>
<td>Annual. Vol (%)</td>
<td>11.91</td>
<td>19.03</td>
<td>32.99</td>
<td>23.40</td>
</tr>
<tr>
<td>Annual. Skewness (%)</td>
<td>-13.6</td>
<td>-6.64</td>
<td>6.06</td>
<td>-7.79</td>
</tr>
<tr>
<td>Sharpe ratio (%)</td>
<td>11.5</td>
<td>19.5</td>
<td>22.3</td>
<td>8.7</td>
</tr>
<tr>
<td>Number of assets</td>
<td>1.00</td>
<td>2.00</td>
<td>6.44</td>
<td>1.00</td>
</tr>
</tbody>
</table>

This table reports the cross-sectional distribution of portfolio characteristics. All portfolio characteristics are computed as in section 3.3, then taken the average cross years (1999-2007). Expected mean return, volatility, and skewness are annuized by multiplying by $12, \sqrt{12}$, and $1/\sqrt{12}$ respectively. Market portfolio return is the MSCI world index return, the expected return of market portfolio is the historical sample mean of MSCI world index return over 1983 - 2009.
Table 7: Correlation of firm characteristics

<table>
<thead>
<tr>
<th></th>
<th>tskew</th>
<th>qskew</th>
<th>tvol</th>
<th>mktcap</th>
<th>BM ratio</th>
<th>mom</th>
<th>aMAX</th>
<th>aMIN</th>
<th>price</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>-0.908</td>
<td>0.030</td>
<td>0.062</td>
<td>4.43</td>
<td>0.170</td>
<td>0.154</td>
<td>1.336</td>
<td>-1.292</td>
<td>106</td>
</tr>
<tr>
<td>s.d.</td>
<td>4.253</td>
<td>0.151</td>
<td>0.319</td>
<td>24.01</td>
<td>6.885</td>
<td>1.151</td>
<td>5.145</td>
<td>1.519</td>
<td>2205</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>tskew</th>
<th>qskew</th>
<th>tvol</th>
<th>mktcap</th>
<th>BM ratio</th>
<th>mom</th>
<th>aMAX</th>
<th>aMIN</th>
<th>price</th>
</tr>
</thead>
<tbody>
<tr>
<td>tskew</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>qskew</td>
<td>0.053</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>tvol</td>
<td>-0.199</td>
<td>-0.177</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mktcap</td>
<td>0.020</td>
<td>0.010</td>
<td>-0.115</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BM ratio</td>
<td>-0.010</td>
<td>-0.011</td>
<td>0.014</td>
<td>-0.049</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mom</td>
<td>0.024</td>
<td>0.322</td>
<td>-0.048</td>
<td>0.043</td>
<td>-0.038</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>aMAX</td>
<td>0.190</td>
<td>-0.089</td>
<td>0.757</td>
<td>-0.148</td>
<td>0.010</td>
<td>-0.017</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>aMIN</td>
<td>0.275</td>
<td>0.251</td>
<td>-0.820</td>
<td>0.129</td>
<td>-0.016</td>
<td>0.085</td>
<td>-0.541</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>price</td>
<td>-0.034</td>
<td>0.015</td>
<td>-0.028</td>
<td>0.094</td>
<td>-0.024</td>
<td>0.050</td>
<td>-0.070</td>
<td>0.039</td>
<td>1.000</td>
</tr>
</tbody>
</table>

This table reports summary statistics and correlations of firm characteristics. It is based on daily return of stocks listed on major Nordic exchanges. *tskew* and *qskew* are based on past year daily excess returns, the measures are described in section 3.3. We 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.
Table 8: Regression of portfolio Sharpe ratio on skewness

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>skewness(IV)</td>
<td>0.246***</td>
<td>0.245***</td>
<td>0.237***</td>
<td>0.227***</td>
<td>0.226***</td>
<td>0.224***</td>
</tr>
<tr>
<td></td>
<td>(6.82)</td>
<td>(7.09)</td>
<td>(6.88)</td>
<td>(6.26)</td>
<td>(6.34)</td>
<td>(6.36)</td>
</tr>
<tr>
<td>Concentration</td>
<td>0.167***</td>
<td>0.182***</td>
<td>0.196***</td>
<td>0.191***</td>
<td>0.191***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(8.78)</td>
<td>(10.52)</td>
<td>(8.22)</td>
<td>(8.15)</td>
<td>(8.19)</td>
<td></td>
</tr>
<tr>
<td>Demographics</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>4-factor loadings</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>vol x Demographics</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>factor loadings x Demographics</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Magnitude (%)</td>
<td>7.9***</td>
<td>7.8***</td>
<td>7.6***</td>
<td>7.2***</td>
<td>7.2***</td>
<td>7.2***</td>
</tr>
<tr>
<td>Adjusted-R2</td>
<td>0.332</td>
<td>0.364</td>
<td>0.375</td>
<td>0.391</td>
<td>0.398</td>
<td>0.402</td>
</tr>
</tbody>
</table>

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.
Table 9: Fama-MacBeth regression of portfolio Sharpe ratio on skewness

<table>
<thead>
<tr>
<th></th>
<th>2000</th>
<th>2001</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
<th>2005</th>
</tr>
</thead>
<tbody>
<tr>
<td>skewness(IV)</td>
<td>0.247***</td>
<td>0.229***</td>
<td>0.221***</td>
<td>0.228***</td>
<td>0.225***</td>
<td>0.224***</td>
</tr>
<tr>
<td></td>
<td>(5.01)</td>
<td>(4.86)</td>
<td>(4.76)</td>
<td>(4.73)</td>
<td>(4.79)</td>
<td>(4.70)</td>
</tr>
<tr>
<td>concentration</td>
<td>0.163***</td>
<td>0.175***</td>
<td>0.191***</td>
<td>0.186***</td>
<td>0.186***</td>
<td>0.186***</td>
</tr>
<tr>
<td></td>
<td>(6.27)</td>
<td>(7.20)</td>
<td>(5.05)</td>
<td>(5.00)</td>
<td>(5.12)</td>
<td>(5.12)</td>
</tr>
<tr>
<td>Demographics</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>4-factor loadings</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>tvol x Demographics</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>factor loadings x Demographics</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Average-R2</td>
<td>0.128</td>
<td>0.181</td>
<td>0.200</td>
<td>0.261</td>
<td>0.273</td>
<td>0.289</td>
</tr>
</tbody>
</table>

This table reports the result of Fama-MacBeth regression of portfolio Sharpe ratio on skewness based on 9 years unbalanced panel. Newey-West with lag number of 4 is applied. The last line reports the average $R^2$ of cross-sectional regression.
## Table 10: Regression of portfolio Sharpe ratio on skewness (World index)

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

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.
### Table 11: Regression of portfolio Sharpe ratio on skewness (Fama-French Three-factor model)

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

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

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 equation (9).
Table 13: Estimation of $\alpha_1$ on randomized population

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>AASE</th>
<th>FSSE</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random. of weights</td>
<td>0.0764</td>
<td>0.00026</td>
<td>0.00004</td>
<td>0.07638, 0.07642</td>
</tr>
<tr>
<td>Random. of assets</td>
<td>0.0516</td>
<td>0.00048</td>
<td>0.00004</td>
<td>0.05158, 0.05162</td>
</tr>
</tbody>
</table>

This table reports the sample average of $\alpha_1$ 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.

Table 14: Robustness: Portfolio Rebalance

<table>
<thead>
<tr>
<th></th>
<th>Backward measures</th>
<th>Forward measures</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>$\Delta skew$</td>
<td>-0.00240***</td>
<td>-0.00224***</td>
</tr>
<tr>
<td></td>
<td>(-38.93)</td>
<td>(-35.85)</td>
</tr>
<tr>
<td>$\Delta vol$</td>
<td>-0.148***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-47.39)</td>
<td></td>
</tr>
<tr>
<td>year FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>9,125,862</td>
<td>9,125,862</td>
</tr>
<tr>
<td>Adjusted-R2</td>
<td>0.030</td>
<td>0.031</td>
</tr>
</tbody>
</table>

This table reports the regression result of model (21). 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.
Table 15: Baseline calibration parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Financial assets and labor income</strong></td>
<td></td>
</tr>
<tr>
<td>$r_f$ Monthly risk-free rate</td>
<td>0.001</td>
</tr>
<tr>
<td>$\mu_1$ Expected monthly return of asset 1</td>
<td>0.0032</td>
</tr>
<tr>
<td>$\mu_2$ Expected monthly return of asset 2</td>
<td>0.0031</td>
</tr>
<tr>
<td>$\mu_l$ Expected labor income</td>
<td>0.025</td>
</tr>
<tr>
<td>$\sigma_1$ Volatility of asset 1</td>
<td>0.094</td>
</tr>
<tr>
<td>$\sigma_2$ Volatility of asset 2</td>
<td>0.052</td>
</tr>
<tr>
<td>$\sigma_l$ Volatility of labor income shock</td>
<td>0.02</td>
</tr>
<tr>
<td>$2\delta_1^3$ Skewness of asset 1</td>
<td>0.38</td>
</tr>
<tr>
<td>$2\delta_2^3$ Skewness of asset 2</td>
<td>-0.12</td>
</tr>
<tr>
<td>$2\delta_l^3$ Skewness of labor income shock</td>
<td>-0.04</td>
</tr>
<tr>
<td>$corr(\epsilon_1, \epsilon_2)$ Correlation of asset specific shock between asset 1 and asset 2</td>
<td>0.32</td>
</tr>
<tr>
<td>$corr(\epsilon_1, \epsilon_l)$ Correlation between asset 1 specific shock and labor income shock</td>
<td>0.01</td>
</tr>
<tr>
<td>$corr(\epsilon_2, \epsilon_l)$ Correlation between asset 2 specific shock and labor income shock</td>
<td>0.01</td>
</tr>
<tr>
<td><strong>Preferences</strong></td>
<td></td>
</tr>
<tr>
<td>$\gamma$ Risk aversion</td>
<td>4</td>
</tr>
<tr>
<td><strong>Wealth</strong></td>
<td></td>
</tr>
<tr>
<td>$W_0$ Initial wealth</td>
<td>1</td>
</tr>
</tbody>
</table>

Mean, volatility and skewness of asset 1 are set to be the median value of cross-sectional stocks. Mean, volatility and skewness of asset 2 are set to be the midian value of cross-sectional mutual funds. Correlation between $\epsilon_1$ and $\epsilon_2$ is the mean of correlations between each stock and the market return. Following the literature, correlation between asset returns and labor income is set to be close to 0.
Figure 2: Baseline calibration of portfolio skewness
This table reports the pooled regression of the portfolio skewness on individual characteristics with year fixed effects. (1) regression of portfolio skewness on individual characteristics related to gambling behavior. (2) regression model (19) with all population. (3) regression for subgroup of investors who hold exclusively stocks. (4) regression for subgroup of investors who hold both stocks and funds in their financial portfolio. Standard errors are clustered at the group (business sector-education) level.
Table 17: Pooled regression of the portfolio skewness on characteristics

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>Tobit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>corr mean</td>
<td>0.002***</td>
<td>0.003**</td>
</tr>
<tr>
<td></td>
<td>(2.63)</td>
<td>(2.13)</td>
</tr>
<tr>
<td>corr var</td>
<td>0.001***</td>
<td>0.002***</td>
</tr>
<tr>
<td></td>
<td>(3.01)</td>
<td>(3.02)</td>
</tr>
<tr>
<td>corr skewness</td>
<td>-0.001***</td>
<td>-0.003***</td>
</tr>
<tr>
<td></td>
<td>(-3.54)</td>
<td>(-3.64)</td>
</tr>
<tr>
<td>mean</td>
<td>-0.009**</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(-2.28)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>variance</td>
<td>0.008***</td>
<td>0.018***</td>
</tr>
<tr>
<td></td>
<td>(6.83)</td>
<td>(9.22)</td>
</tr>
<tr>
<td>skewness</td>
<td>0.000</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.57)</td>
<td>(-1.10)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,561,211</td>
<td>1,335,357</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.475</td>
<td>0.402</td>
</tr>
</tbody>
</table>

Figure 3: Trade-off between Sharpe ratio and skewness
Figure 4: Trade-off between Sharpe ratio and skewness

Figure 5: Trade-off between Sharpe ratio and skewness

Sensitivity on correlation between labor income and asset returns